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Comparison of Different Global Climate Models and Statistical Downscaling Methods to Forecast Temperature Changes in Fars Province of Iran

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Abstract

In order to find a suitable climate model to forecast future temperature change in Fars province of Iran, three different Global Climate Models (GCMs); that is HADCM3 with scenarios A2 and B2, CCCMA-A2 and ECHOG with scenario A2a, were compared on coordinate point and whole area basis. GCM temperature variable was taken from Internet (http//www.cera-dkrz.de) and local measured minimum and maximum temperature were taken from 27 Synoptic Weather Stations (1989-2007) in Fars province and neighbouring areas. For downscaling GCMs, a variation of different regression models, namely; linear, second order, third order and multiple linear regression of stepwise type were tried in the form of 6 Methods using a detailed error analysis. In our study, the variables were minimum and maximum temperature and GCM model selection criteria were MSE and SS (Skill Score). The results showed that GCM model selection for the area depended on selection criteria and the kind of variable (being either minimum or maximum temperature). In most parts of the area, CCCMA-A2 was the best with the least error for minimum temperature and ECHOG-A2a for maximum temperature. Also, multiple linear regression of stepwise type, among other regression models, proved to be the best method of downscaling having the least error in all comparisons.

Six methods were then used to obtain temperature from 1950 to 2100. Results of the multiple linear regression of step wise type as the best method showed that the average monthly temperature in the control run (1995-2009) was 292.83 and for future period (2085-2099) was 297.95 degrees Kelvin showing temperature increase of 5.12 degrees for the next 90 years.

Keywords: GCM outputs, climate model, downscaling, error, minimum and maximum temperature, multiple regression, weighing technique, stepwise

1. Introduction

Recent use of fossil fuels, human life activity and technological developments have led to climate change on a world wide scale according to NRC (National Center for Atmospheric Research) and IPCC (Inter-governmental Panel on Climate Change) reports. Increase of green house gases has caused the temperature of the earth to sharply increase in recent decades and expected to increase in the coming future. This non-periodical increase can have different effects on climate of various parts of the world in different manner (David, Piercea, Barnetta, Benjamin, Santerb, & Glecklerb, 2009). Also, different climate change may have different effects on water resources (Beldring et al., 2006; Fowler et al., 2007; Hamlet et al., 2009; Misra et al., 2003; Wilby et al., 2006; Chen et al., 2003).

The main problems facing the researchers are how to downscale GCM outputs to consider the local effects and selection of suitable GCM model in any area to decrease the model errors involved (Jones et al., 1980; Hamlet et al., 2009; Hoar, 2008; Wilby et al., 2006). Due to large variability of GCM models and their outputs from different organizations throughout the world, care should be taken while selecting the models; one model may give good results in one area or point and the other one may give unacceptable errors in the same area considering the downscaling methods used. Thus the source of error can come from downscaling method on one hand and selection of the model itself on the other. Pros and cons of different GCM models and downscaling methods other than statistical are discussed in in various articles (Hoar & Nychka, 2008; Davis et al., 2009) and also by NRC and IPCC reports.

It is assumed that selecton of a GCM model variable on the fly for an area without a previous study on its suitability can cause eronious results. As an assumption in our study, there may be no specific GCM model for the south west of Iran and downscaling method is also of concern. The motivation, therefore, behind this research is two fold; first to find the specific GCM model for the area and second to find the suitable downscaling method for maximum and minimum temperature to adjust for local effects for the south west of Iran. In the latter case, different regression equations were tried to select a suitable downscaling method for the area.

2. Materials and Methods

2.1 Study Area and Selection of Common Interpolating Coordinates

The study area is located in south western Iran and extends in 50-55.375 degrees longitude and 26-33 degrees latitude. Figure 1 shows the area along with the major downloaded GCM points and local weather stations.

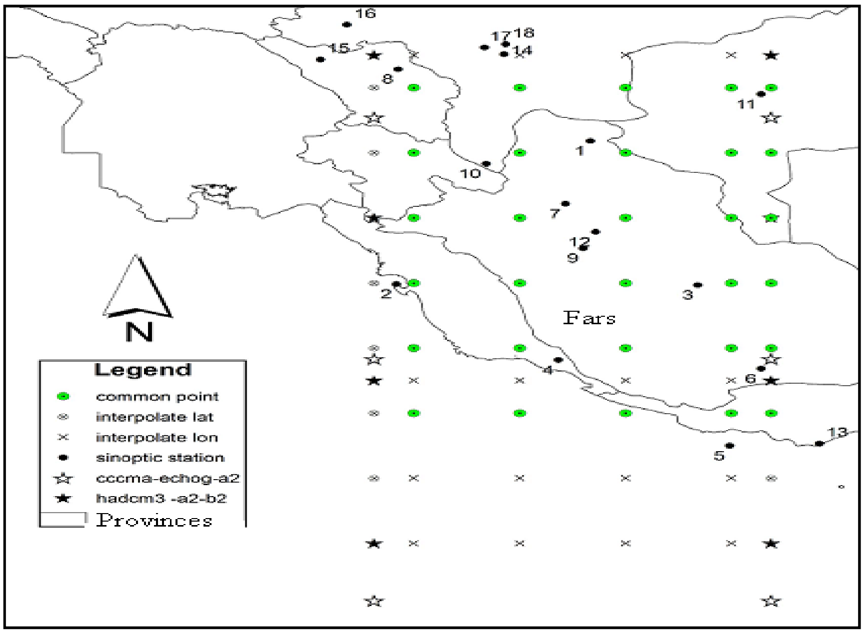

Figure 1. Graghical representation of the study area in south western Iran showing original and interpolated GCM locations along with Synoptic stations

Table 1 shows coordinates of different GCM models at which the data were downloaded.

Table 1. Coordinates of available downloaded GCM temperature data covering the area. Each box indicates a geographic coordinate point

GCM	Latitude-Longitude			
HADCM3 A2	32.5-50.625	30-50.625	27.5-50625	25-50.625
HADCM3 B2	32.5-54.375	30-54.375	27.5-54.375	25-54-375
ECHOG-A2	35.256-50.625	31.545-50.625	27.833-50.625	24.122-50.625
	35.256-54.375	31.545-54.375	27.833-54.375	24.122-54.375
ECHOG-B2	35.2556-50.625	31.5445-50.625	27.8334-50.625	24.1223-50.625
	35.2556-54.375	31.5445-54.375	27.8334-54.375	24.1223-54.375

Using these coordinates, the new coordinates common to all GCM models and measured data were constructed (Table 2).

Table 2. Coordinates of common points interpolated for each GCM model and measured data covering the area used for comparison purposes

Latitude-Longitude				
32 : 51	32 : 52	32 : 53	32 : 54	32 : 54/375
31 : 51	31 : 52	31 : 53	31 : 54	31 : 54/375
30 : 51	30 : 52	30 : 53	30 : 54	30 : 54/375
29 : 51	29 : 52	29 : 53	29 : 54	29 : 54/375
28 : 51	28 : 52	28 : 53	28 : 54	28 : 54/375
27 : 51	27 : 52	27 : 53	27 : 54	27 : 54/375

The common points (green)are also shown in Figure 1. The original GCM coordinates were linearly interpolated based on $1^o \times 1^o$ to get the common points. Temperature variable time series of three different global climate models; HADCM3 with scenarios A2 and B2, CCCMA-A2 and ECHOG with scenario A2 were taken from Internet (http//www.cera-dkrz.de). Resolution of the first model was $3.75^o \times 2.5^o$ $(367.5 \times 295\,Km^2)$ and the other two were $3.75^o \times 3.711^o$ $(367.5 \times 438\,Km^2)$. The temperature data were interpolated using the following relations (Aghajanzadeh, 2010):

$$TLa_N = \frac{(La_N - La_I) \times (TLa_F - TLa_I)}{(La_F - La_I)} + TLa_I \tag{1}$$

$$TLo_N = \frac{(Lo_N - Lo_I) \times (TLo_F - TLo_I)}{(Lo_F - Lo_I)} + TLo_I \tag{2}$$

where Lo and La are longitude and latitude, indices F, I and N correspond to coordinates of end, first and interpolated points, T is the temperature in respect to coordinates. Equations 1 and 2 are used to interpolate points for latitudes (columns) and longitudes (rows) respectively.

2.2 Measured Local Data and Interpolating Corresponding Points to GCM Outputs

Average monthly measured temperature data for 1989-2007 were taken from 27 weather stations (Iranian Synoptic Weather Organization) located within $50 - 55.375$ degrees longitude and $26 - 33$ degrees latitude of the study area. Only 18 stations which had common data in the period were selected. A detailed preprocessed time series data analysis consisting of finding lost data points using regression analysis, test of temporal data homogeneity using Double Mass analysis, test of stochastic nature of temperature data using Run Test technique were performed for further certainty purposes (Aghajanzadeh, 2010). There were no temporal outlier points in the data. Local temperature data were so determined to correspond with GCM data points using IDW (Inverse Distance Weighted) weighing method:

$$D_i = \sqrt{((Lo_N - Lo_S) \times 98)^2 + ((La_N - La_S) \times 118)^2} \tag{3}$$

$$W_i = \frac{1/D_i}{\sum_{i=1}^{n} 1/D_i} \tag{4}$$

Where indices S and N are, respectively, stations and interpolated points(i.e., common points), Di is the distance between S and N points, N is the number of stations within 1 degree (lat. & Lon.) of the interpolated GCM points, numbers 89 and 118 are equatorial distance (lat. and lon. respectively obtaind by the area map) in kilometer, Wi is the weight of each station. Therefore, for each GCM data point, the number of weather stations used in weighing method was between 1 to 6 each having a weight between 0 to 1. The weight of each station used in IDW method is given elsewhere in details (Aghajanzadeh, 2010). Finally, 27 common points out of 30 for which measured temperature data existed were used in comparing GCM models. The weights were applied to the time series of each station data and summed up according to Equation 4 so as the interpolated points to have a new time series corresponding to GCM point time series. In this way, number of temporal data points were

1800 (150 years) in 27 spatial locations, whereas, number of temporal measured data points were 228 (19 years; 1989-2007) in 27 spatial locations. This period is devided into tow periods; one is for calibration (1989-2005) and the other for validation (2006-2007). GCM and measured maximum and minimum mean monthly temperature were compared separately in the study.

2.3 Model Selection Criteria

Mean Squared Error, MSE and Skill Score, SS given in Equations 5 and 6, respectively, were the criteria for comparing measured and GCM data. However, to eliminate the effects of data unit and scattering in the error analysis (David et al., 2009), MSE was converted to SS (Skill Score) according to Equation 6:

$$MSE(m,o)=\frac{1}{N}\sum_{k=1}^{N}(m_k-o_k)^2 \tag{5}$$

$$SS=1-\frac{MSE(m,o)}{MSE(\mu,o)}\ ;\ SS<1 \tag{6}$$

Where m is GCM data, μ is the mean observations and o is observed value, N is the number of observations and k is data index. It should be noted that whenever SS is closer to unity, it shows a better model capability. In case of zero SS, the model predicts temperature variable around mean observations. Percent error was calculated as follows:

$$\%Error=\frac{|\bar{o}-\bar{m}|}{\bar{o}} \tag{7}$$

2.4 Downscaling Methods

A variation of linear, second order, third order and multiple linear regression equations were tried with 3 GCM models to define six downscaling Methods. These Methods are so defined to be referenced easily in the text.

Method 1-Raw GCM model data were first compared with local measured data at each point and depending on errors calculated, the best model was selected for that point. The selected model was then downscaled using linear, second and third order regression equations. The best regression model was selected with the highest correlation coefficient R^2.

Method 2- Three GCM models were directly downscaled separately at each point using linear, second and third order regression; the best regression model was selected with the highest R^2. Finally, all models for each point were compared with observations whichever had lowest error was selected for that point.

Method 3-Applying weights to the raw GCM outputs according to their respective errors and then downscaling the new time series according to the following equations (Aghajanzadeh, 2010; David et al., 2009):

$$W_i=\frac{e_i}{\sum_{i=1}^{4}e_i} \tag{8}$$

$$e_i=\frac{MSE(\mu,o)}{MSE(m,o)}=\frac{1}{1-SS}\ ;\ i=1,2,3,4 \tag{9}$$

$$Nm=\sum_{i=1}^{4}W_i\times m_i\ ;\ i=1,2,3,4 \tag{10}$$

Where W_i is the weight of each GCM model for each point, Nm is the new and m_i is the four old time series data for each point (that is a total of 1800 values for 150 years at each point for new data). Equation 10 was used to convert the old to new time series of the selected GCM model. New time series data were then downscaled using linear, second and third order regression analysis. The best regression model was selected for each point.

Method 4-Applying weights to downscaled outputs S_i (instead of m_i in method 3) and then the new time series were downscaled again(double downscaling). Equations 8 to 10 were used accordingly as discussed in method 3.

The only difference is that Equation 11 is used instead of Equation 10 in which a new parameter S_i is introduced here. The methods 3 and 4 may be called weighing techniques.

$$Nm' = \sum_{i=1}^{4} W_i \times S_i \tag{11}$$

Method 5-Direct downscaling of outputs using multiple linear regression of the stepwise type in all GCM raw data using Equation 12:

$$DS = b_0 + \sum_{i=1}^{4} b_i \times m_i \tag{12}$$

Where b is the regression coefficient which could either be zero or non-zero. Four GCM models (i=1,2,3,4) were used in this method for each point. Each point, however, might need 1 to 4 GCM model to get the highest regression coefficient.

Method 6-The downscaled GCM data from Method 2 were downscaled again applying multiple linear regression of the stepwise type to already downscaled GCM data (double downscaling). Equation 13 is used for double downscaling:

$$DS' = b_0 + \sum_{i=1}^{4} b_i \times S_i \tag{13}$$

where S_i, downscaled data, were selected from Method 2. Briefly, for each point, 1 to 4 already downscaled GCM models were downscaled again using multiple linear regression of the stepwise type. Therefore, in methods 5 and 6, step wise multiple regression technique was used for downscaling. It should be noted that in all above mentioned downscaling methods, a point error analysis was first performed and was averaged over entire area to get a better picture of model selection.

3. Results and Discussion

3.1 Error Analysis

Error analysis for all coordinate points and entire area was performed and only typical results are shown here. The errors are based on MSE and SS appropriately. A typical point error analysis based on SS for CCCMA-A2 is given in Table 3 which shows that for each coordinate point certain error is obtained; therefore, different models may be selected for each point.

Table 3. Typical error analysis results based on SS for CCCMA A2 minimum temperature variable as compared with measured data (1989-2005)

Lat/Lon	51	52	53	54	54.375
32	0.8119	0.8341	0.8038	-0.1169	-0.2093
31	0.8542	0.8297	0.8048	0.1100	0.0365
30	0.8630	0.7900	0.7259		
29	-1.9358	0.8546	0.8099	0.7255	0.6943
28	-1.5594	-0.2144	0.2506	0.4739	0.4115
27		-0.0666	-2.0949	-2.4583	-2.4239

The range of errors is from -2.4583 to 0.8630 on SS basis. Range of errors, values of MSE and SS are all given in Table 4 for minimum and maximum temperature when comparing all raw GCM models.

Table 4. Comparison of GCM model temperature variable with different selection criteria (1989-2005)

Models	Min. MSE	Max. MSE	MSE over area	Min. SS	Max. SS	SS over area
			Minimum Temperature			
CCCSM3-A2	6.6799	130.4608	47.33	-2.4583	0.8630	0.02
ECHOG-A2a	16.0736	215.7153	109.87	-3.4230	0.7888	-1.2
HADCM3-A2	5.1999	196.1556	47.65	-3.0220	0.901	0.13
HADCM3-B2	4.8637	198.3750	47.62	-3.0675	0.9057	0.12
			Maximum Temperature			
CCCMA A2	17.3229	86.4460	35.93	-0.3158	0.8058	0.5
ECHOG-A2a	3.9219	63.0972	15.54	0.3157	0.9554	0.8
HADCM3-A2	6.4315	58.6877	28.84	0.2377	0.9282	0.61
HADCM3-B2	8.0748	57.2878	28.30	0.2519	0.9098	0.62

Minimum and maximum MSE and SS for minimum and maximum temperature are given in this table. The errors averaged on entire area are also given in this table. Based on mean MSE and SS over the entire area, CCCMA-A2 and HADCM3-A2 were the most suitable model for minimum temperature, respectively(shaded boxes in the Table 4). However, HADCM3 A2a was the most suitable based on the criteria mentioned. Table 5 shows appropriate model for points for minimum temperature which were used in downscaling Method 1.

Table 5. Models for each point having maximum SS for minimum temperature, Method 1, (1989-2005)

	51	52	53	54	54.375
32	CCCMA-A2	HADCM3-B2	HADCM3-B2	ECHOG-A2	ECHOG-A2
31	CCCMA-A2	CCCMA-A2	HADCM3-B2	ECHOG-A2	ECHOG-A2
30	CCCMA-A2	CCCMA-A2	HADCM3-A2	-	-
29	HADCM3-A2	CCCMA-A2	CCCMA-A2	CCCMA-A2	HADCM3-A2
28	HADCM3-B2	HADCM3-B2	CCCMA-A2	CCCMA-A2	CCCMA-A2
27	-	HADCM3-B2	HADCM3-B2	HADCM3-B2	HADCM3-B2

The empty boxes in this table are because no measured data were available at these points. Similar table was obtained for maximum temperature. Table 6 shows average weight of each GCM model over entire area for minimum and maximum temperature which indicates different model contribution to the area whether the model being raw or downscaled.

Table 6. Average weight of each GCM model for Method 3 and 4 (weighting Methods)

Models	W_i			
	Method 3		Method 4	
	Tmin	Tmax	Tmin	Tmax
CCCMA-A2	0.3402	0.1488	0.3093	0.0874
ECHOG-A2a	0.1525	0.4488	0.1164	0.4532
HADCM3-A2	0.2529	0.201	0.2879	0.2265
HADCM3-B2	0.2544	0.2014	0.2865	0.2329

Models CCCMA-A2 and ECHOG-A2a had more weight depending on downscaling method and minimum or maximum temperature. For example, comparing Method 3 and 4 and considering minimum temperature, CCCMA-A2 had nearly 34% and 30% weight, respectively. The errors for all raw GCM models are given in Table 7 for validation period (2006-2007).

Table 7. Error values of raw GCM models for entire area and validation period. Tmin and Tmax are minimum and maximum temperature

Models	2006–2007			
	MSE		SS	
	Tmin	Tmax	Tmin	Tmax
CCCMA-A2	47.7853	38.1010	0.0121	0.4810
ECHOG-A2a	118.9524	14.1343	-1.3703	0.8156
HADCM3-A2	53.9809	31.0899	-0.0001	0.5799
HADCM3-B2	54.3870	28.8593	-0.0023	0.6130

The errors for calibration period (1989-2005) are given in Table 4 discussed previously. Errors for minimum and maximum temperatures along with the type of selection criteria are also given in these Tables. Table 7 shows that for validation period and minimum temperature, based on both criteria, CCCMA-A2 is the most suitable but ECHOG-A2a is the most suitable when predicting maximum temperature. The errors, therefore, depend on selection criteria and the GCM variable being minimum or maximum temperature. The point is that for minimum temperature with SS criteria, Tables 4 and 7 do not give the same exact results. Downscaling methods were also compared and the error values are given in Tables 8 and 9 for both calibration and validation period, respectively. In calibration period, the methods differ depending on MSE or SS, and minimum or maximum temperature. Method 5 is the most suitable for this period. In validation period, method 5 is preferred (Shaded area in Tables 8 and 9).

Table 8. Error values of different downscaling methods for calibration Period. Tmin and Tmax are minimum and maximum temperature (Degrees, K)

Methods	1989–2005			
	MSE		SS	
	Tmin	Tmax	Tmin	Tmax
Method1	44.6683	38.5038	0.1729	0.4588
Method2	46.9830	37.9614	0.1303	0.4764
Method3	16.2622	39.5832	0.6750	0.4999
Method4	3.5566	3.3157	0.9266	0.9572
Method5	1.6674	3.0798	0.9681	0.9597
Method6	1.6987	3.2071	0.9675	0.9581

Table 9. Error values of different downscaling methods for validation period. Tmin and Tmax are minimum and maximum temperature (Degrees, K)

Methods	2006–2007			
	MSE		SS	
	Tmin	Tmax	Tmin	Tmax
Method1	45.2790	39.5010	0.1637	0.4467
Method2	48.5031	38.5605	0.1019	0.4713
Method3	19.6730	39.0506	0.6107	0.5132
Method4	4.6136	4.0862	0.9050	0.9460
Method5	2.3335	3.8310	0.9546	0.9487
Method6	2.4495	3.9826	0.9526	0.9467

Percent errors for all raw and downscaled GCM models are summarized in Table 10 for both periods.

Table 10. Percent error for all GCM models and downscaling methods averaged over entire study area for two periods

Model	% Error			
	2006–2007		1989–2005	
	Tmin	Tmax	Tmin	Tmax
CCCMA-A2	40.56%	16.79%	76.14%	7.27%
ECHOG-A2a	64.14%	10.62%	24.08%	10.40%
HADCM3-A2	22.66%	15.01%	24.40%	9.97%
HADCM3-B2	22.97%	14.56%	12.29%	10.60%
Methods				
Method 1	13.52%	12.83%	26.90%	9.32%
Method 2	18.63%	14.38%	16.04%	10.50%
Method 3	13.79%	15.91%	7.32%	4.21%
Method 4	11.36%	7.66%	6.43%	4.27%
Method 5	9.57%	7.48%	6.33%	4.36%
Method 6	9.72%	7.58%	20.65%	22.35%

Table 11. Priority of GCM models and downscaling methods for entire area and validation period (2006-2007)

	MSE		SS	
Models	Tmin	Tmax	Tmin	Tmax
CCCMA-A2	6	7	7	8
ECHOG-A2a	10	4	10	4
HADCM3-A2	8	6	8	6
HADCM3-B2	9	5	9	5
Method1	5	10	5	9
Method2	7	8	6	10
Method3	4	9	4	7
Method4	3	3	3	3
Method5	1	1	1	1
Method6	2	2	2	2

This Table shows that method 5 has the lowest percent error compared to other methods. As far as the raw GCM model comparison is concerned, the GCM model selection are based on selection criteria(MSE or SS) and the type of variable (here minimum or maximum temperature) as expected (see Tables 4 and 7). Model selection priority is also given in Table 11 for validation period. This Table also emphasizes that downscaling method 5 has the first priority for the study area and priority of raw GCM data selection are based on selection criteria type (MSE or SS) and the GCM variable, minimum or maximum temperature. The priority of the GCM models and downscaling methods for calibration period gives the same results (Aghajanzadeh, 2010) (data not shown).

3.2 Graphical Model Comparison

Comparison of three raw GCMs using monthly average observed minimum and maximum temperature are given in Figures 2 and 3 respectively, for validation period.

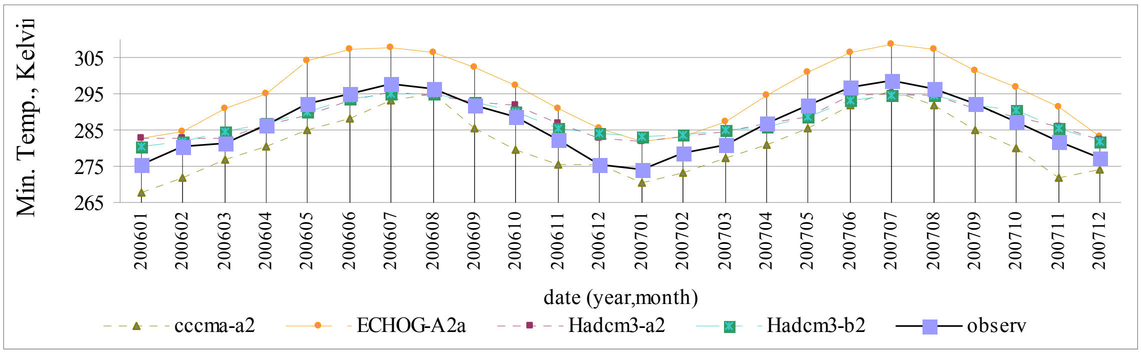

Figure 2. Comparison of different raw GCM models in validation period for average monthly minimum temperature (2006-2007)

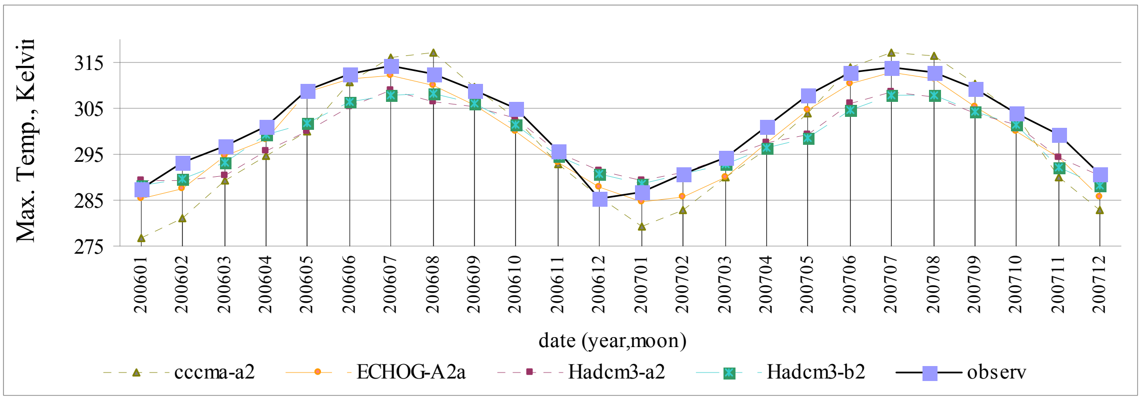

Figure 3. Comparison of different raw GCM models in validation period for average monthly maximum temperature (2006-2007)

Comparisons of six downscaling methods are given in Figures 4 and 5 for minimum and maximum temperature and validation period, respectively.

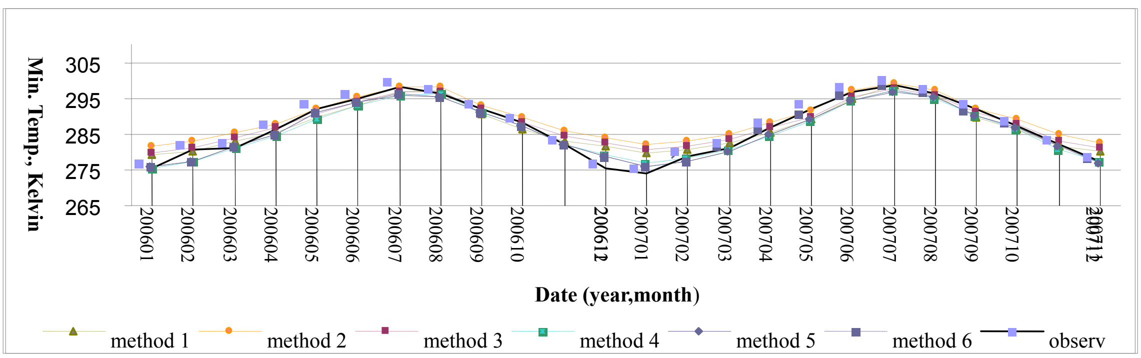

Figure 4. Comparison of different downscaling methods for average monthly minimum temperature (2006-2007)

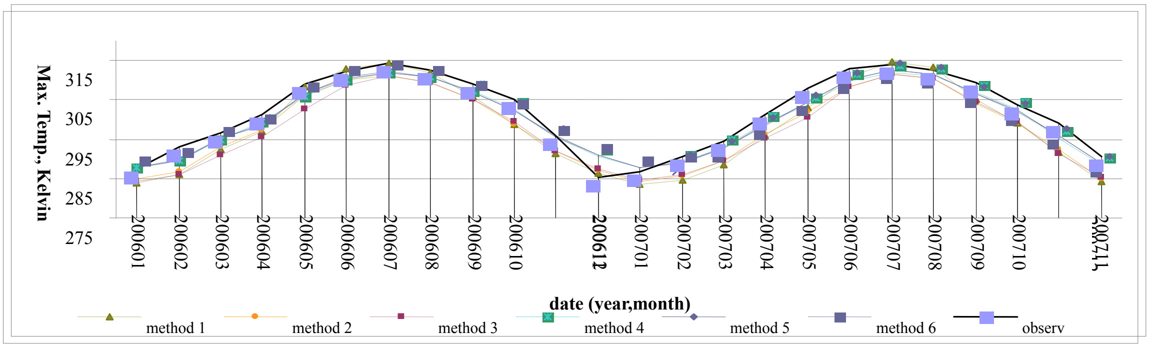

Figure 5. Comparison of different downscaling methods for average monthly maximum temperature (2006-2007)

Monthly average minimum and maximum temperatures are used to correspond to Figures 2 and 3. Graphical comparison of using raw and downscaled GCM models in the area indicates the need for downscaling before using the GCM models for local study. When no downscaling is done, the errors are high (about 26% for both calibration and validation period according to Equation 7) since the local effects such as terrain elevation and plant cover are not accounted for. Due to downscaling (i.e., using Method 5 and for validation period) these effects are considered and the errors are greatly diminished to about 9.57% and 7.48% for minimum and maximum temperature, respectively. Other downscaling methods, however, show a declining error trend somewhat different from the above compared to raw GCM models (Table 10).

Scatter diagrams comparing observed and estimated minimum and maximum temperature averaged over entire area for 1989-2005 and 2006-2007 periods were constructed for all GCM models and downscaling methods. Typical results for downscaling Methods 5 and 6 are given in Figures 6 and 7 for mean monthly maximum temperature, respectively.

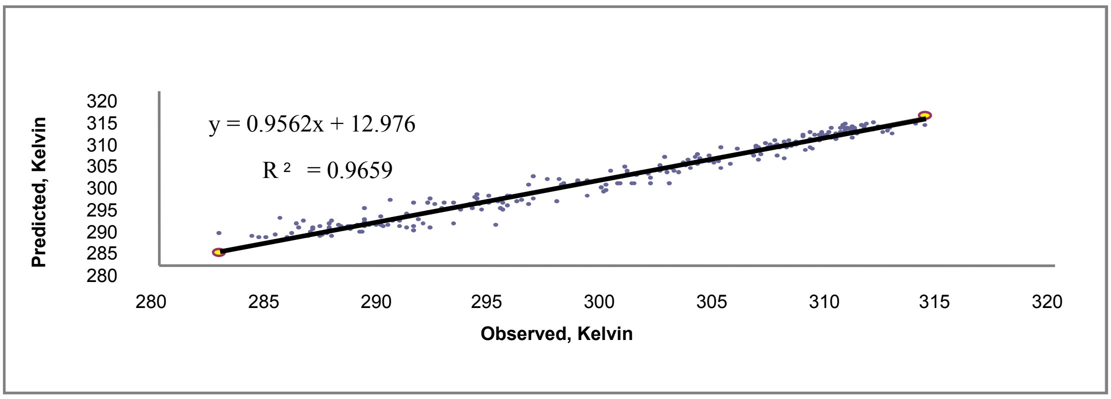

Figure 6. Scatter diagram for downscaling Method 5 for average monthly maximum temperature (1989-2005)

The regression equations and R^2 values for each diagram are shown in the Figures. Method 5 in Figure 6 as expected shows the best fit for maximum temperature with a R^2 value of 0.9659. This value for Method 6 is 0.9651. Also, the best fit for minimum temperature was ascertained for Methods 5 and 6 (Figures 8 and 9).

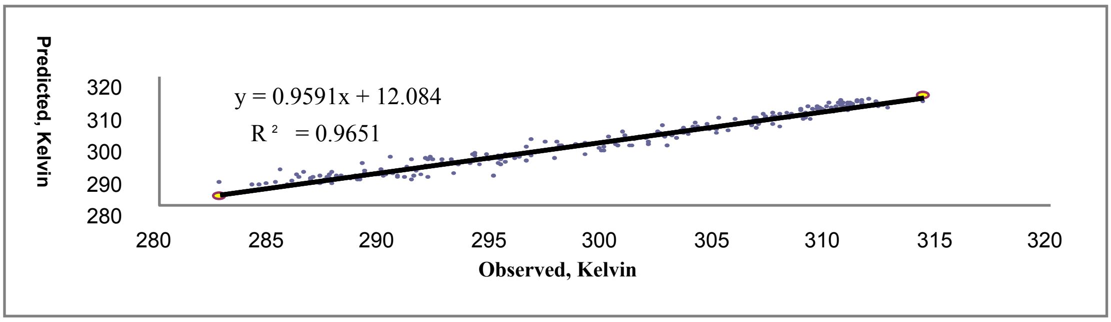

Figure 7. Scatter diagram for downscaling Method 6 for average monthly maximum temperature (1989-2005)

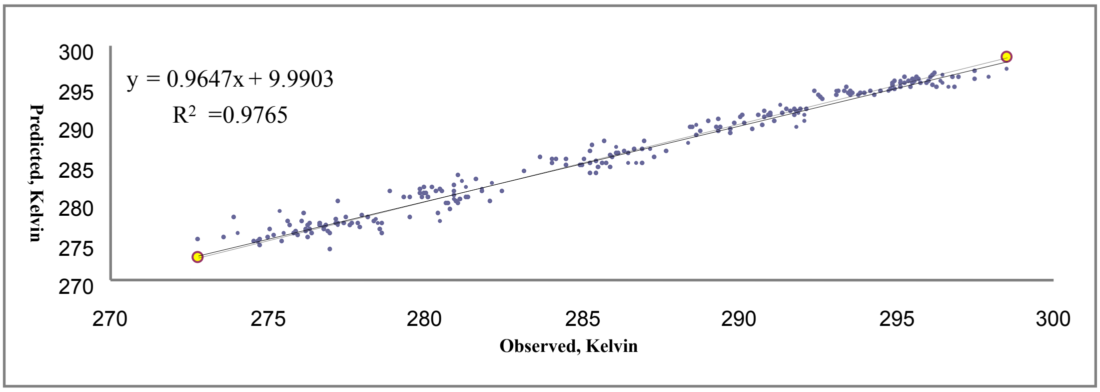

Figure 8. Scatter diagram for downscaling Method 5 for average monthly minimum temperature (1989-2005)

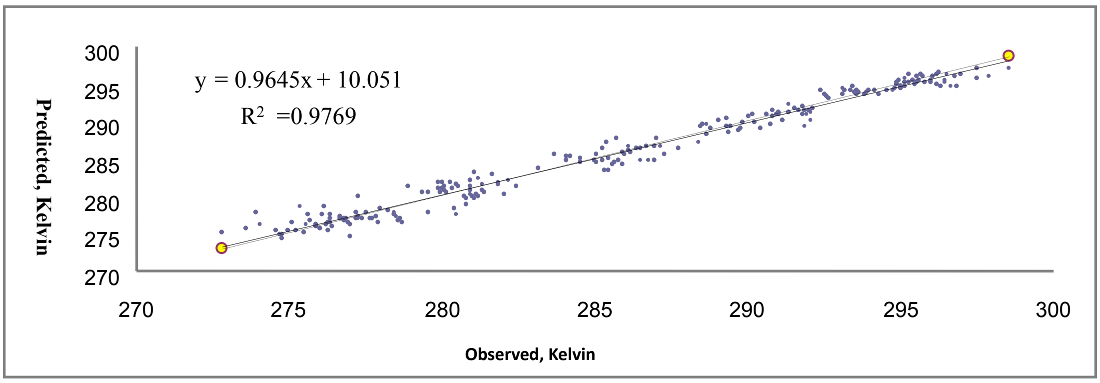

Figure 9. Scatter diagram for downscaling Method 6 for average monthly minimum temperature (1989-2005)

Briefly speaking, the results indicate that the multiple linear regression of stepwise type for downscaling GCM data in our study area is superior to linear, second and third order regression equations used in Methods 1 through 4.

3.3 Forecasts

Using all downscaling Methods already discussed, monthly and yearly minimum and maximum temperatures of the study area were predicted for period 1950 to 2100. A 15 year average of temperature data for 1950 to 2100 is typically shown in Figure 10 where the average temperature is calculated as follows:

$$Average \quad Temp = \frac{\overline{T}\, min + \overline{T}\, max}{2} \tag{14}$$

Since suitable regression equations were selected in calibration period for downscaling purpose, we have to use the same downscaling equations for future study to ascertain identical relationship between GCM and local temperature data. All downscaling Methods shown in this Figure indicate an overall average 4.91 degrees centigrade increase from present period or control run (1995-2009) to last 15 year period (2085-2099) in future for the study area. Separate data analysis indicated that temperature increase from present period to last 15 year period was 4.82 for minimum and 5.42 degrees for maximum temperature using Method 5 downscaling. The increase, however, depends on downscaling method and the GCM model type used in the study area (Table 12).

Table 12. Temperature increase using different downscaling methods from present (1995-2009) to future (2085-2099) in the study area. Temperature unit is in degrees Kelvin

Methods	Tmin Present	Tmin Future	Tmin increase	Tmax Present	Tmax Future	Tmax increase	Average Increase
Method 1	286.9154	290.8326	3.91721	298.1605	305.212	7.051527	5.484368
Method 2	289.172	293.0478	3.875824	297.6666	303.3017	5.635078	4.755451
Method 3	287.6803	291.4034	3.723104	297.2718	302.6302	5.35842	4.540762
Method 4	285.6941	290.0068	4.312736	300.0185	304.5322	4.513699	4.413217
Method 5	285.8574	290.674	4.816637	299.8011	305.2247	5.423676	5.120157
Method 6	285.8635	290.7341	4.8706	300.0366	305.4611	5.424597	5.147599
Average	286.8638	291.1165	4.252685	298.8258	304.3937	5.567833	4.910259

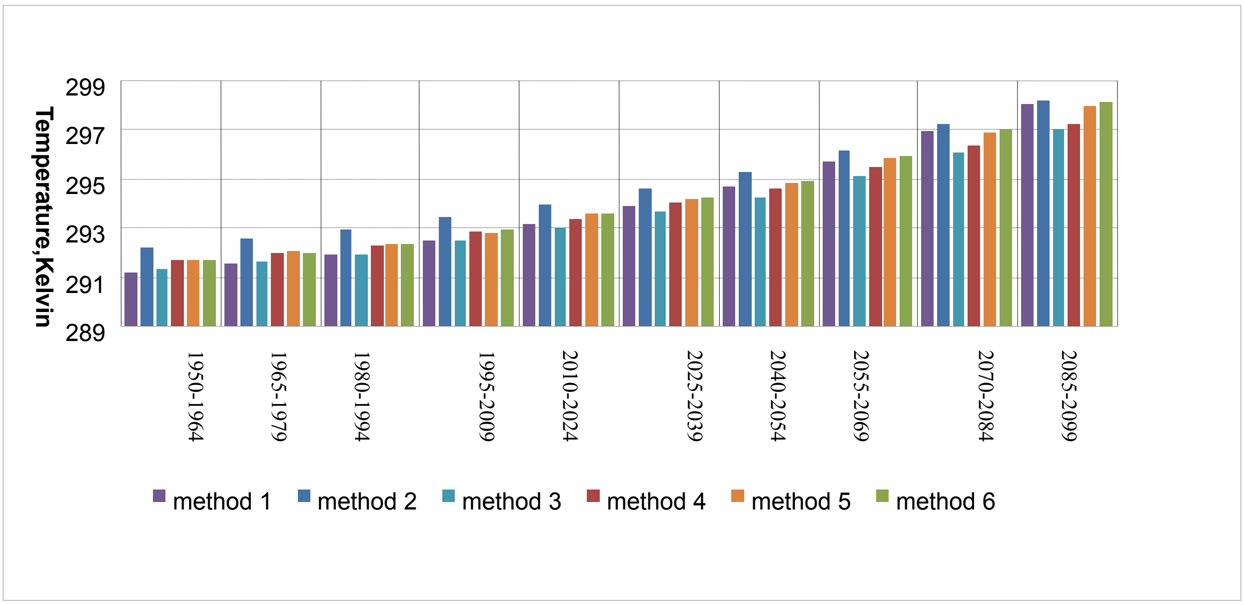

Figure 10. 15 year average of mean temperature change in the study area (1950-2099)

4. Conclusion

The significant finding of the study is that selection criteria (i.e., MSE or SS), type of regression equations for downscaling, type of variable retrieved from GCM models(in this case, minimum or maximum temperature) all can affect the type of GCM model selection in south west of Iran. Among all the regression equations used in this study, multiple linear regression of stepwise type proved to have the best fit. GCM temperature data downscaled with this regression equation was then used to obtain temperature from 1950 to 2100. The average monthly temperature for control run (1995-2009) was 292.83 and for future period (2085-2099) was 297.95 degrees Kelvin showing temperature increase of 5.12 degrees for the next 90 years.

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