The Analysis of Climate Change Uncertainty by Means of SDSM Model (Case Study: Kermanshah Province, Iran)

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ABSTRACT
SDSM downscaling model is used as a tool to downscale weather data statistically. Global Circulation Models (GCM) provide the best information about climate change regarding to greenhouse gasses increase. Applying downscaling models, GCM outputs change into variable with the scale of under study basin. In the present study, prediction of climate change model was carried out according to 3 scenarios, A2, B2, and A1 based on 2 global circulation models, HadCM3 and CGCM1. Bootstrap method has been used to estimate accuracy amount and statistics sample distribution. This method is based on data resampling idea which has been developed during the recent years using computers. In order to investigate uncertainty, bootstrap confidence intervals were calculated for estimated means and variances of daily weather parameters in every month. The predictor variables of CGCM1 model did not create an acceptable correlation with precipitation; therefore, precipitation data were downscaled only by HadCM3. The uncertainty of the means and variances in the minimum and maximum daily temperature of CGM1 model were less than HadCM3, and were closer to the observed data. The daily precipitation of the observed data in most months had less uncertainty than HadCM3. The precipitation in HadCM3 increased up to 54% in A2 scenario, and 51.5% in B2 scenario during 2010-2039 time period. The minimum and maximum daily temperature in all scenarios will increase during 2010-2039 time period.

Keywords: Bootstrap, circulation model, downscaling model, GCM, precipitation.

Abbreviations:
GCM: Global Circulation Models; SDSM: Statistical Down Scaling Model.

INTRODUCTION
Climate change is spreading slowly all over the world and affecting its related parameters. It is predicted that the process will also continue in future. According to Global Circulation Models (GCM), which simulate the climate of the earth, the temperature of the earth will increase about 1 to 3.5°C by the year 2100. The effects of climate change on hydrological cycle are in the form of changes in water level in ground waters, aquifers, lakes, and also change in the amount and temporal distribution of precipitation and rivers runoff (IPCC, 2000). In IPCC’s fourth assessment report (AR4), climate experiences in several GCMs, and different circulation scenarios were run according to many data sets of climate change projects in future by 18 global modeling groups (Semenov and Stratonovitch, 2010). Using downscaling techniques, GCM outputs can be changed into surface variables at the scale of the basin under study. Downscaling, in general, is defined as a relationship creator factor between large-scale cycles (predictors) and the climate variables at the local scale (predictands) (Wilby and Dawson, 2004).

SDSM (Statistical Down Scaling Model) has been developed by Wilby et al. (2002) as a tool for statistical downscaling. The basis of this model is multiple regression. It is used to predict climate parameters such as precipitation and temperature in a long period with regard to the weather large-scale signals. Since in statistical downscaling model, building meteorological data is performed by combining the two probabilistic and regression methods, in classifying different downscaling models, statistical downscaling model is among the best models (Wilby et al., 2002; Artler et al., 2013). IPCC (2014) predicted climate change model by carrying 3 scenarios (A2, B2 and A1) among the presented scenarios in SRES.

In an analysis, Lane et al. (1999) predicted that climate change can increase the runoff in regions with high latitude due to an increase in precipitation and snow melting. But in regions with
low latitudes a decrease in runoff is expected. Khan et al. (2006) evaluated the uncertainties seen in the downscaled results of daily precipitation and minimum and maximum daily temperatures which were obtained from three downscaling models, namely SDSM statistical downscaling model, LARS-WG, and ANN Artificial Neural Network. The results of the evaluation of uncertainty indicates that SDSM was capable of maintaining the different statistical characteristics of observed data at the 95% confidence level for downscaled data better than other models.

Hreiche et al. (2007) investigated the climate change effects on water resources of Lebanon catchments. They concluded that by using MEDOR rainfall runoff model and climate models, for every two degrees increase in the environment temperature, the maximum discharge flow would happen 2 months sooner. They also concluded that the droughts would happen 15 days to a month sooner. Semenov (2008) studied the ability of Lars-WG weather generator model for simulating the extreme weather events using 20 stations data all over the world with different climates. The 95% confidence intervals (CI95) were calculated for the statistics under study. The maximum yearly means and the amounts of the return period of the synthetic daily precipitation were placed in the 95% confidence intervals (CI95) of the observed data. But the maximum daily temperature data were produced with a less accuracy, and for about half of the stations the synthetic data means were placed out of the 95% confidence interval. The aim of the present study is long-time prediction of precipitation and temperature in a single site during different time periods by applying different scenarios.

MATERIALS AND METHODS

Data:
There are 23 meteorological stations in Kermanshah province, Iran. Regarding the fact that weather parameters of the base period in 1960-2000 were calculated by circulation scenarios, the data of the stations which possess daily data in this period are usable. Thus, the only station which possesses enough data in this period is Kermanshah synoptic station which was regarded as the index station. The data of the predictors were received from Canadian Climate Change Impacts Scenarios Group (CCISG) site, and all the data were normalized.

Stochastic Downscaling Model (SDSM):
SDSM is a statistical weather generator which is used for simulating the weather data in a given station under the current and future conditions under the effect of climate change. Its data are in the form of daily time series for some weather variables such as precipitation (mm), minimum and maximum temperature (°C), and other weather parameters. The parameters of the regression equation are estimated by dual simplex algorithm. Suitable large-scale predictors are selected by correlation analyses, partial correlation, and also by regarding the physical sensitivity between the predictors and the predictands, in the catchment under study.

This model is produced in the form of a monthly model for daily precipitation data which is produced in 12 regression equations for the 12 months of the year. In this model, precipitation is modelled in the form of a conditional process; it means that the precipitation amount will have correlation with the wet days. These wet days have correlation with weather predictors at the local scale. Temperature is modelled in the form of an unconditional process. In such situation, it is considered that there is a direct relation between the predictors and the predictands.

Uncertainty Evaluation in Downscaled Data:
Efron presented bootstrap method to estimate the accuracy amount and sample distribution of the statistics in 1979. It is based on the idea of resampling of data that bootstrap method has developed by using computers during the recent years. If \( x_1, \ldots, x_n \) iid are from \( F \) and are estimated by \( \hat{F} \), by replacing \( \hat{F} \) by \( F \) of the bootstrap estimator, the variance of \( T \) is calculated as follows:

\[
\text{var}(T_n(x_1, \ldots, x_n) \mid x_1, \ldots, X_n) = E'[T_n - E'(T_n)]^2
\]

in which \( \{X_1^*, \ldots, X_n^*\} \) is a iid sample from \( \hat{F} \), and is called the bootstrap sample, and \( \text{var}(\{X_1^*, \ldots, X_n^*\}) \) is a conditional variance with \( x_1, \ldots, x_n \) condition.

The above equations are usually complicated and \( \text{var}(T_n) \) is not an explicit function from \( x_1, \ldots, x_n \). Therefore, Monte Carlo method is used for approximation. Thus, bootstrap method is a combination of two methods: Substitution Principle and Monte Carlo approximation. When \( \text{var}(T_n) \) is an explicit function of \( x_1, \ldots, x_n \), bootstrap equates exactly with classical substitution principle, otherwise bootstrap uses Monte Carlo approximation for approximation (Di Cicco and Efron, 1996).

Confidence intervals present some information about the uncertainty of estimating mean and variance in estimating means and variances. The present study makes use of the most common nonparametric method, bootstrap for finding the confidence intervals of the means and variances. The idea of bootstrapping is to resample a large number of new data sets with
replacement from the original data set. This method starts with a sample size of \( n \), and its algorithm is as follows:

1. Creating a new sample of size \( n \) with replacement from the original sample.
2. Calculating the mean or variance of the new sample which is called \( m_0 \).
3. Repeating steps 1 and 2, 1000 times, and the \( i \)th new sample mean or variance is called \( m_i \).
4. Plotting the distribution of these 1000 sample means or variances.
5. Producing the 95\% confidence interval for the mean or variances by finding the 2.5\% and 97.5\% percentiles of this produced distribution.

Bootstrap confidence intervals were calculated for the daily precipitation and daily minimum and maximum temperature estimated means and variances in every month. For instance, if the daily precipitation data length in January is 40 years, an observed sample of size \( =1240 \) (40 years observed daily precipitation data of January gives \( 31 \times 40 = 1240 \)) has been used. Then 1000 new samples, each of the same size as the observed data, are drawn with replacement from the observed data. The 1000 resamples are drawn because this is the recommended minimum for estimating percentiles, required for estimating confidence interval for the means and variances (Khan et al., 2006).

The mean is first calculated using the observed data and then recalculated using each of the new samples, yielding a bootstrap distribution of the statistics of mean. From this distribution, the bias-corrected and accelerated (BCa) percentiles are estimated. The BCa percentile is more accurate than the empirical percentile. The empirical percentiles are simply the percentiles of the empirical distribution of the replicates while the BCa method transforms the specified probability values to determine which percentile of the empirical distribution most accurately estimate the percentiles of interest, and then applying corrections for bias and standard error; BCa confidence interval is estimated as follows (Di Ciccio and Efron, 1996; Wang et al., 2013):

\[
97.25\text{th. percentile} = \varphi(z_0 + z_{0.025})
\]

\[
2.5\text{th. percentile} = \varphi(z_0 - z_{0.025})
\]

RESULTS AND DISCUSSION
Precipitation and Temperature Prediction by SDSM:

In order to select the most effective predictor variables among the 26 effective predictor variables in the area, the correlation between the predictors and predictand was calculated for 1961-2000 time interval. The variables of CGCM1 did not create an acceptable correlation with the precipitation of the site. Therefore, in order to downscale the precipitation data just HadCM3 was used. Regarding the correlation coefficients and P-Value, these 3 predictor variables (Table 1) among the 26 predictor variables have the most correlation coefficient with precipitation. The time series of simulated daily precipitation data were carried out according to the selected weather predictor variables regarding HadCM3. The means and standard deviation of the observed and simulated monthly precipitation are presented in Table 2.

<table>
<thead>
<tr>
<th>Predictor Variable</th>
<th>Direct Correlation</th>
<th>Partial Correlation</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vorticity ( p_{-z} )</td>
<td>0.196</td>
<td>0.173</td>
<td>0.000</td>
</tr>
<tr>
<td>850 hPa vorticity ( p_{8_z} )</td>
<td>0.205</td>
<td>0.151</td>
<td>0.000</td>
</tr>
<tr>
<td>Relative Specific humidity at 500 hPa height ( r_{500} )</td>
<td>0.210</td>
<td>0.146</td>
<td>0.000</td>
</tr>
</tbody>
</table>

The amounts of direct and partial correlation between the meteorological variables and daily temperature of CGCM1 are presented in Table 3, and of HadCM3 in Table 4.
amounts are small. Two 500 hPa geopotential height (P500) and the mean temperature (Temp) variables from CGCM1 have an acceptable correlation with daily temperature. These variables which have acceptable P-Value, were considered as daily temperature predictor variables in CGCM1. In HadCM3, regarding the correlation coefficients and the calculated P-Value, these predictor variables have the most correlation coefficients with daily temperature: Mean Sea Level Pressure (MSLP), 500 hPa geopotential height (P500), and mean Temperature (Temp). These variables were considered as daily temperature predictors. The mean and the standard deviation of observed and simulated monthly precipitation are presented in Table 5.

### Table 3. Amounts of the predictor variables correlation of CGCM1 with daily temperature.

<table>
<thead>
<tr>
<th>Predictor Variable</th>
<th>Direct Correlation</th>
<th>Partial Correlation</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>p500</td>
<td>0.607</td>
<td>0.629</td>
<td>0.000</td>
</tr>
<tr>
<td>Temp</td>
<td>0.699</td>
<td>0.497</td>
<td>0.000</td>
</tr>
</tbody>
</table>

### Table 4. Amounts of the predictor variables correlation of HadCM3 with daily temperature.

<table>
<thead>
<tr>
<th>Predictor Variable</th>
<th>Direct Correlation</th>
<th>Partial Correlation</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSLP</td>
<td>-0.779</td>
<td>-0.784</td>
<td>0.000</td>
</tr>
<tr>
<td>p500</td>
<td>0.789</td>
<td>0.730</td>
<td>0.000</td>
</tr>
<tr>
<td>Temp</td>
<td>0.898</td>
<td>0.588</td>
<td>0.000</td>
</tr>
</tbody>
</table>

### Table 5. Mean and standard deviation of observed and simulated minimum and maximum temperature (°C).

<table>
<thead>
<tr>
<th></th>
<th>JAN</th>
<th>FEB</th>
<th>MAR</th>
<th>APR</th>
<th>MAY</th>
<th>JUN</th>
<th>JUL</th>
<th>AUG</th>
<th>SEP</th>
<th>OCT</th>
<th>Nov</th>
<th>DEC</th>
<th>JAN</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Min.</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>7.14</td>
</tr>
<tr>
<td>Observed</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.26</td>
</tr>
<tr>
<td>Temp.</td>
<td>3.61</td>
<td>3.37</td>
<td>2.57</td>
<td>1.78</td>
<td>2.09</td>
<td>1.48</td>
<td>0.94</td>
<td>1.29</td>
<td>0.88</td>
<td>0.92</td>
<td>1.44</td>
<td>1.98</td>
<td>1.01</td>
</tr>
<tr>
<td><strong>Max.</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>7.63</td>
</tr>
<tr>
<td>Observed</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>14.63</td>
</tr>
<tr>
<td>Temp.</td>
<td>0.92</td>
<td>0.89</td>
<td>0.89</td>
<td>0.66</td>
<td>1.01</td>
<td>0.62</td>
<td>0.51</td>
<td>0.44</td>
<td>0.54</td>
<td>0.77</td>
<td>0.83</td>
<td>0.60</td>
<td>0.23</td>
</tr>
</tbody>
</table>

**Bootstrap Confidence Intervals:**

95 percent confidence intervals was determined for every month. The confidence intervals are presented in Fig. 1. The uncertainty of precipitation in HadCM3 was almost similar to the observed data. But, totally, the uncertainty of CGCM1 was closer to the observed data. About the minimum daily temperature, also, the uncertainty in HadCM3 was more than the observed data in most months. But, the uncertainty of CGCM1 was closer to the observed uncertainty in each month.

Bootstrap confidence intervals for the variances of every month were determined too (as seen in Fig. 2). The observed data precipitation had less uncertainty than HadCM3, except in dry months of the year. Back to the minimum daily temperature, also, the observed data had less uncertainty than the models under investigation. The uncertainty of the dry months of the year in CGCM1 was closer to the observed data. Taking the maximum daily temperature in to account, CGCM1 had less uncertainty than HadCM3 in different months, and were closer to the observed data. Khan et al. (2006) gained almost the same results for SDSM model in daily precipitation and minimum and maximum temperature downscaling (there are differences in the results of some months).

**Climate Change Effect:**

The global circulation models under investigation were HadCM3 with A2 and B2 scenarios, and CGCM1 with A1 scenario. According to this, precipitation and minimum and maximum daily temperature parameters were calculated in 2010-2039 time period. The estimated monthly precipitation mean in the
present time and future is presented in Fig. 3. Besides, the precipitation changes compared to the base period can be observed in Table 6. As mentioned above, the predictor variables of CGCM1 did not have any acceptable correlation with precipitation in the region under study, and it is because of this fact that precipitation was not calculated by this model.

In both HadCM3 scenarios, precipitation will increase in most months of the year. Precipitation in this model will increase 54% in 2010-2039 time period in A2 scenario, but will not change considerably in summer months. But in B2 scenario, precipitation will increase 51.5% and the precipitation change will be significant in summer; for instance, the precipitation in June and July will be 50.8 and 24 mm respectively. Most of the studies show fluctuation in precipitation changes and the results of different areas of the world are different (IPCC, 2007 and 2014).

The estimated minimum monthly temperature in the present time and future is presented in Fig. 4. Besides that, the minimum temperature changes compared to the base period are presented in Table 7. The minimum yearly temperature mean in both HadCM3 scenarios, will increase about 0.2 °C. The minimum temperature will decrease in summer and autumn, and increase in winter and spring. In CGCM1 the minimum yearly temperature will increase about 0.6 °C which will occur in summer and autumn months.

The estimated maximum monthly temperature in the present and future is presented in Fig. 5. Its changes compared with the base period are presented in Table 8. The maximum yearly temperature mean in A2 scenario of HadCM3 will increase about 1.8 °C, and 1.9 °C in B2 scenario. This temperature increase will not be significant in April and May. It will vary between 1 to 3.7 °C. In CGCM1 the minimum yearly temperature will increase about 0.6°C which will occur mostly in summer and autumn. In winter and spring the maximum temperature will not have a significant increase or decrease. In spite of the precipitation changes, the minimum and maximum temperatures have been the same in most of the studies. As previously reported only temperature increase amount is different in different scenarios (IPCC 2007, 2014).
Fig. 1. Bootstrap 95% confidence intervals estimates of the weather parameters mean.

Fig. 2. Bootstrap 95% confidence intervals estimates of the weather parameters variance.

Fig. 3. Estimated monthly precipitation mean of different models under investigation.

Fig. 4. Estimated minimum monthly temperature mean of different models under investigation.
CONCLUSION

The present study reports an investigation of climate change effect by SDSM (by A2, B2, and A1 scenarios) according to 2 GCMs (HadCM3 and CGCM1) on daily weather parameters. The results are presented for 2010-2039 time period. Regarding bootstrap confidence intervals and the calculated precipitation variance, the uncertainty of HadCM3 was closer to the observed data, although, in general the observed data had less uncertainty. About the minimum and maximum temperature, also, the uncertainty in CGCM1 was less than HadCM3 and was closer to the observed data. By calculating weather parameters for 2010-2039 time period, precipitation increase in most months of the year, which will be more significant in dry months of the year. The minimum temperature will decrease in summer and autumn, and will increase in winter and spring. The maximum temperature will increase in most months, especially in summer and autumn months. The maximum temperature will have an insignificant increase or decrease in winter and spring.

In this study climate change effect on precipitation climate parameters and minimum and maximum daily temperature was studied using HADCM3 model with A2 and B2 scenarios and CGCM1 model with A1 scenario. Regarding to GCM models, the results are presented for 3 time periods: 2010-2039, 2040-2069, and 2070-2099.

During the first to the third time period in A2 scenario within HADCM3 model there will be an increase in precipitation which will be respectively 54 %, 51.3 %, and 34.3 %. In B2 scenario there will be also an increase in precipitation will be respectively 51.5 %, 54.1 %, and 44.3 %.

There will be an increase in minimum and maximum daily temperature in all scenarios in the future time periods. This increase in the minimum temperature in A2 scenario in HADCM3 model during the first to the third time periods will be respectively 0.2, 1.1, and 2.6 degrees. It will be respectively 0.2, 0.9, and 1.6 degrees in B2 scenario during the first to the third time period and 0.6, 1.0, and 1.6 degrees in A1 scenario in CGCM1 model.

In A2 scenario in HADCM3 model in the first to the third time periods the maximum daily temperature will be 1.8, 3.7, and 6.6 degrees respectively. In B2 scenario it will be respectively 1.9, 3.3, and 4.75 degrees, and in A1 scenario in CGCM1 model it will be 0.6, 1.1, and 1.8 degrees respectively.

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REFERENCES


IPCC. 2014. Climate change 2014: Impacts, adaptation, and vulnerability. IPCC working group II contribution to AR5. Geneva, Switzerland: IPCC.


Wang, D., S. C. Hagen and K. Alizad. 2013. Climate change impact and uncertainty analysis of extreme rainfall
