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Assessment of climate change using SDSM downscaling Model (A case study: West of Iran)

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Abstract

Climate change impacts are very dependent on regional geographic features, local climate variability and socio-economic status. Therefore, impact assessment researches on climate change must be launched at the local or at the regional level so that the evaluation of consequences can take place. Climate scenarios are produced by Global Circulation Models for the entire Globe with spatial resolutions of several hundred kilometers. For this reason, downscaling methods are used to bridge the gap between the large-scale climate scenarios and the fine scale where local impacts happen. In order to overcome limited computing power and for catchments with limited data, statistical downscaling is the most feasible approach in obtaining climate data for future impact investigations. So a decision support model named SDSM was used to downscale the data. Model errors and uncertainties were estimated using non-parametric statistical methods at the 95% confidence interval for precipitation, maximum temperature and minimum temperature for the mean and variance for a single site in Kermanshah in the western part of Iran. The comparison between the observed dataset and the simulations showed that the SDSM model was able to better represent the minimum and maximum temperature while for precipitation simulations are slightly under-estimated but still acceptable according to statistical tools. It is also presented simulations for the A2 SRES scenario for the 2041-2069 periods showing that the method can produce similar general tendencies.

Keywords: AOGCMs, downscaling, greenhouse gases, SDSM, SRES scenarios.

1- Introduction

Climate change is a top growing issue that has been largely studied since the past two decades. The climate system and ecosystem are very complex and only parts of it have been understood, so the uncertainties involving this issue go from the optimistic perspective that there is a chance that the impacts won't be as bad as predicted, but there is also the pessimistic argument that the impacts will be greater and quicker than predicted really. The Intergovernmental Panel on Climate Change (IPCC) fourth assessment report clearly states that even if humanity continues restraining its emissions within the next decade's consequences like temperature and sea level rise, changing weather patterns, spreading of pests and diseases and ocean acidification endangering coral reefs and other marine life are more likely to happen than not to happen. Even if the emissions remain the same from the year 2000, the Earth average temperature is expected to increase about 0.1 °C per decade. Projections from general circulation model (GCM) simulations must be downscaled to the high spatial resolution needed for assessing local and regional impacts of climate change, but uncertainties in the downscaling process are difficult to quantify(Spak et al., 2007). Global climate model predictions for the 21st century indicate that global warming will continue and accelerate (even if humanity can successfully restrain its emissions). By 2100 predictions show increases in the global average temperature ranging from 1.8 °C to about 4 °C and sea level would rise between 0.18 and 0.59 meters (IPCC climate change synthesis report, 2007).

The IPCC reported the observed global mean surface temperature from 1850–1900 to 1986–2005 had increased by about 0.61 per decade, due to worldwide climate change over the last century [IPCC, 2014]. Extreme events such as floods, droughts and heat waves are expected to increase in frequency and intensity even with relatively small average global temperature increases. Climate change is not homogenous over the planet. Some geographic areas are more sensitive to climate change than others are. Even in a country, semi-arid areas where precipitation and temperature changes will be significant, stressors are particularly sensitive to climate changes (the physical science basis, IPCC 2007). The Earth's climates result from interactions between many processes in the Atmosphere, Ocean, Land surface and Cryosphere. In the earlier 20th century, mathematicians and meteorologists started to try to explain the general circulation of the atmosphere, with the main practical purpose of producing weather forecasts using the basic physics of the atmosphere. However, it was only after the year 1988 that the advances in computer power enabled the first coupled ocean-atmospheric models to be developed. Since then, these models have grown to be more and more sophisticated to include effects of different parameters such as solar radiations and activities, volcanoes, shallow and deep interactions, salinity, biosphere responses and many more. Today's coupled Atmosphere-Ocean General Circulation Models (AOGCMs) such as HadCM3, GFDL-R30 and CSIRO-MK2 etc. are based on weather forecasting models but have to be used for understanding and projecting climate change. In this paper, they are referred to as Global Climate Models (GCMs). Projecting climate change with GCMs is based on scenarios of the future particularly on the greenhouse gas emissions in each scenario driving the greenhouse gas concentrations in the atmosphere. It is important to understand that scenarios are consistent and coherent alternative stories of the future, but they are neither predictions nor forecasts (IPCC, 2000). Since the late 1990s there has been a big effort to construct realistic future emissions scenarios representing the complex and interrelated dynamics of demographic, socio-economic development and technological change (IPCC, 2000). Pieter de Jong et al., 2018, et al. (2018) studied the climate change impacts and rainfall changes in the Sao Francisco basin. The most comprehensive studies have been released by IPCC named Special Report on Emission Scenarios better known by its acronym SRES, that generate the greenhouse gas emissions, served as input for most GCM future climate studies. The SRES present four storylines for possible future scenarios (A1, A2, B1 and B2). The A1 scenario describes a future world of very rapid economic growth, a global population that picks the mid-century and declines thereafter and a rapid introduction of new and more efficient technologies. The A2 scenario describes a very heterogeneous world with continuously increasing global population and regionally oriented economic growth. The B1 scenario describes a convergent world with the same global population as in A1 storyline but with rapid changes in economic structures toward a service and information economy while reductions in material intensity and introduction of clean and resource-efficient technologies. Finally, the B2 scenario describes a world in which the emphasis is on local solutions for economic, social and environmental sustainability, with continuous increasing population (but lower than A2) and intermediate economic development. Though many global socio-economic and technological scenarios are being developed, so far only SRES ones have been used as inputs for the sophisticated GCM runs. Therefore, SRES scenarios are actually the only candidates when it comes to performing a coherent downscaling of future panoramas of demography, society, economy, technology, emissions and climate. Climate scenarios are produced by Global Circulation Models for the entire Globe with spatial resolutions of several hundred kilometers. For this reason, downscaling methods are used to bridge the gap between the large-scale climate scenarios and the fine scale where local impacts happen. GCMs are widely used to assess climate change at a global scale, i.e the global warming. However, the GCMs outputs are not enough to assess the detailed changes at regional/local levels. Most impact studies are done for spatial resolutions of the order of a few square kilometers. This is lesser than the horizontal areas of the grid-boxes used by GCMs especially for the regions of complex topography and in regions of highly heterogeneous land-cover (Wilby, 2004). In these cases, it would be better to resort to Regional Clime Models (RCMs), with spatial resolution of tens of kilometers or even less. Nevertheless, bridging the gap between the resolution of global climate models and local scale weather represents a considerable technical problem. Recently there has been a lot of effort from the climate community on the development of dynamical and statistical downscaling techniques to represent climate change at a local and regional scale. RCMs are the paradigmatic example of dynamical downscaling. RCMs are based on numerical simulations of the physical processes operating in nature. Unfortunately, RCM still have several drawbacks, for example, they have a limited number of experiment/scenario runs and time periods. The main problem generally is depending on domain size and resolution, that they can be very time demanding from a computational viewpoint. Additional problems related the need of sophisticated training for the modelers and to difficulties in model calibration and validation (Mearns, 2001). As an alternative to dynamic models, statistical downscaling models have been developed. They are based on the view that regional climate is mostly a result of the large-scale climatic state and regional/local physiographic features, e.g. topography and land-use (Wilby, 2004). A major advantage of these techniques in comparison with dynamical models is that they are computationally much cheaper and can be more easily applied to the output of different GCM experiments, for various scenarios, this enables an assessment of the uncertainty in future scenarios. The major theoretical weakness of statistical downscaling is that the statistical relationships developed for present day climate will also hold for different forcing conditions in the future climates (Fowler, 2007). However, in overall statistical downscaling is more applicable in basis with limited and scarce recording gauges with different land-uses. The SDSM is a model for simulating future scenarios to assess the impact of climate change. This model is a stochastic approach using a linear regression method (Wilby et al. 2002; He, B.; Takara et al., 2011; Wilby and Dawson., 2008). SDSM provides adjustment during the model calibration in some parameters such as event threshold, bias correction, and variance inflation. The goal of this research is to provide an up-to-date information on climate change downscaling technique using a hybrid model called SDSM. Localized RCM has not been developed yet. Seemingly, different GCMs should be tested and verified using observed datum before trying to develop localized domestic RCMs.

2- Materials and Methods

Downscaling methods are used to assess climate change impacts at higher spatial resolutions, namely in regional and local studies. Before using any downscaling technique to assess the impact of climate change, it is very important to take into account the project aims and objectives. Statistical downscaling methods are applied to single sites, being very difficult to apply in regional and national studies mainly due to the lack of good quality and quantity of data. IPCC presented an overview on statistical downscaling methods (Wilby et al., 2004). It is well established that the best available tools to obtain information on climate scenarios of warmer world, due to increasing concentrations of greenhouse gases in the atmosphere, are coupled ocean-atmosphere general circulation models (OAGCMs) Corte-Real et. al. (1999). The general scheme for obtaining climate scenarios using downscaling approaches is summarized in Figure (1).

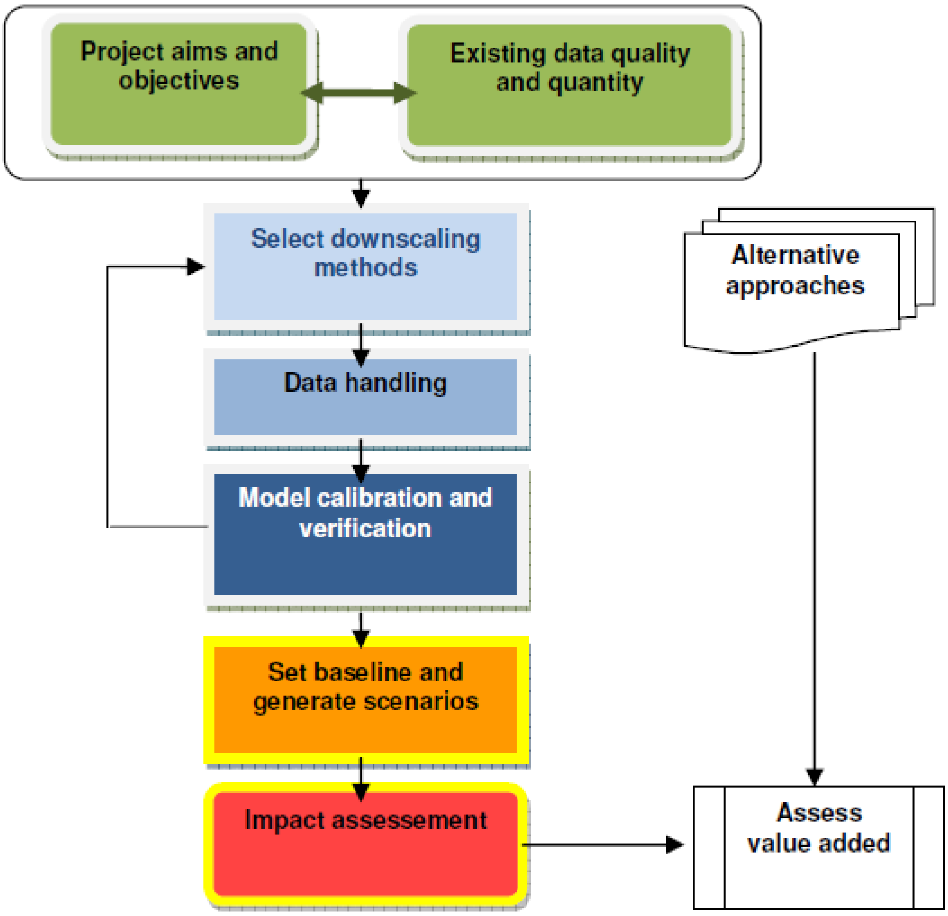

Fig. 1– Schematic flow chart of statistical approaches in obtaining and using downscaled climate scenarios, (Lopez, 2008)

When using a statistical method, it is important to assess model errors by comparing the climate simulations with independent observed climate. For example, if the observed dataset for the 1971-1990 period is used for model construction, then the same dataset must not be use to validate the simulations. An independent data such as the 1991-2000 dataset is preferred for validation. This step is very important to define if the simulations are representative or not of the local climate variability and if the statistical methods can be applied.

For this study, the GCM HadCM3 daily data were collected. The predictors for the A2, B2 scenarios in the SDSM tool can be acquired at the Canadian Climate Change Scenarios Network (CCCSN) or from National Center for Environmental Prediction (NCEP). Daily observed data (predictants) were collected from local synoptic station in Kermanshah. Figure (2), shows a schematic map of the study area.

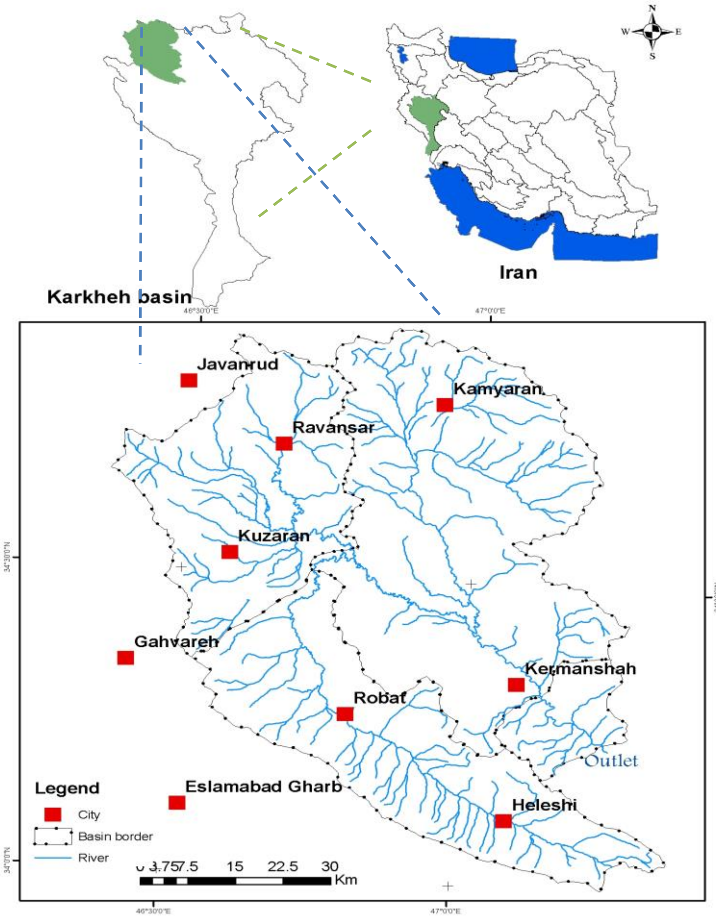

Fig. 2- Study area in the western part of Iran

This research was implemented using the SDSM (Statistical Down-scaling Model) tool developed by Wilby, Dawson and Barrow, 2002. The climatic inputs for statistical method were daily precipitation, daily maximum temperature and daily minimum temperature for Kermanshah during the 1961-1990 periods, usually model calibration and validation is done with thirty years of daily meteorological records often 1960 to 1990. Observed predictors for model calibration also correspond to the same period allowing the establishment of the predictor-predictand. The validation procedure of the simulations was implemented by comparing daily-observed data from 1981-1990 time periods with thirty years of simulated daily time series for maximum temperature, minimum temperature and precipitation. Model validation and uncertainties were analyzed using non-parametric statistical techniques based on a simulation of daily weather maximum/minimum temperature and precipitation for one synoptic station in Kermanshah. The GCM chosen was the coupled atmosphere-ocean HadCM3 developed by the Hadley Centre, with a horizontal resolution of 2.5° of latitude and 3.75° of longitude producing a global grid of 96 x 73 grid cells. The HadCM3 GCM covers the IPCC following criteria's IPCC (2001): full 3D coupled ocean-atmospheric GCMs, documented in the peer reviewed literature, has performed a multi-century control run (for stability reasons), has participated in CMIP2 (Second Coupled Model Intercomparison Project), has performed a 2 x CO_2 mixed layer run, has participated in AMIP (Atmospheric Model Intercomparison Project), has a resolution of at least 3° latitude x 3° longitude, and considers explicit greenhouse gases (e.g. CO2, CH4 , etc.) For this study the GCM HadCM3 daily data were collected in two different sources. The predictors for the A2 scenario used in the SDSM tool were acquired at the Canadian Climate Change Scenarios Network (CCCSN), and the input for the LARS-WG tool were collected at the British Atmospheric Data Centre, from the Climate Impacts LINK Project. Usually model calibration and validation is done with thirty years of daily meteorological records, often from 1960 to 1990. Most of the observed predictors for model calibration also correspond to the 1960-1990 period allowing the establishment of the predictor-predictand relationships that provide the basis for producing climate change scenarios when using statistical downscaling models. SDSM does the task of statistically downscaling weather series in five steps: (i) quality control and data transformation, (ii) screening of predictors variables , (iii) calibration of model and selection, (iv) model valdation and finaly (v) scenario generation from GCM predictors. SDSM uses predictors such as mean sea level pressure and geo-potential height that can be downloaded from the NCEP/NCAR reanalysis project. Quality control and data transformation were done. Some of the most common transformations include: logarithm, power, inverse. For this study only precipitation data was transformed using fourth rout. After that, screening of downscaling predictor variable should be done. Herein the main goal is to establish the relationship between predictors and the site predictant. This selection was based on the observed time series for the 1961-1980 period. Four criteria were taken into account to constract the most suitable model: (i) seasonality, (ii) the predictor-predictant process, (iii) the predictor-predictant correlation and (iv) the application of an auto-correlation term. To test the significance of predictor-predictant relationship, the correlations at 95% confidence interval was calculated. Finally to smooth the inter-monthly curve, an autoregressive term was used. This process is very common when modelling time series.The predictors chosen for each climate variable are Soil Conservation and Watershed Management Research Institute in table (1).

Model calibration was done to improve the models results for the predictor-predictant relationship by doing a sensitivity analysis. After selecting the most suitable predictor variables, the model based on multi-regression equation was applied and the selection of the best model was based on checking normality, homogenity and independence assumptions by plotting a histogram of reseduals versus the predicted variable and calculating the Durbin-Watson statistics to respectively assess each assumption. the Durbin-Watson statistic is a statistical test used for detecting the presence of autocorrelation in the residuals from a regression analysis. A value of 2 indicates there appears to be no autocorrelation, if less than 2, there is an evidence of positive serial correlation and if it is less than 1.0, it is probable that we have autocorrelation and independence assumption is violated. Model validation was performed by simulating synthetic time series of daily precipitation and daily maximum and minimum temperature for 30 years and compared with observed daily precipitation and daily maximum and minimum temperature for the 1981-1990 period. The model errors in the estimates of means and variances were evaluated using non-parametric statistical tests at the 95% confidence level. All outliers that represent unusual trends or variations which were not typical were removed in order to have a representation of normal climate behavior and variability.

3- Results and discussion

Figures (3) to (10) shows the correlations between the selected predictors and predictants. The first criteria were applied based on local knowledge and inter-month climate variability in Kermanshah.

Table 1- List of predictors chosen for each climate variable

Precipitation (mm)	Maximum temperature (°C)	Minimum temperature (°C)
Surface zonal velocity	Surface zonal velocity	Surface air flow strength
850 hpa zonal velocity	500 hpa geo-potential height	Surface vorticity
850 hpa air flow strength	850 hpa zonal velocity	Surface specific humidity
850 hpa geo-potential height	Mean temperature at 2 m	Mean temperature at 2 m
Near surface relative humidity		

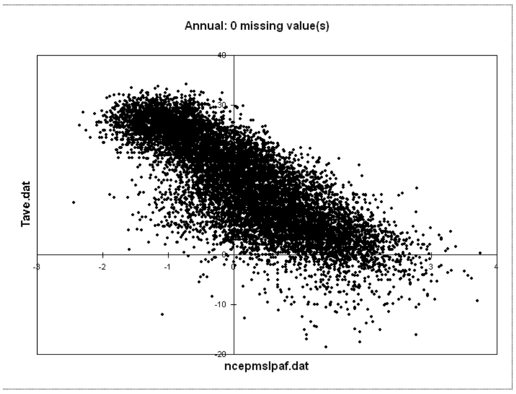

Fig. 3- Relation between average temperature and Ncepmslpaf(Mean Sea Level Pressure)

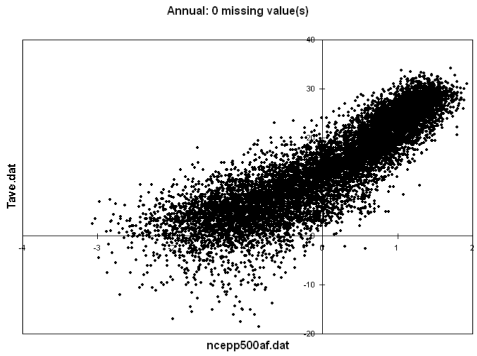

Fig. 4- Relation between average temperature and Ncepp500(500hPa Geopotential)

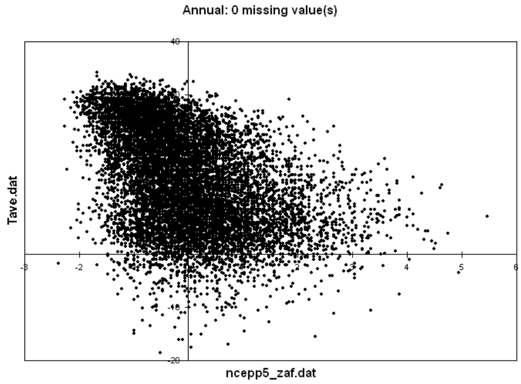

Fig. 5- Relation between average temperature and Ncepp5_zaf(500hPa Vorticity)

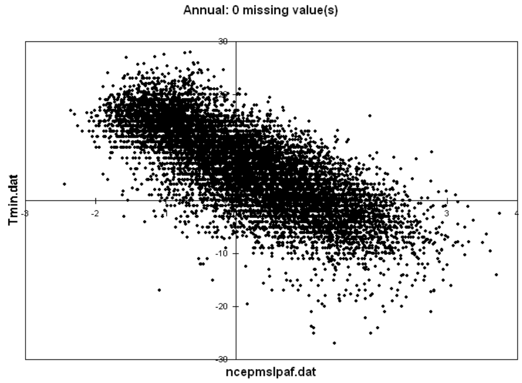

Fig. 6- Relation between minimum temperature and Ncepmslpaf(Mean Sea Level Pressure)

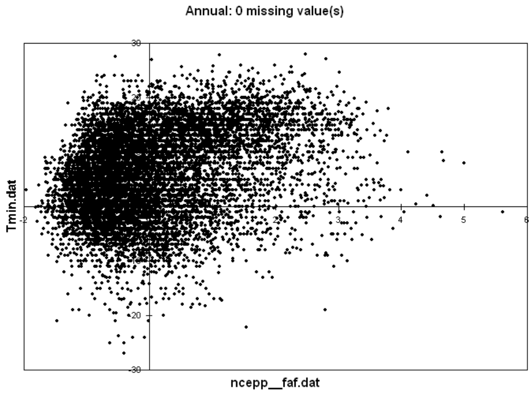

Fig. 7- Relation between minimum temperature and Ncepp_faf(Surface Airflow Strength)

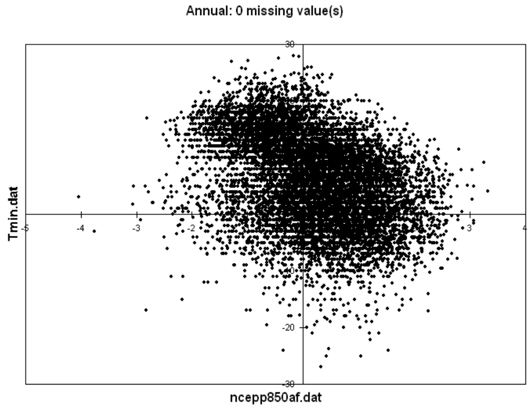

Fig. 8- Relation between minimum temperature and Ncepp850af(850hPa Airflow Strength)

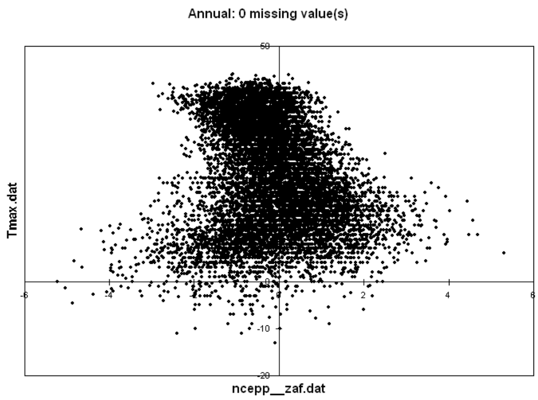

Fig. 9- Relation between maximum temperature and Ncepp_zaf(850hPa Airflow Strength)

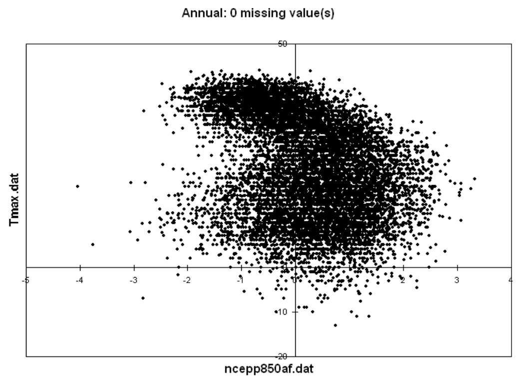

Fig. 10- Relation between maximum temperature and Ncepp850af(850hPa Airflow Strength)

Figures (3) to (10) there are very good correlation between the predictants and main predictors.

Table (2) to (4) show the coefficient of determination and Durbin-Watson statistics for maximum and minimum temperature and mean precipitation respectly.

Table 2- Coefficient of determination R^2 and Durbin-Watson statistics for validating the independence assumption for maximum temperature model

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
R^2	0.468	0.504	0.698	0.707	0.776	0.747	0.666	0.609	0.733	0.726	0.622	0.534
Durbin-Watson	**2.098**	**2.011**	1.875	1.733	1.734	1.719	1.620	1.705	1.736	1.937	2.025	2.008

Table 3- Coefficient of determination R^2 and Durbin-Watson statistics for validating the independence assumption for minimum temperature model

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
R^2	0.641	0.682	0.668	0.6680	0.675	0.700	0.590	0.505	0.663	0.674	0.699	0.711
Durbin-Watson	1.878	1.871	1.732	1.776	1.773	1.891	1.809	1.913	1.913	1.878	1.815	1.803

Table 4- Coefficient of determination R^2 and Durbin-Watson statistics for validating the independence assumption for mean precipitation model (n.a= not available)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
R^2	0.447	0.435	0.416	0.399	0.405	0.344	0.123	0.204	0.336	0.477	0.452	0.474
Durbin-Watson	n.a	n.a	n.a	n.a	n.a	n.a	n.a	n.a	n.a	n.a	n.a	n.a

The Durbin Watson (DW) statistic is a test for autocorrelation in the residuals from a statistical regression_analysis. The Durbin-Watson statistic will always have a value between 0 and 4. A value of 2.0 means that there is no autocorrelation detected in the sample. Values from 0 to less than 2 indicate positive autocorrelation and values from 2 to 4 indicate negative autocorrelation.

Before using the statistical downscaling method, the relationship between the climate model precipitation and the observed station precipitation was evaluated. After evaluating the performance of the SDSM model in downscaling climatic variables, i.e., precipitation and temperature at different meteorological stations over the KRB, precipitation was downscaled to the basin scale in the station based on the calibrated model. Subsequently, precipitation time series were generated for each rain station. Rainfall is a conditional process and is projected by a stochastic weather generator conditioned on the predictor variables [21]. The precipitation dataset is not generally normalized and because of the skewed nature of the precipitation distribution, the fourth root transformation was applied in this study [21,39]. The observed time series of temperature and precipitation were divided into two periods: the calibration period 1971–1985 for developing the SDSM, and the validation period 1986–2000 for testing the model performance and comparing it with the downscaled results. In the validation period, monthly mean values of precipitation and temperature were downscaled with predictor variables of NCEP reanalysis data. The monthly average of 20 simulated series of precipitation and maximum and minimum temperature demonstrated a good correlation with the observed precipitation in the calibration period. Table1 shows the values of statistical measures between observed and downscaled monthly mean precipitation and temperature in the validation period (1986–2000). Figure 11 shows mean temperature changes in Kermanshah station in observational and future periods. In addition, Figure 12 presents mean precipitation changes in Kermanshah station in observational and future periods. As clearly seen in the Figures, the A2 and B2 scenarios have a similar trend in predicting precipitation in the future. Precipitation decreases over the near future and far future, except in the month of winter.

Moreover, Changes in summer precipitation were not significant in both periods because of the usual dry summers in this catchment. Furthermore, according to predictions, a small increase in precipitation in December is expected in the near future than the far future. Increase in precipitation is expected in the near future than the far future.

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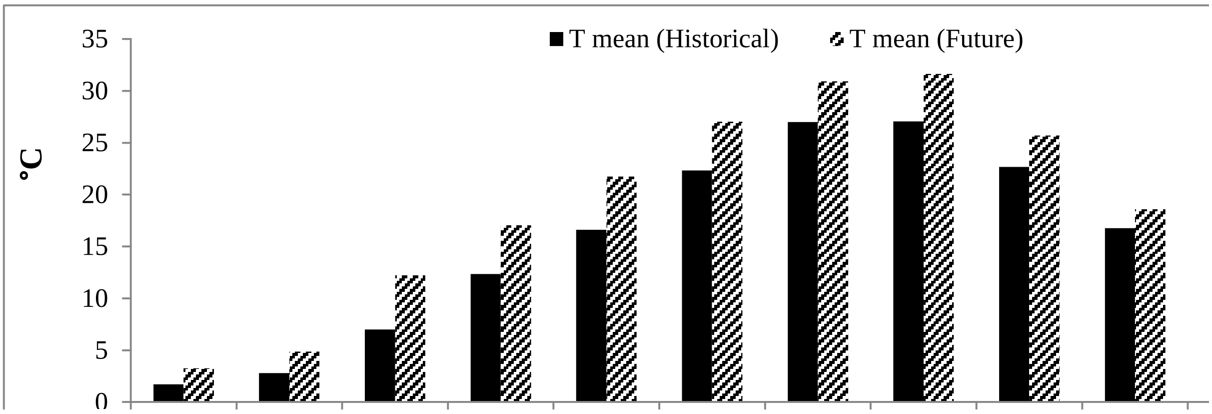

Fig. 11- Mean temperature changes in Kermanshah station in observational and future periods

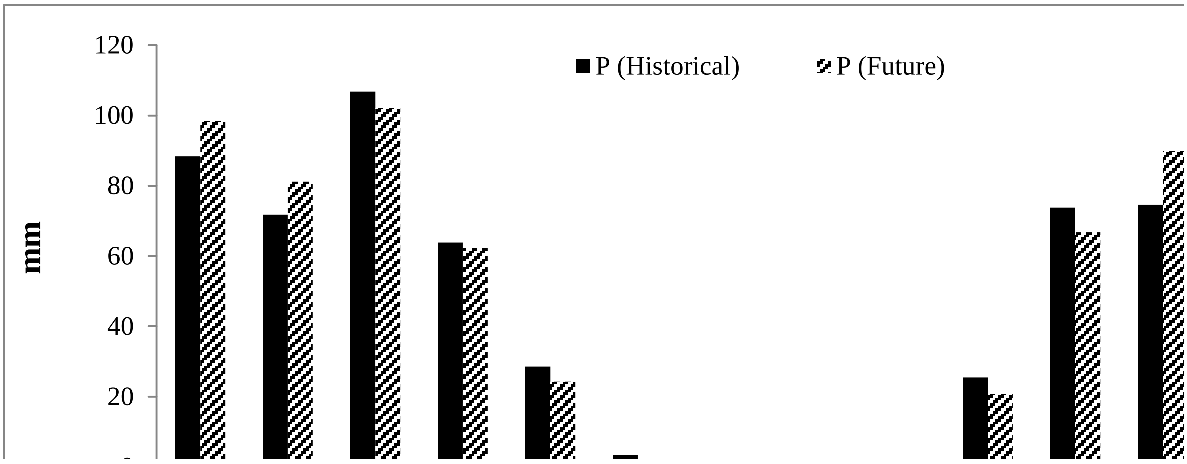

Fig. 12- Mean precipitation changes in Kermanshah station in observational and future periods

4- Conclusions

The residual analysis showed that there is no violation of normality, homogenity and independence assumptions. Also spread of the residuals versus observed precipitation plot shows some line of points that is due to the large number of zero of observed precipitation. SDSM tool was unable to calculate the Durbin-Watson statistics for conditional models. Here the null hypothesis is that there is no difference between the two population means. For $p<0.05$ the null hypothesis is rejected at 95% confidence level. The null hypothesis is accepted when $p>0.05$. Linking the gap between global future climate scenarios and regional or local climate predictions is becoming more robust but is still too difficult for non-experts to do any impact assessment of climate change with higher spatial and temporal resolutions. Global climate predictions will have local consequences and consequently it is urgent to include in the local climate change impact studies downscaling techniques. To realize this, the climate modeling community has produced series of climate scenarios run with several GCMs and has made it easily available. Statistical downscaling is one alternative to assess climate change impact at a local scale, however there are some limitations. Downscaling climate change using statistical methods at a local scale means that scenarios are built at the level of the meteorological station which is representative from the region or local variability. The analysis of the results showed that model uncertainties for mean are very close to the observed data in all months. To assess model uncertainties, a non-parametric bootstrap approach was calculated for the mean and variance. To go futher even in model comparisons, the skewness and wet spell length of precipitation was also analysed. The simulation of wet spell was slightly underestimated this value. In conclusion model errors, variability and uncertainties are close to the observed dataset for maximum temperature and minimum temperature, while for precipitation, it is slightly varied. The analysis of the total monthly precipitation indicates a decrease in the total monthly precipitation and also decreasing in wet spell length. The temperature results indicates an increase and shift of maximum and minimum temperature. In conclusion model errors, variability and uncertainties are close from the observed dataset for precipitation, maximum temperature and minimum temperature. The results gained from this research are in agreement with the Massah et al., (2006), Goodarzi and Chubeh (2019), Lopez, (2008). While in precipitation pattern it is in opposite with Beheshti et al. (2019). With a reveiw of different researches and thesis about climate change impacts, we clearly understand that there is less disagreement in increase in temperature but as for the precipitation , the results may be quite different. Even in different models and different scenarios, there is a great agreement and very raely we notice a research showing decrease in temperature especially in minimum temperature. It is expected that temperature will rise and solid precipitation would change to rain. Therefore, snow reservoirs of the mountains will be reduced. It was found that the runoff follows the precipitation pattern. Annual runoff would increase in the future periods during rainy seasons, while stream flow would decrease totally. The monthly runoff peak also switches from April to March in both A2 and B2 scenarios, which is caused by the increase in winter precipitation, rise in the temperature, earlier snowmelts, dry summers and less snow storage in the mountains. Evaporation from the surface of the reservoir should also be taken into consideration for the reservoir too. It is worth monitoring and mentioning the large uncertainties involved in predicting climatic variables as well as simulating future runoff, water balance elements and evapotranspiration under various scenarios. Therefore, further deep multipurpose researches are required to consider the uncertainties of the other climate model projections. In conclusion, mitigation strategies are necessary to take into account both the negative effects of climate change impacts and possible positive impacts while trying to provide maps of prone areas and vulnerable regions during certain periods of the future.

5- Acknowledgment

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6- Conflicts of Interest

No potential conflict of interest was reported by the authors.

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