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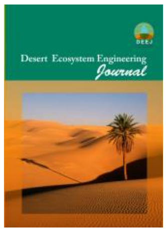

Assessment and Application of Two General Circulation Models (HadCM3 and MPEH5) for Investigating Climate Change (Case Study: Khorramabad Synoptic Station, Iran)

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Abstracts

A popular method for climate change prediction are General Circulation Models which are at coarse spatial resolution and must be downscaled. In this study, observed data of temperature, precipitation and potential evapotranspiration over a base period under two emission scenarios in three time intervals were used to implement SDSM as a downscaling tool for HadCM3 model output. From another standpoint, MPEH5 model predicts data under three emission scenarios for three future periods. Results indicated that all parameters would increase in comparison to the base period. Predictions for all periods under all emission scenarios indicated an increasing trend for all parameters, although it is predicted almost as constant precipitation trend for the future. According to predictions by both models, the greatest increase has been estimated for 2080s under A2 scenario. In SDSM model, the greatest increases in mean monthly temperature would be respectively 6.9, 4.5, 6.2 °C for July and for potential evapotranspiration would be in June by 1.08 mm per day, which are predicted in the 2080s under A2 scenario. For precipitation, the greatest reduction under the same conditions, would be in May by 0.9 mm per day. In LARS-WG model, the greatest increase in mean monthly temperature in the studied station was predicted respectively by 5.5, 5.5, 5.6 °C for August. The greatest reduction in precipitation, would be in February (by 0.88 mm per day). The future uncertainty results of predicted parameters in both models and various scenarios show that uncertainty of the predictions increase towards the end of the century.

Keywords: Climate change, HadCM3, SDSM, MPEH5, LARS-WG, Uncertainty, Khorramabad.

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Introduction

Climate change is one of the biggest future challenges of human (Spickett et al. 2011). This phenomenon is the result of increasing concentrations of greenhouse gases that make global warming. Increasing absolute humidity in the atmosphere layers near the Earth's surface causing changes in global precipitation regime for current century (Chmura et al. 2011).

Warming of the climate system is unequivocal, and since the 1950s, many of the observed changes have been unprecedented over decades to millennia. The atmosphere and oceans have warmed, the amounts of snow and ice have diminished, sea level has risen, and the concentrations of greenhouse gases have increased (IPCC 2013). According to the IPCC[5] Special Report on Emission Scenarios (SRES), global surface temperature would increases by the end of the 21st century, which is likely to exceed 1.5 °C relative to the 1850 to 1900 period for most scenarios, and is likely to exceed 2.0 °C for many scenarios (Rehan Dastagir 2014).

In most climate change studies, GCMs have been used to project future climatic variables. However, due to the limitation of GCMs to incorporate local topography (spatial and temporal scales), the direct use of their outputs in impact studies on the local scale e.g. hydrological catchments is restricted. To bridge the information for policy making and gaps between the climate model and local scales, downscaling is commonly used in practice. Dynamic downscaling and statistical downscaling are the most popular methods (Pinto et al. 2010; Schoof et al. 2009; Wilby et al. 1999). Dynamic downscaling by Regional Climate Models (RCMs) ensures consistency between climatological variables, however they are computationally expensive. Statistical downscaling models, on the other hand, are based on statistical relationships and hence require less computational time. Extensive research has been carried out with both approaches (Rana et al. 2014; Chen et al. 2012; Teutschbein et al. 2011; Willems and Vrac 2011; Maraun et al. 2010).

Numerous studies have been done in the field of climate change and its impacts in the world and Iran.

Samadi et al. (2011) conducted a research study in Khorasan Razavi province (Iran), and concluded that SDSM among several models, yields a very good simulation and its output has only 5% error. Hashemi et al. (2011) among the downscaling techniques recommended SDSM and LARS-WG models. Their results showed that both models have good ability to simulate the maximum precipitation event, so can confidently be recommended to study climate change. Zhao Yong et al. (2010) did a numerical simulation and evaluation of regional climate change in Southwest China in which a regional climate model (RegCM3), and a coupled atmosphere-ocean model MPI-OM ECHAM5 (MPEH5) were used. They concluded that those of simulations for annual precipitation average in the summer season is much better than winter and simulated amounts in winter are higher than observation. Nasoohyan et al. (2013) in a research studied the effects of climate change on precipitation and temperature in the plains of Borujen and Shahrekord during the period of 2020-2049 using two GCMs (CGCM3 and HadCM3) and downscaling model of LARS-WG for A2 and A1B scenarios. According to the results, temperature over the study areas compared to the baseline will become warmer for all the seasons. Rate of increases in average temperature during 2030s compared to the base period in Shahrekord would be 1.7°C and in Borujen approximately 1.4°C. The precipitation predictions differ from the base period in Shahrekord, so that except the HadCM3-A2 predictions which shows a decrease in precipitation, all other cases show increase in precipitation. However, in Borujen all models agree on the reduction of precipitation during the period of 2020 to 2049.

Hao et al. (2013) evaluated the ability of 22 GCMs to reproduce temperature and precipitation over the Tibetan Plateau. The results showed that, all the GCMs underestimate temperature and most models overestimate precipitation. Also, the results suggested that, the temperature and precipitation will both increase in all three periods under different scenarios, with scenario A1 increasing the most and scenario A1B increasing the least. Chen et al. (2015) using 10 climate model simulations, tested the bias stationary of climate model outputs over Canada and the contiguous United States (U.S.) by comparing model outputs with corresponding observations. Results indicated that, in comparison, temperature bias can be considered to be approximately stationary for most of Canada and the contiguous U.S. when compared with the magnitude of the climate change signal and they advised that natural climate variability and climate model sensitivity be better emphasized in future impact studies.

Mirdashtvan et al. (2017) presented a procedure that characterizes the changes of climatic variables for a period of time under representative concentration pathway (RCP) scenarios in of the

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Karaj-Jajrud in the South Alborz Range, Iran. They concluded that, there is a consistent warming in mean air temperature for all the RCP scenarios, whereas the results indicated decreasing precipitation compared with the baseline. On the other hand, analysis the impacts of the downscaling process uncertainty on the prediction results indicated that, the contribution of this uncertainty source to the prediction uncertainty is relatively high, as about 30% of the downscaled temperature and precipitation data fall inside the 95% simulation condense intervals. Salajegheh et al. (2017) compared the results of two downscaling models (SDSM vs. LARS-WG) for considering the error criteria of daily rainfall, daily minimum and maximum temperatures within two stations of Ravansar and Kermanshah. The results indicated that in either of the calibration and validation periods, SDSM model benefits from a more appropriate performance than LARS-WG in the simulation of daily minimum and maximum temperatures at the two stations, whereas LARS-WG model presents a more acceptable performance than that in the simulation of daily rainfall.

So far, various studies in the field of predicting climate change and its impacts on the national and regional level have been carried out in Iran, each of which represents harmful effects of the climate change. Lorestan province as one of the semi-arid provinces, even suffers from climate change, and many signs of these effects on natural resources, agriculture and industry can be seen. So, due to the fact that income of many people depends on natural resources, livestock and agriculture in this province, awareness of climate change process, projecting climate change in future and the introduction of a model suitable for use at national scale assessments particularly in relation to natural disasters seem to be necessary. The purpose of this study was to assess SDSM model algorithm to simulate precipitation and temperature. The obtained results show that SDSM model has very powerful algorithm, so that with noise removal in the data, it can accurately predict changes. Hence, in this study, outputs of two general circulation models HadCM3 under A2 and B2 scenarios, and MPEH5 under A2, A1B and B1 scenarios are used in order to project changes of monthly, seasonal and annual values in maximum temperature (Tmax), minimum temperature (Tmin), mean temperature (Tmean) and precipitation (Pcpn) variable until the end of the current century for the synoptic station of Khorramabad (Iran). For downscaling the outputs of HadCM3 the SDSM software is used and for MPEH5 model the LARS-WG is used. Finally, uncertainties of climate models are evaluated and compared between past period and projections in SDSM and LARS-WG models.

Materials and methods

Study area

Khorramabad synoptic station has been selected for the current study, which is located in the Lorestan Province in Iran. Khorramabad station latitude is 33° 25′ 57″ N and longitude is 48° 16′ 42″ E and altitude above sea level is 1147 m. Mean precipitation in Khorramabad station is around 509.9 mm; summer precipitation is less than the ones in winter and autumn. In this area mean annual temperature is 17.2 ℃, mean maximum temperature is 25.3 ℃ and mean minimum temperature is 9.1 ℃. Figure 1 shows the location of Khorramabad synoptic station (Meteorological Organization of Lorestan province, 2010).

Methodology

In this study general circulation climate models output of HadCM3 under A2 and B2 emission scenarios (although there are also RCP scenarios with different assumptions, but SRES scenarios are still valuable and they are applied in different studies for predicting future climate condition) are used and climate model MPEH5 under A2, A1B and B1 scenarios are used to predict changes in maximum temperature (Tmax), minimum temperature (Tmin), mean temperature (Tmean), and precipitation (Pcpn), for four analysis periods, i.e., baseline (period 1961 to 1990 for HadCM3 and period 1982 to 2013 for MPEH5), and future periods of 2010 to 2039, 2040 to 2069, and 2070 to 2099 (which are denoted as 2020s, 2050s, and 2080s, respectively). For downscaling HadCM3 output, SDSM and for MPEH5 outputs LARS-WG were used. Finally, uncertainty of climate modeling was evaluated thorough comparison of the past period and the projections in SDSM and LARS-WG models.

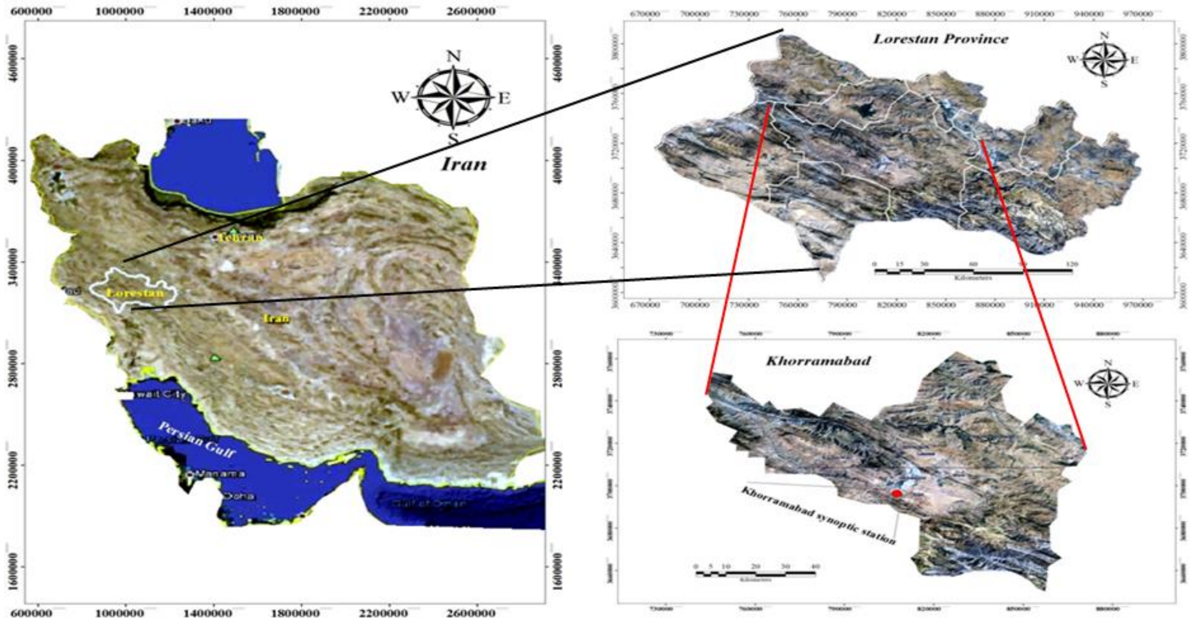


Fig 1. Khorramabad synoptic station location

Downscaling HadCM3 outputs using SDSM

To run the SDSM model, two series of observed and large-scale data of GCM are needed. First series including daily Tmax, Tmin, Tmean and Pcpn data were provided by General Directorate of Meteorological organization of Lorestan province. The second series including large-scale variables of general circulation models, e.g., HadCM3 were obtained from the Environment Canada data portal (www.cccsn.ec.gc.ca/?page=pred-hadcm3) and related websites.

In next step, the daily observed data (Tmax, Tmin, Tmean and Pcpn) were divided into two periods from 01/01/1961 to 12/31/1990 for calibration of SDSM and from 01/01/1990 to 31/12/2001 for validation of this model.

To prepare data in SDSM model each of the large-scale data files of NCEP (1961 to 2001) were used as observation for calibration and for validation of model. The data were divided into two periods of 01/01/1961 to 12/31/1990 in order to calibrate the SDSM model and period of 01/01/1990 to 31/12/2001 for validate the model. Each of the 26 large-scale data files (H3A2a (1961-2099) and H3B2a (1961-2099)) were divided in three periods 01/01/2010 to 12/31/2039, 01/01/2040 to 12/31/2069 and 01/01/2070 to 12/31/2099 in order to predict variables and period of 01/01/1961 to 12/31/1990 were used as the base period.

SDSM is a statistical downscaling tool which is used to simulate climate data in a given station under current and future conditions affected by climate change. Its data are in the form of daily time series for some climate variables such as precipitation (mm), minimum and maximum temperature (°C) and other climate parameters. In the process of downscaling in this model, a linear multiple regression develops among a limited number of large scale predictor variables and predictants at local scale like precipitation and temperature. The parameters of regression model are estimated by dual simplex algorithm. Suitable large scale predictors are selected by using correlation analyses and partial correlation between predictors and predictants in the study area (Wilby et al. 2004, Rajabi and Shabanlou 2010).

Downscaling MPEH5 outputs using LARS-WG

To run the LARS-WG for downscaling the MPEH5 model, two series of observed and large-scale data of GCM are needed. First series include daily maximum temperatures, minimum temperatures, precipitation and solar radiation (or sunshine hours) data which were prepared by General Directorate of Meteorological organization of Lorestan province. LARS-WG software has an internal database which contains more than 200 MB output of various scenarios and models.

In LARS-WG model, the observation daily data from 1/1/1982 to 31/12/2013 were used to simulate the station climate behavior. In this model, it is necessary to input files consisting of four climatic parameters minimum temperature, maximum temperature, precipitation and sunny hours. Sunny hours data of Khorramabad station are available since 1982. Hence, due to this statistical deficiency observation, data were used for simulations since 1982.

Error and uncertainty calculation in modeling of parameters

In many climate change studies, uncertainties have not been studied in estimating parameters. Hence, considering the uncertainties in evaluation stages of climate change impacts, can improve the certainty of the final output. In this study, the uncertainties in estimated climate modeling for the past period and predicted values were evaluated and compared in SDSM and LARS-WG models.

For assessing the models performances and comparing results, some necessary criteria are used, which include R^2, *RMSE*, *BIAS* and *NSE* (Nash-Sutcliffe Efficiency):

$$R^2 = \left[\frac{\frac{1}{n} \sum_{i=1}^{n} (X_{sim} - \overline{\mu_{sim}}) \cdot (X_{obs} - \overline{\mu_{obs}})}{\delta_{X_{sim}} \cdot \delta_{X_{obs}}} \right]^2$$

$$NSE = \left[1 - \frac{\sum_{i=1}^{n} (X_{obs} - X_{sim})^2}{(X_{obs} - \overline{\mu_{obs}})^2} \right] * 100$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (X_{obs} - X_{sim})^2}{n}}$$

$$\mathrm{BIAS} = \frac{\sum_{i=1}^{n} (X_{obs} - X_{sim})}{\sum_{i=1}^{n} X_{obs}}$$

where X is data, $\bar{\mu}$ is the mean of data, δ is the variance and n is the number of data, indexes *obs* and *sim* represent observation (climatic variables) and model generated prediction. The criterion R^2 shows a linear relationship between large-scale variables and downscaled data, ranging from 0 to 1, so the higher value of R^2 the stronger the relationship is. Also, other criteria show the difference between large-scale and downscaled data. Besides R^2, criteria *RMSE* and *BIAS* are used here as two creditable statistics. The lower value of *RMSE* and the absolute value of *BIAS* statistics, the stronger relationship is, indicating no specific description for their thresholds (Samadi et al. 2010, Moriasi et al. 2007).

To analyze the uncertainty in the predictions of models, box plots were also used. To draw box plots, decadal averages of predicted parameters given by the two models, under A2 and B2 scenarios for SDSM and B1, A2 and A1B scenarios for LARS-WG were used. Then the average of observed data (1961-2013), the first quantile, the distance between the first quantile and the median, distance between median and the third quantile of predictions for each studied variables are calculated in order to draw the box plots. In the Box plots the greater distance between the third quantile and the first quantile (boxes height) or the distance of the first quantile from median or the third quantile from median is, the higher predicting uncertainty is.

Results and discussions

Calibration and validation results for monthly, seasonal and annual observation and predicted parameters were compared, which are presented in the following sections. Also, the results of monthly, seasonal and annual predictions are compared for both of the models implemented over three future periods. The generic predictor sets selected in this study are summarized in Table 1.

Table 1: Selected climate predictor variables used for downscaling at Khorramabad station, for each month of the year; P stands for precipitation, T for mean temperature, I for minimum temperature, and A for maximum temperature

No	NCEP	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	Mslpf	I	I	I	IT	IT	I	I	I	IT			I
2	P5-vf		P	P	P								
3	P500f	ATP	AT	AT	A	A	AT	ATP	ATP	AP	P	ATP	AT
4	P850f				I	I				I			
5	r850f	P	P	P	P	P	P	P	P	P	P	P	P
6	Rhumf	AIT	AIT	AT	AT	AT	AIT	AIT	AIT	AT	A	I	AIT
7	Shumf	P	P	P	P	P	P				P	P	P
8	Tempf	IAT	IAT	IAT	AT	IAT	IAT	IATP	IATP	IATP	IAT	IAT	IAT

mslpf = mean sea level pressure; p5_vaf = 500 hPa meridional velocity; p500af = 500 hPa geopotential height; P850f = 850 hPa geopotential height; r850af = relative humidity at 850 hPa; rhumaf = near surface relative humidity; shumaf = surface specific humidity; tempaf = mean temperature at 2 m

The monthly, seasonal and annual comparisons between observed and simulated data during the calibration period (1961-1990) in Figure 2 (A, B, C, D and E) and validation period (1991-2001) are illustrated in this Figs F, G, H, I and J. For Tmean, Tmax, Tmin, and ETP, the simulated curves replicated the actual data using NCEP predictors fairly good, indicating that future projections would be replicated well. In the case of Pcpn the monthly, seasonal and annual values are less matched. SDSM result of downscaling the current climate (1961-90) given by HadCM3 model, comparing to actual values, will further demonstrate the ability of SDSM to produce accurate projections.

The calibrated SDSM models are used to downscale HadCM3 data to obtain 40 ensembles of synthetic daily Tmax, Tmin, Tmean, and Pcpn time series for the A2 and B2 climate scenarios for four analysis periods (baseline, 2020s, 2050s, 2080s). Monthly, seasonal and annual projections for each climate variable, as well as each three periods, as depicted in Figure 3, show a considerable variability. According to these figures, in all three periods; monthly, seasonal and annual projections for Tmax, Tmin and Tmean and both climate scenarios, compared to the baseline period show a rising trend.

In the case of precipitation, trends in monthly projections under the A2 scenario, for the 2020s except for January, November and December, for the 2050s except for January and December, and for the 2080s except for January, descends. Under B2 scenario, in the 2020s except for January and December, in the 2050s except for November and December and 2080s except for in January, in other months for each period, a decrease in precipitation have been predicted.

For calibration LARS-WG model, graphical charts and for the validation, statistical tests are used. The monthly comparisons between observed and simulated data during the calibration period (1982-2013) are shown in Figure 4 (A, B and C). For temperature, simulated curves replicated the observed data fairly good, extrapolating that future projections would also be well. For Pcpn the goodness of fit for monthly values was less good. Results of the statistical tests for validation period (1982-2013) are presented in Table 2. The results comparing the observed data with 32 yr of simulated data generated by LARS-WG for distributions of Tmax, Tmin and Pcpn monthly means and its variances. Distributions using the means and variances were compared using the t-test and F-test, respectively.

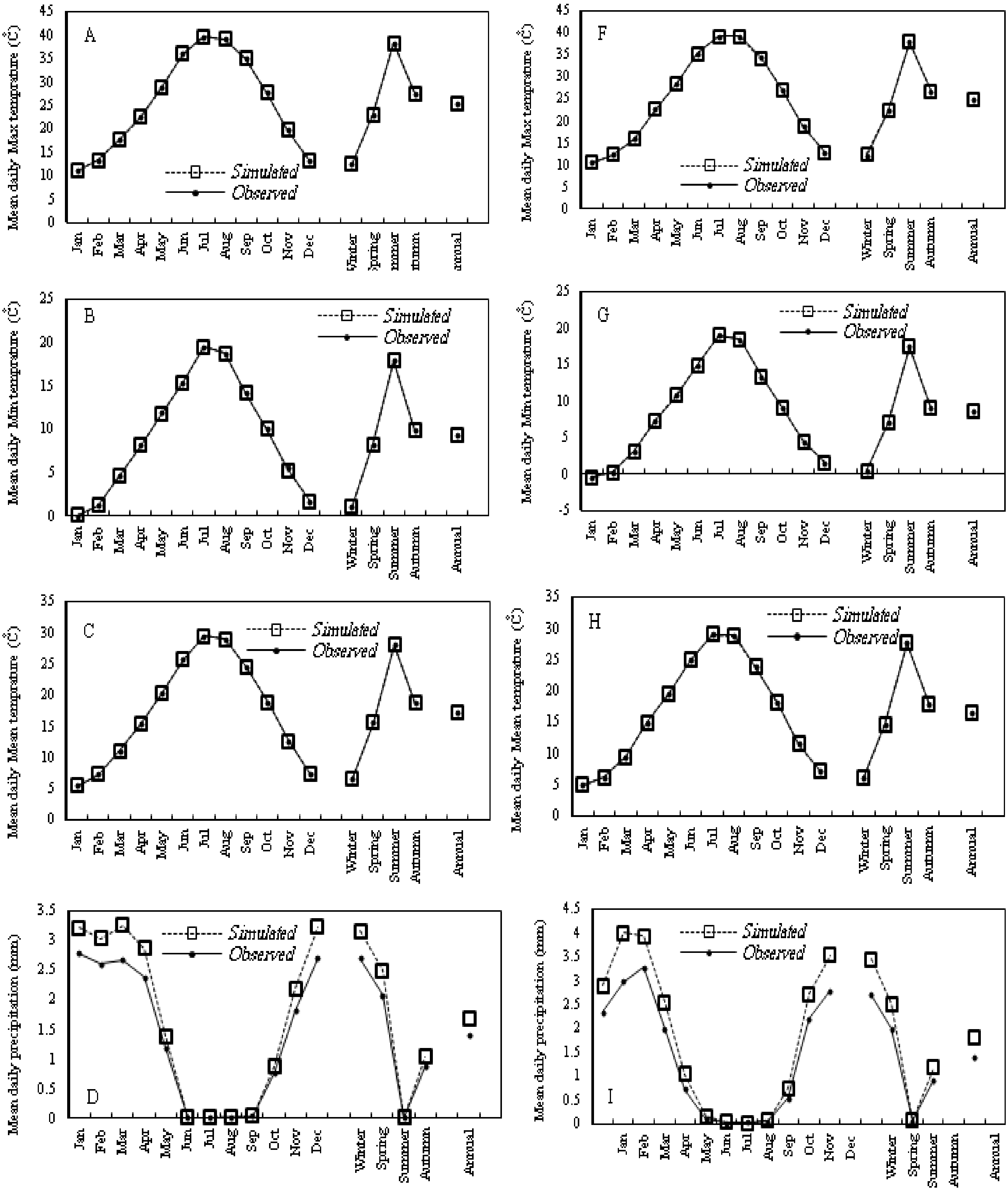


Fig 2: Comparison of daily mean observations and simulations obtained by downscaling NCEP global climate variables, for monthly seasonal and annual: Figs A, B, C and D for Calibration period (1961-90) respectively for Tmean, Tmax, Tmin and Pcpn, and Figs F,G,H and I for validation period (1991-2001) respectively for Tmean, Tmax, Tmin and Pcpn.

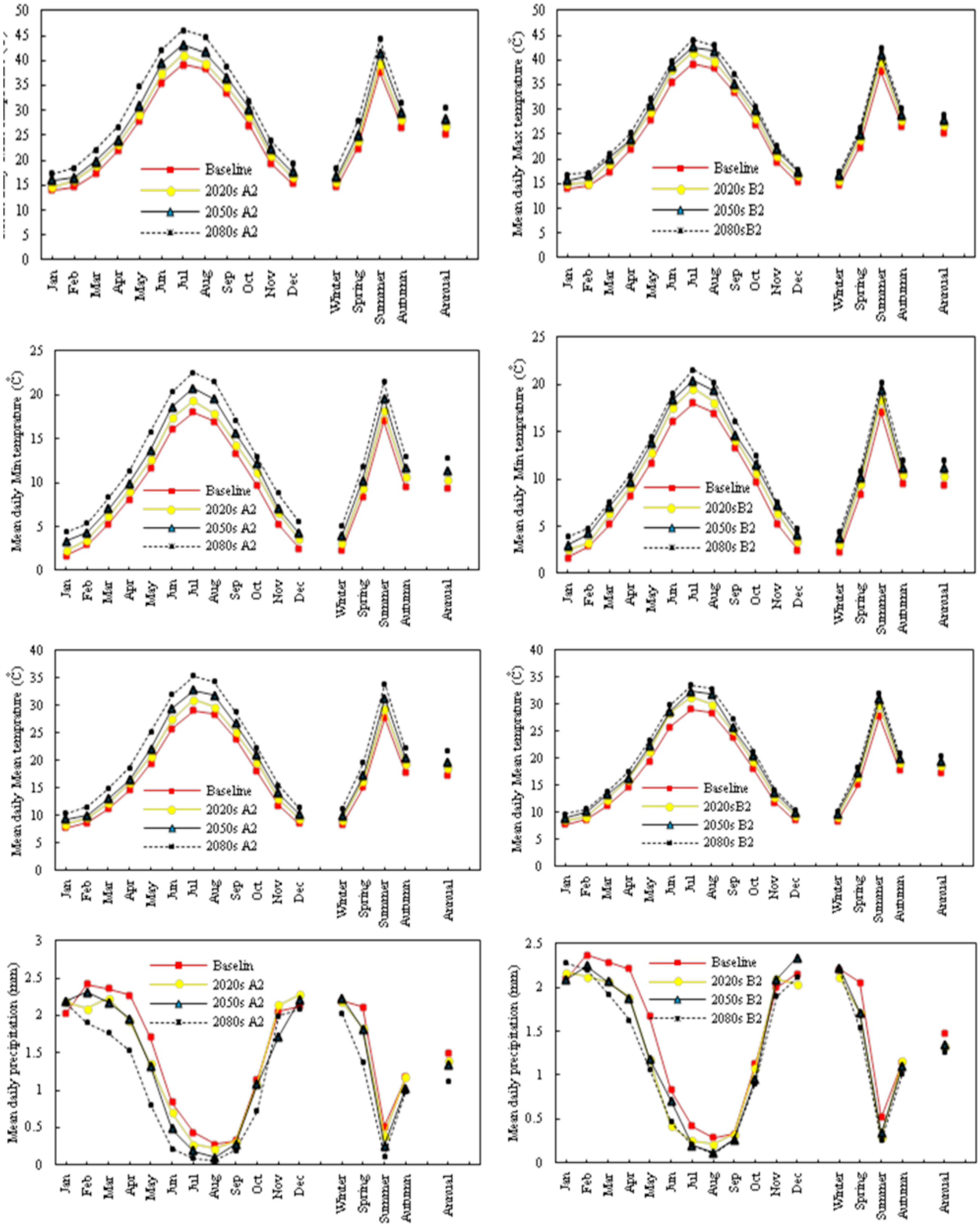


Fig 3: Monthly, seasonal and annual projection of Tmax, Tmin, Tmean and precipitation under A2 (left panel) and B2 (right panel) for 2020s, 2050s and 2080s comparing to baseline using HadCM3 model output downscaled by SDSM.

Table 2: The significance levels (p-value) calculated by the t-test and F-test for the monthly means and variances are shown. A probability of 0.05 or lower indicates a departure from the observations that is significant at the 5% level

		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Tmin (°C)	Observed	-0.9	0.3	3.23	7.18	10.92	14.61	18.67	17.95	13.04	9.14	4.35	0.64
	sd-Obse	1.454	1.587	1.469	1.065	1.312	1.98	1.729	1.911	1.468	1.933	1.328	1.639
	Simulated	-1.06	0.31	3.56	7.39	11.03	14.66	18.74	17.78	13.02	8.81	4.61	0.89
	sd-Simu	0.739	0.923	0.645	0.62	0.743	0.728	0.569	0.49	0.441	0.758	0.831	0.805
	t-statistics	0.638	-0.017	-1.282	-1.065	-0.44	-0.123	-0.236	0.551	0.083	1.007	-1.016	-0.858
	p-values	0.525	0.987	0.204	0.29	0.661	0.903	0.814	0.583	0.934	0.318	0.313	0.394
Tmax (°C)	Observed	10.61	12.67	16.91	22.44	28.69	35.83	39.35	39.04	34.65	27.44	18.58	12.66
	sd-Obse	2.091	1.845	2.407	1.736	1.659	1.285	0.84	0.855	0.847	1.581	1.789	2.119
	Simulated	10.57	12.45	16.98	22.41	29.14	35.61	39.58	39.06	34.47	27.5	18.37	12.56
	sd-Simu	0.563	0.85	1	0.724	0.624	0.457	0.355	0.373	0.476	0.891	0.997	0.768
	t-statistics	0.115	0.59	-0.152	0.108	-1.417	0.929	-1.383	-0.121	1.054	-0.203	0.555	0.246
	p-values	0.909	0.557	0.88	0.914	0.161	0.356	0.172	0.904	0.296	0.84	0.581	0.807
Pcpn (mm)	Observed	64.37	63.42	81.28	66.93	24.49	1.11	0.26	0.19	0.95	23.59	58.85	80.33
	sd-Obse	31.996	36.268	49.854	41.02	22.2	2.938	0.778	0.688	2.782	34.258	48.529	42.804
	Simulated	62.36	53.93	92.2	55.03	28.73	3.85	0.56	0.27	4.44	14.49	84.54	80.02
	sd-Simu	39.053	27.058	45.097	31.166	21.488	5.929	1.346	0.961	6.252	15.068	56.749	52.384
	t-statistics	0.225	1.186	-0.919	1.307	-0.775	-2.339	-1.077	-0.369	-2.883	1.375	-1.947	0.026
	p-values	0.823	0.24	0.362	0.196	0.441	0.023	0.286	0.714	0.005	0.174	0.056	0.979
	f-statistics	1.49	1.797	1.222	1.732	1.067	4.072	2.993	1.951	5.05	5.169	1.367	1.498
	p-values	0.273	0.108	0.58	0.132	0.857	0	0.003	0.067	0	0	0.388	0.266

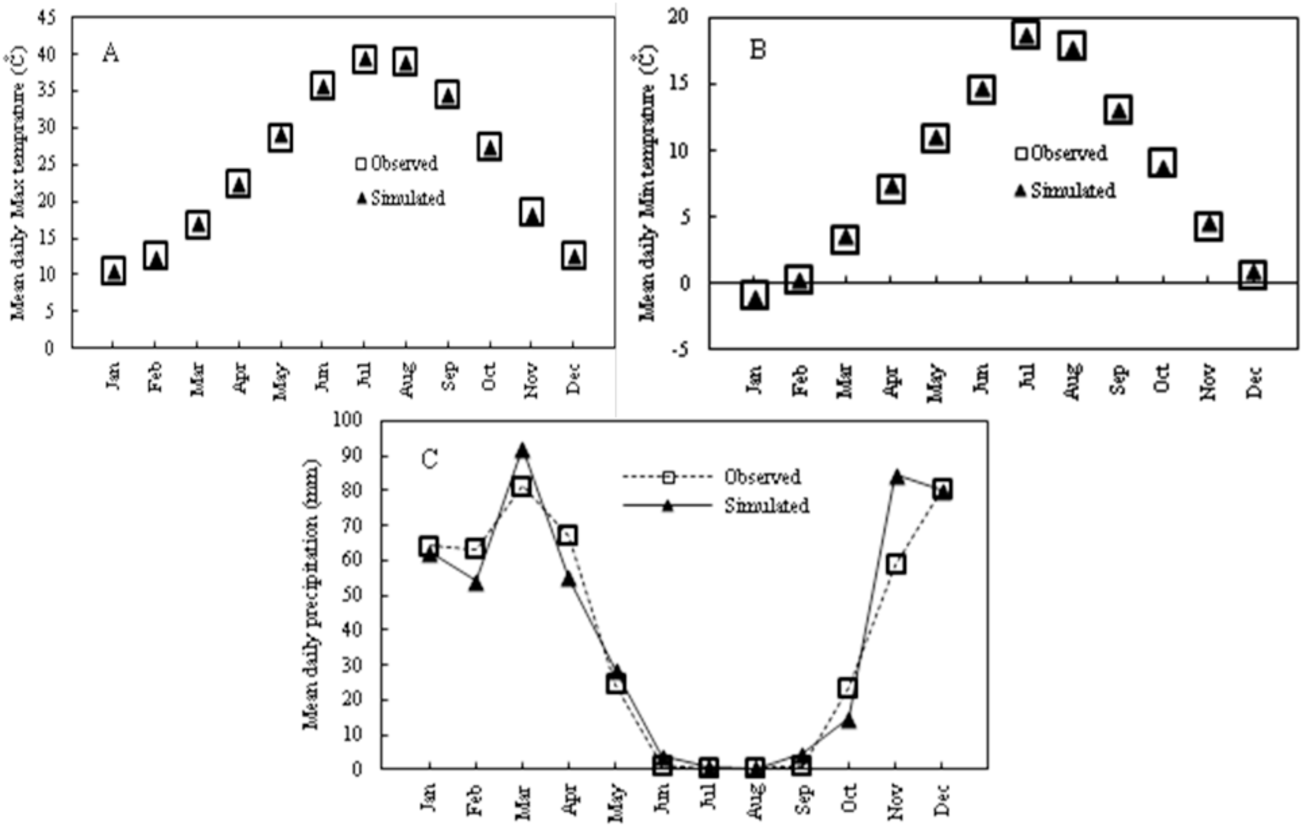


Fig 4: Comparison of daily mean observations and simulations obtained by LARS-WG, for Calibration period; (A) Tmax (B) Tmin and (C) Pcpn.

The calibrated LARS-WG were used to downscale MPEH5 data to obtain daily Tmax, Tmin,Tmean, and Pcpn time series for the A2, B1 and A1B emission scenarios and four mentioned analytical periods. Monthly, seasonal and annual projections for each climate variable, as well as the three periods were depicted in Figure 5. According to the figures, monthly, seasonal and annual projections for Tmax, Tmin and Tmean comparing to the baseline period show a rising trend, but in case of Pcpn, trend of monthly projections under the A2 scenario for the 2020s, in the months of January, February, April, October and December in the 2050s, in February, April and October, and for 2080s in January, February, March, April, May, October and December decreasing and for the other months compared to the baseline increasing have been predicted.

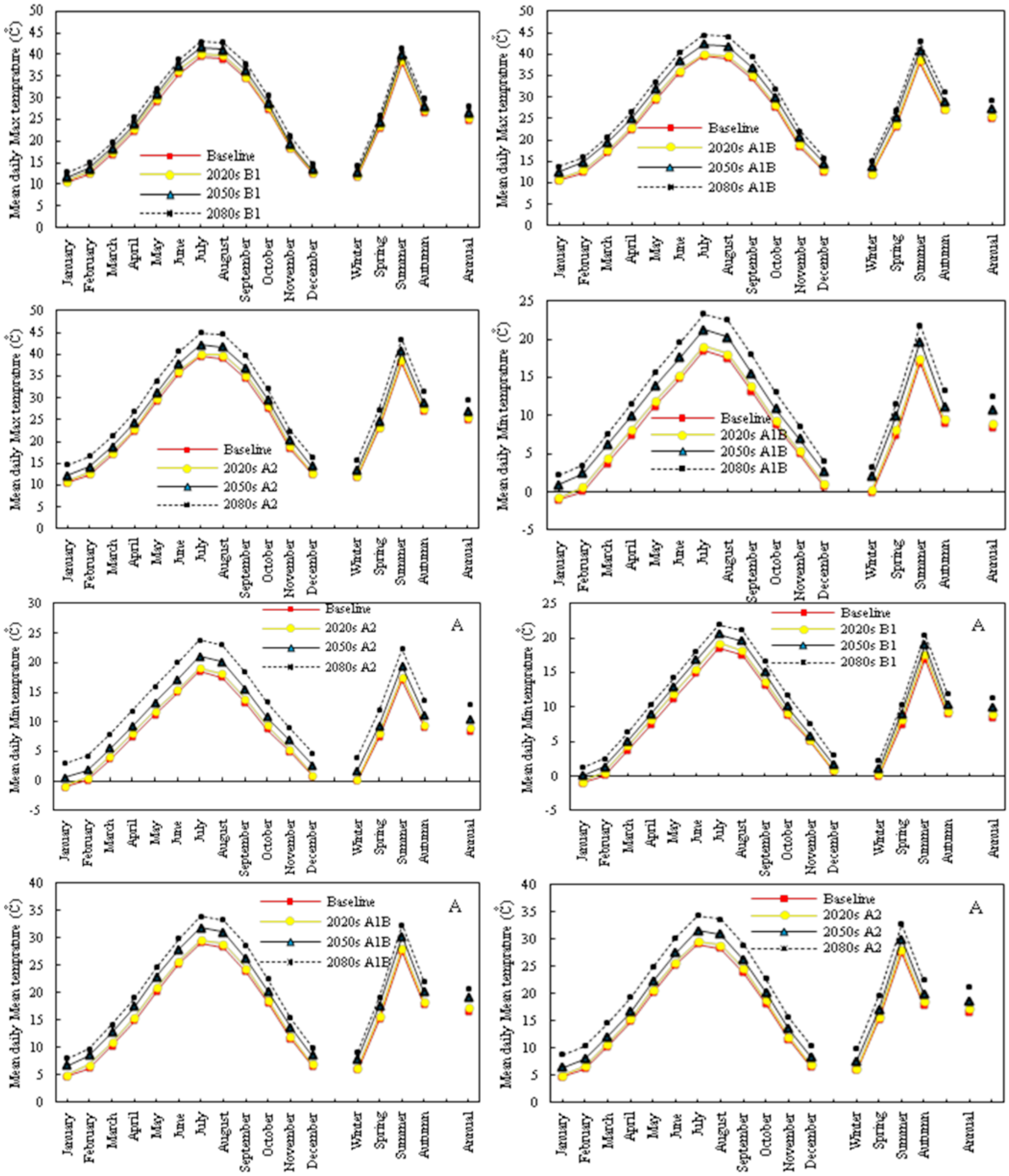
Under the B1 Scenario to the 2020s, in the months of January, February, April, October and December, for 2050s, in January, February, April and October, for the 2080s in January, February, March, April, May, October and December precipitation would decreas and in other months compared to the baseline precipitation would increase. Under the A1B scenario for the 2020s, in the months of January, February, April, May and October, during the 2050s, in January, February, March, April, October and December, and during the 2080s in January, February, March, May, October and December, decreasing precipitation and in other months increasing precipitation have been predicted.

Annual Pcpn projections under the A2 scenario for 2020s and 2080s decrease is predicted, but in 2050s they increased. Under the B1 scenario for 2020s and 2080s increase is predicted and for 2050s is unchanged under the A1B scenario for 2020s and 2080s increased is predicted, and for 2050s would decrease.

For error analysis in modeling of the past period using the SDSM and LARS-WG, criteria of R^2, RMSE, Bias and NSE were used for Tmax, Tmin, Tmean and Pcpn. Results are summarized in Table 3. The calculated R^2 for Tmax, Tmin and Tmean for SDSM were greater to the one which was obtained by LARS-WG, whereas this criterion for Pcpn obtained using the LARS-WG is greater. This shows a stronger relationship between the two groups of data modeled by LARS-WG. For Tmax, Tmean and Pcpn variables, calculated RMSE values for SDSM obtained greater than the values calculated for LARS-WG outputs, indicating less errors and higher accuracy of modeling for the SDSM. For Tmin variable, RMSE for LARS-WG became greater than the one for SDSM, showing less errors and higher accuracy in modeling with LARS-WG. For Tmax,Tmin, Tmean and Pcpn variables, Bias values for SDSM and LARS-WG were close to zero, indicating a high accuracy of modeling for both models. Negative sign in Bias values shows that the model has underestimated the true values. For Pcpn, NSE is obtained for both models close to +1, in which 1 corresponds to a perfect match of modeled values to the observed data. However, the NSE obtained for LARS-WG greater than the one obtained for SDSM, which indicates a stronger correlation between the two groups in LARS-WG model.

Table 3: Comparison the performance of SDSM and LARS-WG using statistical indices

Parameter	Model	NSE	Bias	R^2	RMSE
Tmax	SDSM	–	0	0.955	2.8
	LARS-WG	–	0.01	0.839	0.2
Tmin	SDSM	–	0	0.856	2.8
	LARS-WG	–	0.1	0.838	0.3
Tmean	SDSM	–	0	0.933	2.26
	LARS-WG	–	0.02	0.835	0.64
Pcpn	SDSM	0.646	-0.2	0.748	3.9
	LARS-WG	0.993	-0.1	0.838	0.1


Mean daily Max temprature (°C)
Baseline
2020s B1
2050s B1
2080s B1
Mean daily Max temprature (°C)
Baseline
2020s A1B
2050s A1B
2080s A1B
Mean daily Max temprature (°C)
Baseline
2020s A2
2050s A2
2080s A2
Mean daily Min temprature (°C)
Baseline
2020s A1B
2050s A1B
2080s A1B
Mean daily Min temprature (°C)
Baseline
2020s A2
2050s A2
2080s A2
A
Mean daily Min temprature (°C)
Baseline
2020s B1
2050s B1
2080s B1
A
Mean daily Mean temprature (°C)
Baseline
2020s A1B
2050s A1B
2080s A1B
A
Mean daily Mean temprature (°C)
Baseline
2020s A2
2050s A2
2080s A2
A
January
February
March
April
May
June
July
August
September
October
November
December
Winter
Spring
Summer
Autumn
Annual

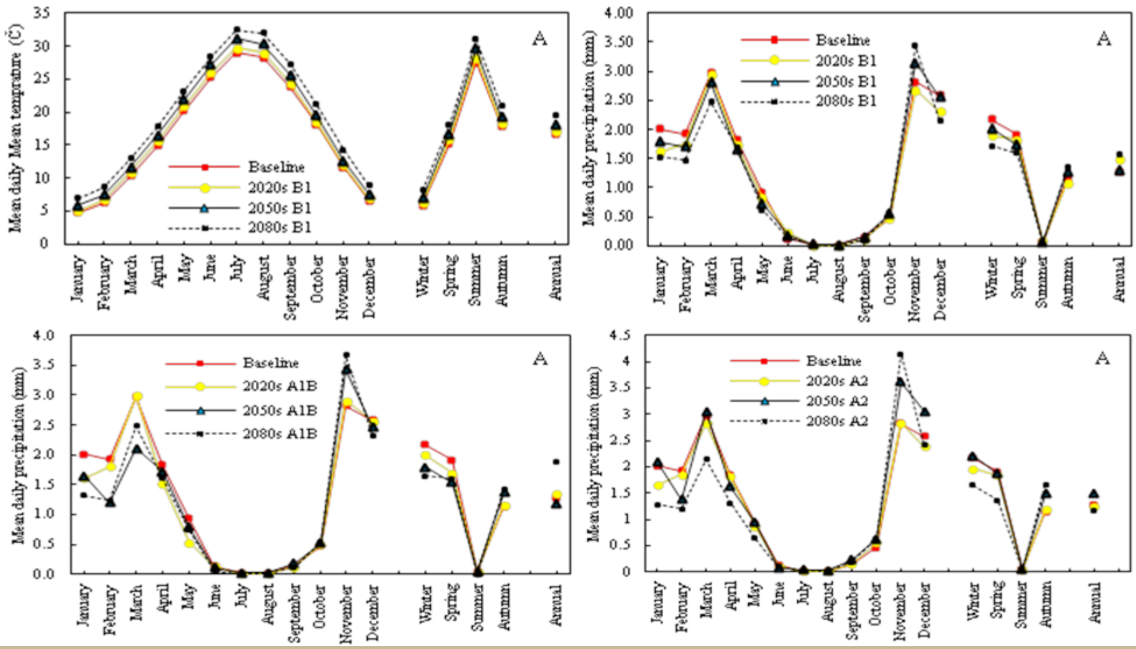


Fig 5: Monthly, seasonal and annual projection of Tmax, Tmin, Tmean and precipitation under B1, A1B and A2scenarios for 2020s, 2050s and 2080s comparing to baseline using MPEH5 model output downscaled by LARS-WG

Uncertainty results of the variables predicted by SDSM and LARS-WG are shown in the form of charts Boxplots in Figure 6. In the right panel, one can be seen, the range of uncertainty increases as prediction period increases in all variables. It can also be seen that the uncertainty in predicted variables Tmax, Tmin and Tmean, increase up to the last decade of the current century, i.e. 2091 to 2100, meaning the trust in the predictions becomes less. Also, in the left panel height of boxplots increase, which also indicates an increasing trend in uncertainty of predictions. Boxes height is very low in decades before the 2060s which indicates a low range of uncertainty in predictions, while the range of uncertainty increases in decades after the 2060s. About precipitation, uncertainty in some of decades is high and in some of decades is low. This can be explained by the fact that precipitation is a conditional parameter which influenced by many factors, whereas temperature is an unconditional variable, and it is less affected by climatic anomalies and other factors.

In Table 4 the distance between first and third quartile (height of boxplots) shows amounts of uncertainty in predictions which increases from the past to future. According to the table, the greatest uncertainty is related to decades of 2070, in which variables of Tmax, Tmin and Tmean, are predicted 28.2 ℃ with error of 2℃ for Tmax, 11.4℃ with error of 2.3℃ for Tmin and 19.9℃ with error of 1.8 ℃ for Tmean. Also, the maximum uncertainty for precipitation calculated for the period 2050s, in which the precipitation is predicted from 2 to 9.1 mm per day. The greatest uncertainty of Pcpn is related to period of 2050s, which is 2 mm/day with an error of 1.9 mm/day.

Table 4: The range of uncertainty in each prediction periods for Tmax, Tmin, Tmean and Pcpn

Decade / Parameters	2010s	2020s	2030s	2040s	2050s	2060s	2070s	2080s	2090s
Tmin (˚C)	9.2	9.2	9.4	10.2	10.2	10.3	11.4	11.5	11.5
uncertainty range	0.5	0.6	0.6	0.6	0.5	0.6	2.3	2.1	1.7
Tmax (˚C)	25.7	25.9	25.9	26.8	26.9	27.2	28.2	28.3	27.6
uncertainty range	0.1	0.6	0.7	0.5	0.4	0.4	2	1.7	0.5
Tmean (˚C)	17.4	17.5	17.6	18.5	18.5	18.7	18.7	19.9	19.9
uncertainty range	0.3	0.7	0.7	0.5	0.5	0.6	1.8	1.5	1.2
Pcpn (mm)	1.6	1.4	1.7	2	1.9	1.9	1.8	1.7	1.7
uncertainty range	0.5	0.3	0.4	0.8	0.7	0.8	0.3	0.5	0.6

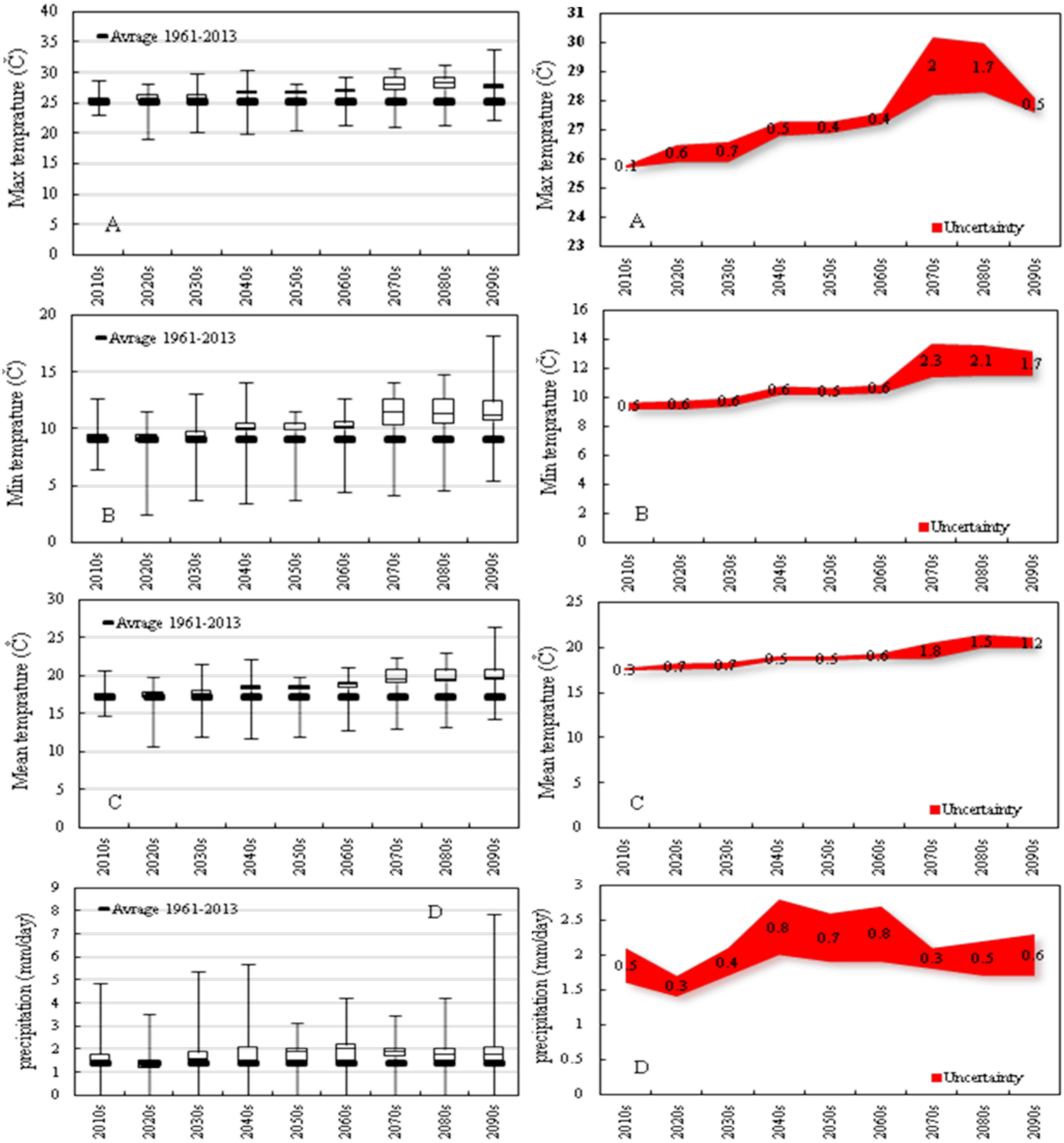


Fig 6: Box plot charts for evaluating model predictions uncertainties: (A) Tmax, (B) Tmin, (C) Tmean and (D) Pcpn

Conclusion

In current study, for evaluating and predicting climate change at Khorramabad synoptic station, HadCM3 and MPEH5 with different scenarios have been used and downscaled using SDSM and LARS-WG, alternatively. The major findings of this study are summarized and discussed as follows:

1) Results of calibration and validation of monthly, seasonal and annual show an acceptable accordance between observations and simulations. The calibrated models were also validated for its ability to predict Tmax, Tmin, Tmean and Pcpn. The validated results for both models showed good performance and ability of two models in the modeling of all under investigation parameters.

2) In this research, the high ability of LARS-WG model, to generate daily data, confirms research conducted by Semenov and Barrow

(2002) and Elshamy et al. (2005). Ability of SDSM model also confirmed research conducted by Rajabi and Shabanlou (2010), Ashraf et al. (2011) and Dehghanipoor et al. (2011) in other regions of Iran.

3) Predictions of Precipitation in future indicate that overall Precipitation may decrease, although there appears to be no consistent trend in the predictions of monthly, seasonal and annual. However, climate change effects on Tmax, Tmin and Tmean are more pronounced, and the results show that three parameters in three predicted periods increased when comparing to baseline period.

4) For error analysis of SDSM and LARS-WG, criteria of R^2, RMSE, Bias and NSE for Tmax, Tmin, Tmean and Pcpn variables have been used. Results indicated a high and strong correlation between observation and simulation. The results of uncertainty analysis of two GCMs, showed that in general, when predictions approach the last decades of present century, the uncertainty of predictions would increase. The most error of predicted variables of Tmax, Tmin and Tmean is related to decade of 2070s, the error value for each variable respectively 2, 2.3 and 1.8℃. In Pcpn, the maximum error is related to two decades of 2060s and 2040s, that the amount of both is equal to 0.8 mm per day.

5) According to the results, criteria of error comparison (R^2, RMSE, Bias and NSE), SDSM model does modeling variables with less errors and more accuracy. Due to large contribution of GCM models, in uncertainty of downscaling models, it can be concluded that HadCM3 has better performance than the MPEH5 in the area of Khorramabad.

6) In general, predicted monthly, seasonal and annual Tmax have the greatest increase compared to the baseline period in both GCMs, under A2 scenario and in the period of 2080s. Under the same conditions, pcpn would decrease in most months and seasons, and in a small number of months would increase.

7) In both GCM models, the greatest increase is predicted for Tmax, Tmin, Tmean for HadCM3 and MPEH5 respectively in July and August and in summer under A2 scenario, and in the period of 2080s. Based on the results of global warming is proved to be, and the temperature increases in most of months, especially in the warmer months of year and the summer season will be evident in the study area.

8) Both downscaling models predict Pcpn with high precision, but LARS-WG powered to be more precise than Tmax, Tmin, Tmean and Pcpn. In this study, Tmax, Tmin and Tmean data has the high correlation to two GCMs compared to Pcpn. Consequently, daily Pcpn is the most problematic variable to study because it is a conditional parameter.

Although using acceptable results have been calculated with both models, the number of additional GCMs exist for assessing precipitation in Khorramabad stations and evaluating the ability of other related models for investigation climate change have been suggested.

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