

Uncertainty analysis of statistical downscaling models using general circulation model over an international wetland

H. Etemadi · S. Samadi · M. Sharifikia

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Abstract Regression-based statistical downscaling model (SDSM) is an appropriate method which broadly uses to resolve the coarse spatial resolution of general circulation models (GCMs). Nevertheless, the assessment of uncertainty propagation linked with climatic variables is essential to any climate change impact study. This study presents a procedure to characterize uncertainty analysis of two GCM models link with Long Ashton Research Station Weather Generator (LARS-WG) and SDSM in one of the most vulnerable international wetland, namely “Shadegan” in an arid region of Southwest Iran. In the case of daily temperature, uncertainty is estimated by comparing monthly mean and variance of downscaled and observed daily data at a 95 % confidence level. Uncertainties were then evaluated from comparing monthly mean dry and wet spell lengths and their 95 % CI in daily precipitation downscaling using 1987–2005 interval. The uncertainty results indicated that the LARS-WG is the most proficient model at reproducing various statistical characteristics of observed data at a 95 % uncertainty bounds

while the SDSM model is the least capable in this respect. The results indicated a sequences uncertainty analysis at three different climate stations and produce significantly different climate change responses at 95 % CI. Finally the range of plausible climate change projections suggested a need for the decision makers to augment their long-term wetland management plans to reduce its vulnerability to climate change impacts.

Keywords Climate change · Regression-based statistical downscaling model · Uncertainty analysis · Wetland management · Arid region

1 Introduction

Climate appears to be generally changeable precipitation and temperature during the last half of the twentieth century particularly in arid regions. Regions with arid climates could be sensitive even to insignificant changes in climatic characteristics (Samadi et al. 2013b). Climate change impacts on inland aquatic ecosystems will be caused by the direct effects of rising temperatures and rising CO₂ concentrations to indirect effects caused by changes in the regional or global precipitation and the melting of glaciers and ice cover (see IPCC 2007; Bates et al. 2008). Consequently future temperature changes in an arid region may have more influences on wetlands hydrology by increasing evapotranspiration rate even without significant changing in precipitation amount.

The mathematical models used to simulate the present climate and project future climate with forcing by greenhouse gases and aerosols are generally referred to as global climate models (GCMs). Because the spatial resolution of GCMs remains quite coarse and it has no accurate for

H. Etemadi
Department of Environmental Science,
University of South Florida, Tampa, FL, USA
e-mail: etemadi.halime@yahoo.com; h.etemadi@modares.ac.ir

H. Etemadi
Department of Environmental Science,
Tarbiat Modares University, Tehran, Iran

S. Samadi
Carolinas Integrated Sciences and Assessments,
University of South Carolina, Columbia, SC 29208, USA
e-mail: Samadi@mailbox.sc.edu

M. Sharifikia (✉)
Department of Remote Sensing,
Tarbiat Modares University, Tehran, Iran
e-mail: sharifikia@modares.ac.ir

climate change impact studies, therefore the use of suitable downscaling methods can make climate change study more reliable. Reliable climatic data series corresponding to future climate scenarios can be derived from GCM outputs using the “downscaling techniques”. A diverse range of empirical/statistical downscaling techniques have been developed over the past few years and each method generally lies in one of the three major categories, namely regression (transfer function) methods, stochastic weather generators and weather typing schemes. This analysis focus on the two most widely used downscaling methods, as called regression downscaling techniques and stochastic weather generators. This two types of statistical (a stochastic and a regression based) downscaling techniques generated the possible future values of local meteorological variables in the study area (Maroon-Jarrahi watershed near biggest international wetland namely Shadegan in south Iran). The first one implements a regression based method and is referred to statistical down-scaling model or SDSM (see Wilby and Wigley 2000; Beersma and Buishand 2003; Huth 2005; Prudhomme and Davies 2009; Zhang et al. 2011; Samadi et al. 2011). While the second is a stochastic weather generator called Long Ashton Research Station Weather Generator or LARS-WG (Semenov et al. 1998). These tools are used to downscale the GCM outputs for the Maroon-Jarrahi watershed where Shadegan wetland is located.

This present research was studied in the biggest international wetland in the Middle East. Literature reviews stressed that changes in global climate will have significant impact on local and regional wetlands hydrological conditions (see Aires et al. 2013; Keith and Tushar 2010; among others), which will in turn affect ecological, social and economical systems. According to the Intergovernmental Panel on Climate Change (IPCC) report in 2001, confirmed in 1995, the global average temperature will rise by about 3.6 °C, with a range of 1.5–4.5 °C, depending on the model used (IPCC 2001). These results are still uncertain, due to the natural temperature variability from place-to place, day-to-day, and season-to-season, as well as the modeling uncertainties. Nevertheless an increasing temperature tendency from climatic projections was identified, but there is less confidence in the future pattern of precipitation because of uncertainty associated to this abnormal climatic variable.

Studies have been shown that it is important to address the effects of climate change on wetlands and lakes (see Aires et al. 2013; Keith and Tushar 2010) since they exhibit extensive biodiversity habitat, function as filters for pollutants, and are important for carbon sequestration and emissions. The changing climate may also affect the water balance and wetland hydrology in the future. Furthermore transform of aquatic thermal regimes, density stratification of water bodies, reduction of dissolved oxygen and

variation in biogeochemical processes could occur (Hamilton 2010) in the future which can effect on wetland biodiversity and habitat Comparisons of worst case developments regarding agricultural intensification and greenhouse gas concentrations showed stronger impact of climate change than of water abstractions on the wetland hydrology and vegetation distribution (Milzow et al. 2010).

To a large extent, the analysis of uncertainty is based on statistics and statistical thinking (Samadi et al. 2013b). In theory, the problem of choosing an appropriate model is satisfied by performing a “validation” study, in which the goodness of-fit of the model is assessed by comparing the results of the model with data (Samadi et al. 2013b). Readers of downscaling uncertainty literature should be warned that there are inconsistent and varying methods associated with uncertainty analysis of downscaling methods. In fact SDSMs have been profitably used in different studies and recent literature on uncertainty associated of downscaling methods is voluminous both in the context of observations and projections (see e.g., Semenov et al. 1998; Qian et al. 2004; Prudhomme and Davies 2009; Zhang et al. 2011; Babaeian and Kwon 2005; Lawless and Semenov 2005; Samadi et al. 2013a; among others). Abbaspour et al. (2009) downscaled climatic variables in 37 climate stations in 2010–2040 and 2070–2100 periods. They found that in general, wet regions of the country will receive more rainfall, while dry regions will receive less rainfall in the future. Little study has specifically focused on assessing uncertainty in downscaling results due to different SDSMs. Prudhomme and Davies (2009) as well as Wilby and Harris (2006) and Chen et al. (2013) studied uncertainties associated to several GCM models, downscaling techniques and hydrological models respectively. They demonstrated that GCMs exhibited the most and downscaling methods showed the least uncertainties during prediction interval. A study by Ho et al. (2012) showed that two downscaling approaches, change factor and bias correction approaches, gave substantial difference results in spatial warming patterns over Europe. Zhang et al. (2011) expressed that uncertainties in integrated downscaling models were primarily derived from the choice of RCM, and were then amplified through the incorporation of different weather generators models. Each combination of RCM and weather generator constituted a plausible solution of projecting future climate at regional scale, but none of them was superior to others. Therefore, results of any impact study based on only one RCM and one weather generator should be interpreted with caution, and the multi-model framework should be advised for generating a comprehensive vision of the future climate. Samadi et al. (2013b) studied the uncertainty analysis of linear and non-linear downscaling methods using parametric and non-parametric approaches over a semi-arid catchment in West Iran. Their results revealed that linear downscaling techniques (SDSM)

were the most proficient model at reproducing various statistical characteristics of observed data at a 95 % confidence level while the non-linear method (artificial neural network) showed to be the least capable in their analysis.

In this present research HadCM3 Hadley Centre Coupled Model with the resolution of 50,000 km² and ECHO-G (ECHO-G (ECHAM4(ECMWF+ Hamburg)/HOPE-G (Hamburg Ocean Primitive Equation model))) global climate model of approximately 350 km horizontal resolution (Min et al. 2005) were used as GCMs models, since the certainty of these GCMs demonstrated upon previous studied on different climatic conditions in Iran (see Babaeian and Kwon 2005; Abbaspour et al. 2009; Samadi et al. 2013a, 2013b). Generally, GCMs are considered to be the largest source of uncertainty for quantifying the impacts of climate change. However, the uncertainty related to the downscaling and bias correction methods must be taken into account for better estimation of the impact of climate change (Quintana Segui et al. 2010). Moreover, although some studies attempted to investigate the uncertainty related to downscaling techniques, but better method may use multi-downscaling techniques (more than one) for quantifying their uncertainty propagation in any climate change impact study. Therefore the goal of this research is to compare two statistical downscaling models namely SDSM, LARS-WG with two different GCM models by quantifying uncertainties associated in their downscaled results using non-parametric techniques and estimate the differences in two downscaling methods. The uncertainty assessment includes both downscaling models results and the corresponding observations incorporating to appropriate uncertainty techniques. The most commonly used statistical methods for assessing model uncertainty includes analyzing 95 % CI for the estimates of means and variances of model results (Caruso 1999). Therefore this paper proposes an approach that generates the downscaled climatic data (e.g., temperature and precipitation data) which reflect both local weather variability and regional trends projected by GCM models. In fact this approach relies on a methodology that combines predictions from individual GCMs into a 95 % CI for a given climate station using different criteria.

2 Study area and data sources

Jarrahi basin is one of the major river in south Iran and Shadegan Wetland lies at the downstream reach of this basin at the head of Persian Gulf (30°00′–31°00′N and 48°20′–49°20′E). The area of Jarrahi basin is approximately 24,310 km² and it is characterized by a Mediterranean climate condition consisting of hot and dry summers and mild and rainy winters. Jarrahi river network

consists of two large reservoirs (Maroon and Jarrehi) which are the main freshwater supplier of Shadegan Wetland especially during dry periods.

Shadegan is the largest international wetland of Iran and the 34th largest of the 1,201 designated Ramsar sites in the world. According to Pandam Consulting Engineers (PCE 2002) and UNEP (2001) reports, Shadegan gradually became the largest wetland in the Middle East even as upstream developments in much of the Mesopotamian marshlands reduced its overall size. Figures 1 and 2 exhibited the location of Shadegan wetland in Maroon-Jarrahi basin. This wetland covers around 4,000 Km² and created a suitable habitat for a number of migrating waterfowls, which fly to this area from north Europe, Canada and Siberia in autumn. The region includes 110 plant species, 40 species of mammals, three species of amphibians, eight species of reptiles, 90 species of fish, and 174 species of birds. Thirteen globally endangered species of birds and one endemic species, namely the Iraqi balber (*Turdoides altirotis*), have been recorded in this wetland (Pandam Consulting Engineer 2002; Kaffashi et al. 2012) as well.

Figure 3 showed the geology map of Maroon-Jarrahi basin, sedimentation yield of both Maroon and Jarrahi rivers are significantly considerable because of wide erodible geological formations in this basin. Consequently it caused increasing wetland sedimentation during recent decades and this situation reveals a necessity of soil and water conservation and practice in upper basin, livestock grazing control, providing replacing fuelwood for local people and increasing general awareness as well. The soil of wetland is laminated with intermittent layers compose of soft condensed sand and silt. In some place there are concentration of lime and chalk in soil profile with poor drainage and heavy textured surface layer. Totally there are two distinct soil groups in Shadegan wetland; hydromorphic and salty soil (Pandam Consulting Engineer 2002) and they effect on wetland water quality and biodiversity significantly. Because of varying tidal effects, various vegetations have been characteristically formed in Shadegan wetland that has created unique biodiversity environment. Figure 4 shows land cover map of shadegan wetland. The vegetation species of *Halodule wrightii*, *Halophila ovalis* and *Nitraria retusa*, based on IUCN standards have known as threatened species in class of critical species, furthermore the vegetation species of *Oenanthe aquatic*, *Nymphaea alba* and *Alisma lanceolatum* have recognized as threatened species in class of vulnerable species (VU) (Pandam Consulting Engineer 2002).

The different datasets which have been used in this work are summarized in Table 1. In this study, observed data collected, from three meteorological stations namely Ramhormoz (R), Mashahr harbor (M), Behbahan (B), since they have sufficient record lengths which are required by

Fig. 1 Location of Maroon-Jarrahi basin in Iran

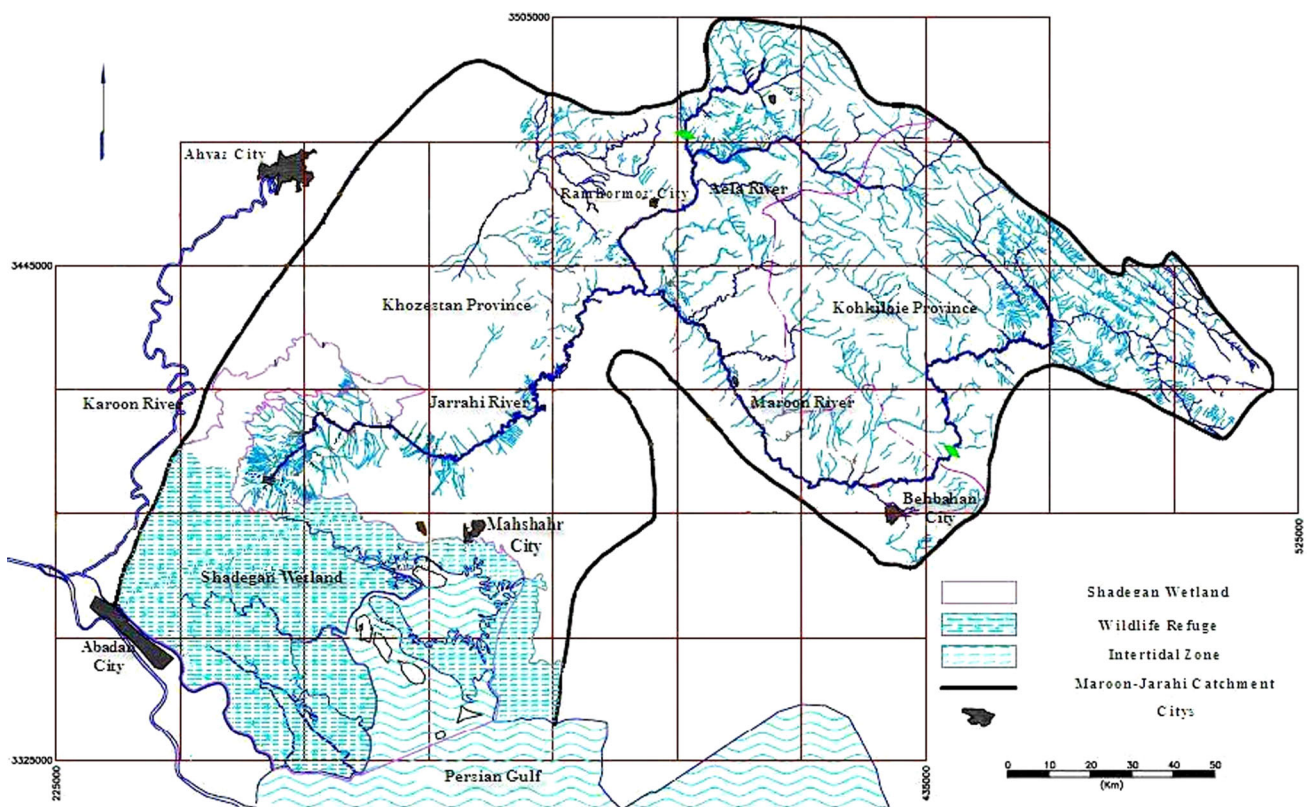
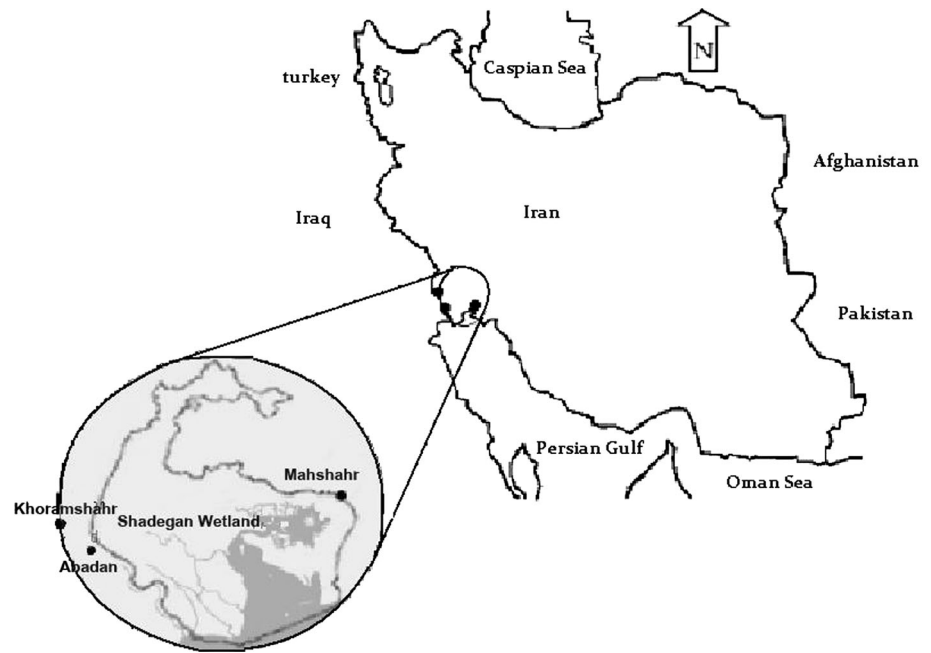


Fig. 2 Location of Shadegan Wetland in Maroon-Jarrahi basin

LARS-WG model. According to climate data analysis, up to 80 % of the mean annual rainfall occurs between December to March and total annual rainfalls are 214, 327 and 335 mm in M, B and R stations respectively. The daily rainfall and temperatures data for R and M stations are

available in 1987–2005 (20 years). The observed data was obtained from Iranian Meteorological Organization (www.irimet.net) on 17th January 2011 and associated information regarding every station information exhibited in Table 2. Daily precipitations (Prec) as well as daily

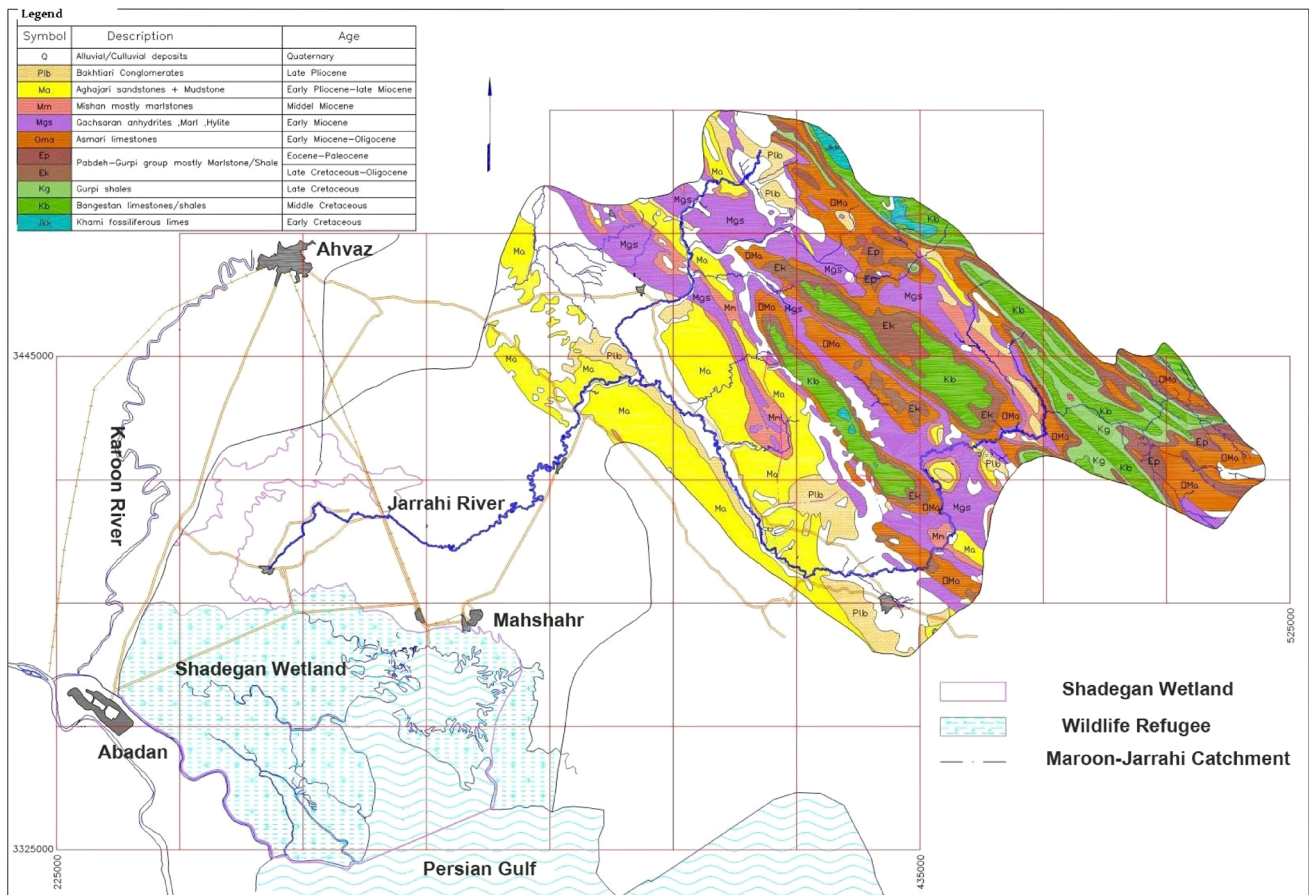


Fig. 3 Geology map of Shadegan Wetland (Pandam Consulting Engineer 2002)

maximum temperature (Tmax) and minimum temperature (Tmin) data represented as predictant for the downscaling experiments and National Center for Environment Prediction (NCEP) large scale variables indicated predictors. Climatic variables corresponding to climate change scenario for the study area are extracted from the ECHO-G GCM output for downscaling LARS-WG model—A2 emission scenariowith 2/8 * 2/8 degree of resolution (300 * 300 km at a grid point) and HadCM3 output applied to downscale the climate change based on SDSM model with A2 emission scenarios. The A2 emission scenario selected due to its position at the higher end of the SRES emissions scenarios which can facilitate the impacts and adaptation studies as well. The story line of the A2 emission is characterized by heterogeneity, also self-reliance and local identities are emphasized (IPCC 2007). Population increases continuously, economic development is regionally oriented, and economic and technological improvements are relatively slow compared to the other story lines (Nakicenovic et al. 2000). The pressure of human activity on Shadegan wetland such as the construction of Maroon dam consequently as well as petroleum activities reduces water quality and changed natural and hydrological

conditions in this vulnerable habitat. On the other hands, the entrance of waste water from sugar cone factories, upstream irrigation development projects, the entrance of oil pollution, land use change and construction of gas power plant sites have severity damaged to the environment of this international wetland which caused severity damages the wetland biodiversity. Accordingly it is expected decreasing the entrance of migratory bird in Shadegan wetland in the future with current pollution and climate change impact overall (Pandam Consulting Engineer 2002; Kaffashi et al. 2011; Davodi et al. 2011; Kaffashi et al. 2012).

3 Methods and material

3.1 Stochastic weather generators

LARS-WG is one of well-known statistical downscaling tools which widely uses for current and future climatic variables projections and it is based on the series weather generator. Readers of this model are referred to Semenov et al. (1998) for more information regarding the model setup and downscaling procedures.

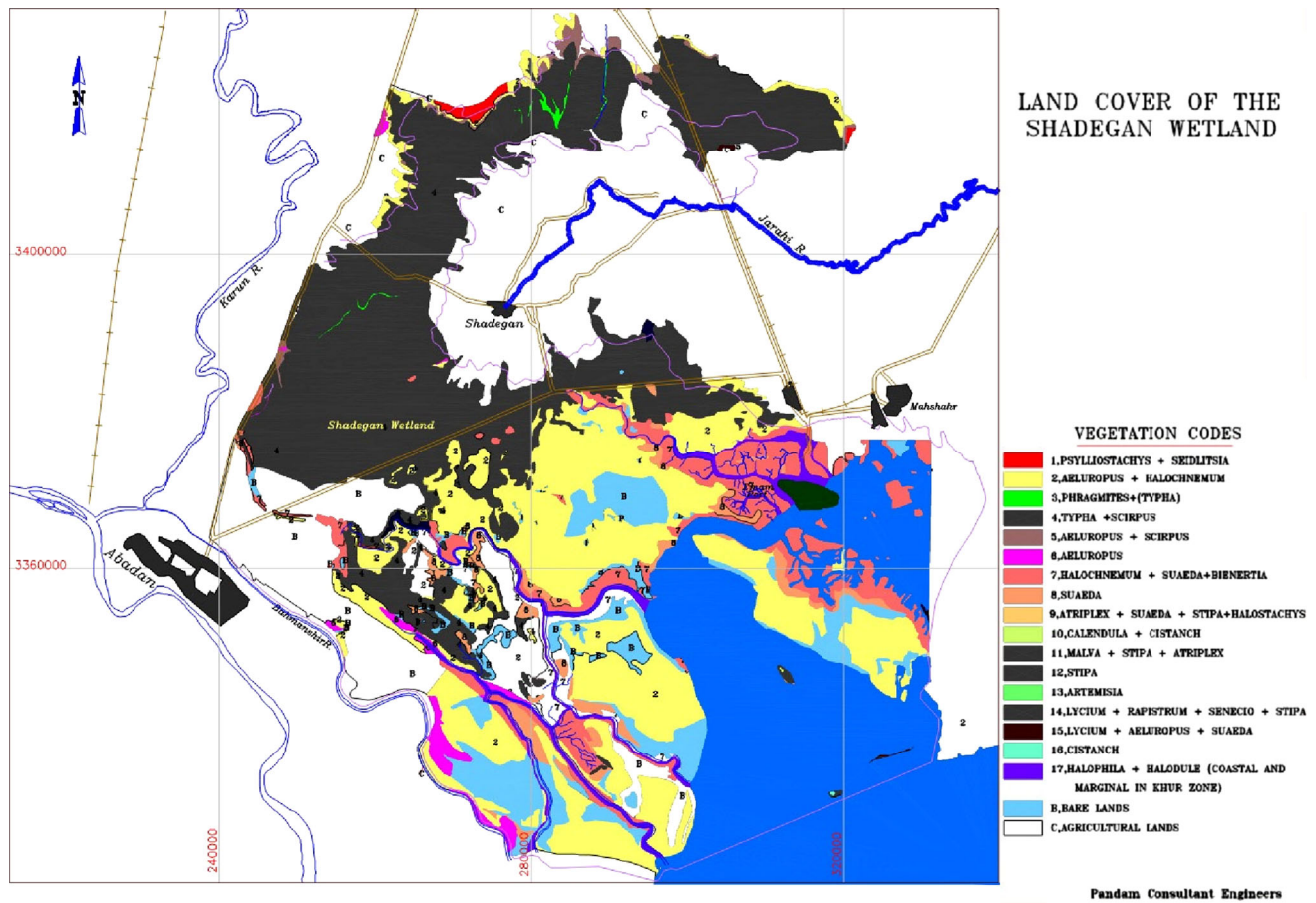


Fig. 4 Land cover of Shadegan wetland (Pandam Consulting Engineer 2002)

Table 1 A summary of associated dataset in this study

No.	Dataset	Period
1	Observed (precipitation, minimum and maximum temperature) [3 station: Behbahan(B), BandarMahshahr(B.M), Ramhormoz(R) (IRMO dataset)]	1987–2005(B.M and R) 1993–2005(B)
2	NCEP predictors	1961–2001
3	HadCM3 predictors	1961–2099
4	ECHO-G	1961–2099

3.2 Downscaling technique of LARS-WGS model

In this study, LARS-WG utilizes semi-empirical distributions for the lengths of wet and dry series, daily precipitation and daily solar radiation respectively. The semi-empirical distribution $Emp = \{a_0, a_i; h_i, i = 1, \dots, 10\}$ is a histogram with ten intervals, (a_{i-1}, a_i) , where $a_{i-1} < a_i$, and h_i denotes the number of events from the observed data in the i -th interval ram with ten intervals. Daily observed precipitation for each month analyzed in LARS-WG model using a first order Markov Chain or spell-length approach, and observed

data applied to obtain statistical characteristics such as the mean and distribution of the daily precipitation as well as the number of dry/wet days for each month of every year. The simulation of precipitation occurrence is modeled as alternate wet and dry series, where a wet day is defined to be a day with precipitation >0.0 mm. The length of each series is chosen randomly from the wet or dry semi-empirical distribution for the month in which the series start. In determining the distributions, observed series are also allocated to the month in which they start. For a wet day, the precipitation value is generated from the semi-empirical precipitation distribution for the particular month independent of the length of the wet series or the amount of precipitation on previous days (Racsko et al. 1991). LARS-WG utilizes separated semi-empirical distributions for minimum and maximum temperatures and the solar radiation respectively. The temperature is assumed to have a normal distribution, with the mean and SD varying daily according to a finite Fourier series. For the minimum and maximum temperatures, time auto-correlations are assumed to be constant throughout the year for a particular site. For solar radiation, semi-empirical distributions with equal interval sizes are used (Semenov et al. 1998) in this model.

Table 2 Characteristics of meteorological stations

Station	Current period	Geographical characteristic			Station type
		Elevation	Latitude	Longitude	
Behbahan	1991–2005	313/0	36.30'N	14.50'E	SYNOPTIC
Ramhormoz	1986–2005	5/105	16.31'N	36.49'E	SYNOPTIC
Mahshahr	1986–2005	6/2	30.33'N	9.49'E	SYNOPTIC

Climate data corresponding to future scenarios were provided using the daily GCM data for both current and future time periods. To incorporate the change in climate condition, one needs to calculate the relative change in monthly mean precipitation and monthly mean wet and dry series lengths from the GCM output of the baseline and future time-period accurately. Similarly, relative change in mean temperature and standard deviation for each month is calculated from GCM outputs. All these values are calculated from the parameter files generated during the site analysis of the corresponding climate variables (GCM outputs) for the base and future time periods. This information is then applied to construct the climate change scenario file which LARS-WG uses to determine how the weather generator parameter values (obtained from the observed precipitation and temperature data) should be perturbed to generate regional climate scenario. That means, the relative changes observed in the GCM outputs are the forcing to LARS-WG based on which it generates the daily weather data representing future climate at a given site.

3.3 Statistical downscaling method

Statistical downscaling method calculates statistical relationships, based on multiple linear regression techniques, between large-scale and local climate variables. The downscaling models are calibrated using National Centers for Environmental Prediction (NCEP) reanalysis as large-scale predictors (Semenov 2007). Observed predictor variables extracted from NCEP data centre. This data is used for extracting the relationships between large scale and regional variables. Table 3 shows the list of predictors in NCEP data centre. Since, all NCEP variables can have different relationships with predictant, therefore the best variable should represent the following characteristics, first it supposed to fit the trend of downscaled data (precipitation and temperature) and second, GCM model should be able to simulate this variable in observed period accurately (Samadi et al. 2013a). Predictors are also provided for a number of GCMs, including HadCM3. SDSM is a two-step conditional resampling methodology. This multi-site method first downscales area-averaged precipitation using a combination of regression-based methods and a

stochastic weather generator approach. Secondly, precipitation and temperature at individual sites are resampled from their distributions dependent on the downscaled area-average precipitation. Full technical details of the SDSM and an evaluation of the conditional resampling method are provided by Wilby et al. (2002).

Statistical relationships of SDSM developed using observed weather data and, assuming that these relationships remain valid in the future and they can be used to obtain downscaled local information for some future time periods by driving the relationships with GCM-derived predictors. The parameters of the regression equation are estimated using the efficient dual simplex algorithm (Karamouz et al. 2007). The model is structured as monthly model for both daily precipitation and temperature downscaling processes, in which case, twelve regression equations are derived for 12 months using different regression parameters. In this research the model was calculated for daily precipitation and daily temperatures using 30 years (1987–2005) as base interval. Since the distribution of the daily precipitation is highly skewed, in this current research a fourth root transformation was applied to the original precipitation before fitting the transfer function (Wilby and Dawson 2007). Mean and variance of downscaled daily precipitation and daily temperature are adjusted by bias correction and variance inflation factor to force model replicate the observed data accurately. Bias correction compensates for any tendency to over- or under-estimate the mean of downscaled variables. Finally twenty ensembles of downscaled daily precipitation and daily temperature have been generated to date; the downscaling algorithm of SDSM has been applied to a host of meteorological stations.

3.4 Model evaluation techniques

In this study the reliability of downscaled climatic data assessed using five different criteria in each station. These criteria are mean absolutely error (MAE), the coefficient of determination (R_2), root mean square error (RMSE), Nash–Sutcliffe coefficient (NSE) and percent bias (PBIAS). Each of the criteria is briefly described here:

$$MAE = 1/n \sum_{i=1}^n (S_i - O_i) \quad (1)$$

Table 3 NCEP and HadCM3 predictors which used in SDSM downscaling method

Predictor variable	Abbreviation	Predictor variable	Abbreviation
Mean sea level pressure	ncepmslp	500 hPa geopotential	ncepp500
500 hPa wind speed	ncepp5_f	850 hPa geopotential	ncepp850
500 hPa U-component	ncepp5_u	1,000 hPa wind speed	ncepp_f
500 hPa V-component	ncepp5_v	1,000 hPa U-component	ncepp_u
500 hPa vorticity	ncepp5_z	1,000 hPa V-component	ncepp_v
500 hPa wind direction	ncepp5th	1,000 hPa vorticity	ncepp_z
500 hPa divergence	ncepp5zh	1,000 hPa wind direction	ncepp_th
850 hPa wind speed	ncepp8_f	1,000 hPa divergence	ncepp_zh
850 hPa U-component	ncepp8_u	500 hPa relative humidity	ncepr500
850 hPa V-component	ncepp8_v	850 hPa relative Humidity	ncepr850
850 hPa vorticity	ncepp8_z	1,000 hPa relative humidity	nceprhum
850 hPa wind direction	ncepp8th	1,000 hPa specific humidity	ncepshum
850 hPa divergence	ncepp8zh	Temperature at 2 m	nceptemp

$$R^2 = \left[\frac{\frac{1}{n} \sum_{m=1}^n (S_i - \bar{S})(O_i - \bar{O})}{\sigma_S \times \sigma_O} \right]^2 \quad (2)$$

$$RMSE = \left[\frac{1}{N} \sum_{i=1}^N (S_i - O_i)^2 \right]^{1/2} \quad (3)$$

$$NSE = 1 - \frac{\sum_{i=1}^N (O_i - S_i)^2}{\sum_{i=1}^N (O_i - \bar{O})^2} \quad (4)$$

$$PBIAS = \left[\frac{\sum_{i=1}^n (O_i - S_i) * 100}{\sum_{i=1}^n (O_i)} \right] \quad (5)$$

where N represents the number of observations in the time series, S_i is the simulated values, O_i is the corresponding observed values, σ is the variance and \bar{O} and \bar{S} are the observation and simulation averages respectively. The coefficient of determination measures the tendency of the simulated and observed values to vary together linearly and ranges from 0 to 1, with higher values indicating less error variance, and typically values greater than 0.5 are considered acceptable (Van Liew and Garbrecht 2003). NSE ranges between $-\infty$ and 1.0, with $NSE = 1$ being the optimal value. Values between 0.0 and 1.0 are generally viewed as acceptable levels of performance, whereas values <0.0 indicates that the mean observed value is a better predictor than the simulated value and reflects a poor model fit as well. The optimal value of PBIAS is 0.0, with low-magnitude values indicating accurate model simulation. Positive values indicate model underestimation bias, and negative values indicate model overestimation bias (Gupta et al. 1999). RMSE varies from the optimal value of 0 to a large positive value, which zero RMSE indicates perfect model simulation. The least RMSE and MAE show the strange relationship, so the lower value indicates the better simulation performance. Results of SDSM and

LARS-WG-WG validation presented in Table 4 and 5 for monthly temperature and precipitation of three climate stations respectively. The results of statistical parameters analyses indicated a good prediction for temperature rather than precipitation because the relatively low R_{sq} for daily rainfall in an arid region can be acceptable in global standards overly. Overall the sequence of both downscaling projections and their outputs can be found in Etemadi et al. 2012, so we do not discuss on downscaling projections here, instead this paper is trying to build a proper connection between downscaling outputs and uncertainty analysis, in which the statistical methods can be a basis for uncertainty propagation of traditional downscaling models in an arid climate condition.

3.5 Uncertainty assessment in downscaled results

Recently much attention has been moved to uncertainty issues in downscaling models due to their great effects on climate prediction and further on decision making. In view of this, it is suggested to evaluate the results when the data are downscaled from more than one statistical model (Samadi et al. 2013b). The uncertainty analysis here includes daily precipitation as well as minimum and maximum temperatures at three different climate stations using appropriate downscaling techniques. In case of daily temperature data, because of their nearly normal distribution, the uncertainty has been assessed with comparison of means of downscaled temperature data with observed ones. In that comparison, deviations (referred to as model errors) between downscaled and observed monthly means and variances of daily Tmax and Tmin have been evaluated at 95 % confidence level moreover, 95 % CI in the estimates of means of downscaled temperature in each month have been compared with observed CIs to assess whether the downscaling models can reproduce uncertainty as found in

Table 4 Modelled monthly temperature and precipitation of LARS-WG in validation period

Statistical factor	Behbahan			Bandar Mahshahr			Ramhormoz		
	Tmin	Tmax	Prcp	Tmin	Tmax	Prec	Tmin	Tmax	Prcp
PBIAS	0.569	0.371	7.373	0.716	0.308	1.492	0.185	0.380	2.795
MAE	-0.097	-0.119	-0.068	-0.132	-0.100	-0.009	-0.036	-0.124	-0.026
RMSE	0.368	0.465	0.309	0.412	0.470	0.189	0.710	0.844	0.148
NSE	0.998	0.998	0.915	0.997	0.998	0.909	0.992	0.993	0.981
RSQ	0.998	0.998	0.920	0.997	0.998	0.914	0.992	0.995	0.986

Table 5 SDSM validation results for monthly temperature and precipitation dataset

Statistical factor	Behbahan			Bandar Mahshahr			Ramhormoz		
	Tmin	Tmax	Prec	Tmin	Tmax	Prec	Tmin	Tmax	Prec
PBIAS	-1.037	2.210	22.885	-2.225	1.555	-27.958	-0.207	1.783	25.743
MAE	0.177	-0.711	-0.213	0.411	-0.505	0.163	0.040	-0.583	0.115
RMSE	1.366	1.320	0.597	1.645	1.433	0.319	1.530	1.492	0.825
NSE	0.967	0.983	0.682	0.947	0.980	0.741	0.962	0.979	0.867
RSQ	0.972	0.991	0.799	0.956	0.983	0.844	0.967	0.984	0.879

the observed data or not. In uncertainty assessment of downscaled daily precipitation data, comparison of means values should not be enough because of non-normality distribution of daily precipitation data and also because of mixed distribution of wet and dry days in a daily precipitation series. Therefore, in assessment of uncertainty in downscaled daily precipitation, in addition to comparing means, monthly mean dry-spell and wet-spell statistics and their CIs, distribution of monthly mean of daily precipitation, and distributions of monthly wet and dry days have been compared. In this study, the most commonly used non-parametric technique, bootstrapping has been used for finding the CIs of means and variances. The idea of bootstrapping is to resample a large number of new data sets with replacement from the original data set. In this study, using the bootstrap CIs for the estimated means and variances have been calculated for daily precipitation, daily maximum and minimum temperatures for each month at three climate stations. 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 according to Khan et al. 2006. Figure 5 exhibited sequence steps of this research study.

4 Result

4.1 Validation of downscaling methods

Monthly validation results of each downscaling method based on five different criteria were presented in Tables 4

and 5. Nash–Sutcliffe coefficient for temperatures in both downscaling methods indicated very fairly relationship between observed and downscaled datasets at all three stations. Overall, both of downscaling methods presented closely predictions to measured data.

The results of rainfall statistical parameters analysis indicated that LARS-WG output is more reliable with Nash–Sutcliffe coefficient equals to 0.909 (NSE = 0.909) while SDSM downscaled precipitation data do not have a good match to observed data based on five criteria. However it can be conclude that the relatively low RSQ value for daily precipitation in an arid region is satisfy for global standards. Besides SDSM has a large component of uncertainty, so we would not expect the model to replicate the exact daily sequences found in observations exactly. Also the level of predictability of site-level precipitation from regional-scale predictors is invariably low.

4.2 Uncertainty analysis of mean minimum and maximum temperatures and precipitation

4.2.1 Minimum temperature

The result of monthly Tmin based on bootstrap techniques exhibited in Figs. 6, 7 and 8 for 1987–2000 and 1993–2000 periods respectively. Figure 6 exhibited the uncertainty associated to LARS-WG method in daily Tmin downscaling approach. According to this figure model downscaled climate data quite well in all months except September in Behbahan station and it indicated that model

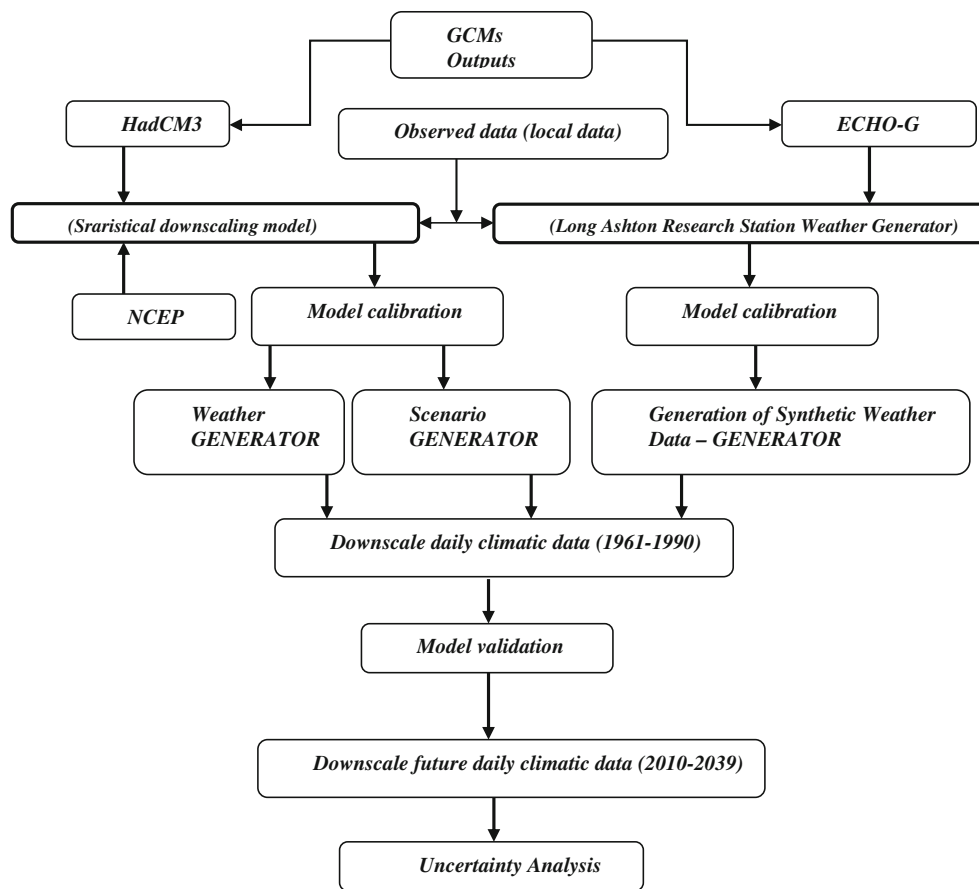


Fig. 5 Schematic illustrating of uncertainty analysis of statistical downscaling approach in this research

overestimated climatic variables in a given period. Also SDSM downscaled T_{min} as closely as to observed data in summer and beginning of autumn seasons (June, July, August and September) but over-predicted in the end of autumn and winter seasons, respectively. Furthermore SDSM model under-predicted T_{min} in spring season (April and May) in all three stations. LARS-WG downscaled T_{min} pretty close to observed data and these results indicated that the LARS-WG downscaled data and observed data are similar at 95 % significance level in most of the months, therefore LARS-WG model is more reliable than SDSM to reproduce observed T_{min} in Shadegan wetland as well. It is worth to mention that an important reason for precipitation reduction in downscaled outputs is related to passage of Mediterranean anticyclone crosses during cold season in this area which affects regional climate conditions (see Samadi et al. 2013a). Also, the important winds of the area consist of the Western winds that transfer the relative humidity of the Atlantic Ocean and Mediterranean to the territory of this area in the winter causing some rainfall events (Samadi et al. 2013a). Furthermore the Northern wind that blows in the frontier zone makes the climate very hot and intolerable in summers and also

causing damages which all these natural events are disregarded in GCM projections (see Samadi et al. 2013a).

4.2.2 Maximum temperature

The uncertainty of model and observed T_{max} at 95 % CI presented in Figs. 9, 10 and 11. In the case of monthly maximum temperature, the graphical comparison of monthly observed and model datasets indicated that the SDSM model variability is closely enough with the observed variability except in May at Behbahan station where model under-predicted maximum temperature, while the LARS-WG model produced T_{max} data as closely as the observed one in all months except in February at Ramhormoz station as well. Overall this result indicated a high capability of LARS-WG model to estimate T_{max} values in the future.

4.2.3 Uncertainty of maximum and minimum temperatures in the 2,025 period

Table 6 represented the outputs of monthly mean T_{min} using SDSM and LARS-WG models for 2010–2039

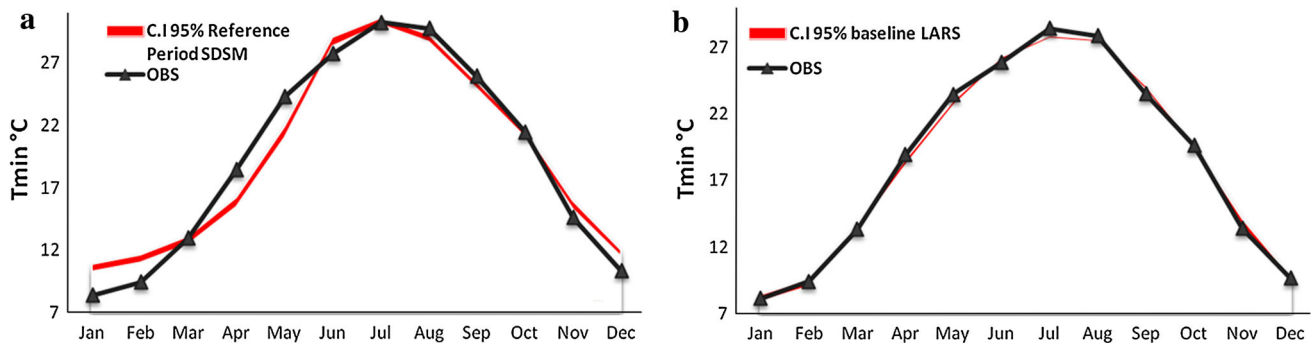


Fig. 6 Monthly bootstrap means of observed and modeled Tmin at 95 % CI in SDSM (a) and LARS-WGS (b) model in Mahshahr station respectively

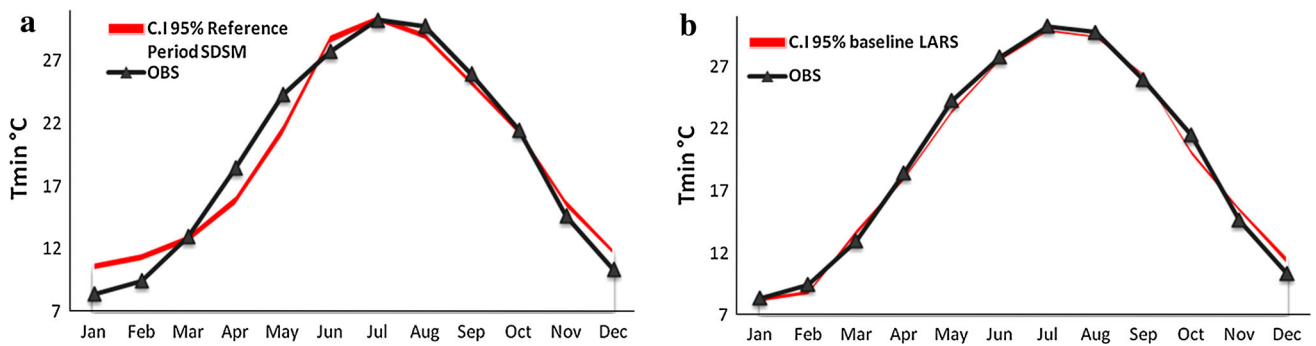


Fig. 7 Monthly bootstrap means of observed and modeled Tmin at 95 % CI in SDSM (a) and LARS-WGS (b) model in Ramhormoz station respectively

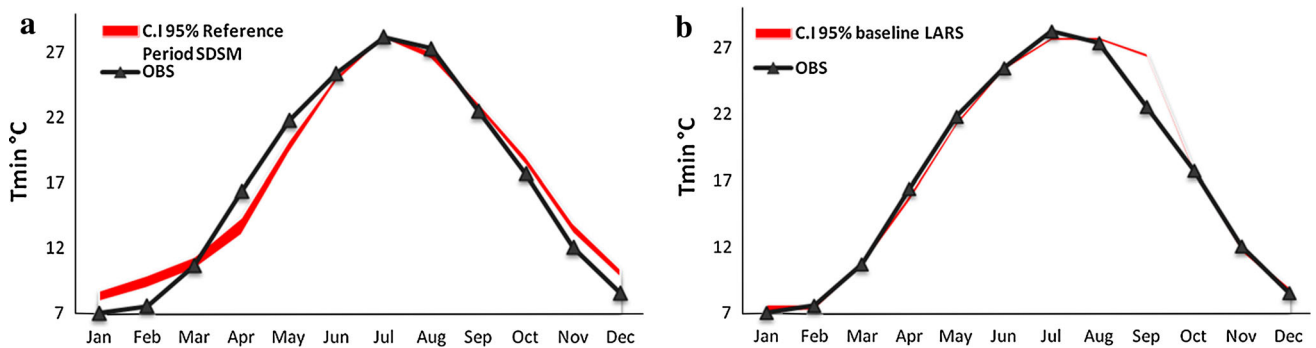


Fig. 8 Monthly bootstrap means of observed and modeled Tmin at 95 % CI in SDSM (a) and LARS-WGS (b) model in Behbahan station respectively

interval based on bootstrap analysis. According to this result, SDSM model predicted distinct warming trend in Tmin in cold months (January, February, March, November and December) at all tree stations. In fact it predicted maximum increasing of +7.3 °C at B station in November while predicted maximum reduction of -5.48 °C in M station in August respectively. In the other hands, SDSM estimated that Tmin will increase up to +3.3, +1.4 and +3.1 °C in winter and +3.9, +1.6 and +4.2 °C in autumn at M, R and B stations, respectively. Furthermore Tmin will decrease up to -1.8, -1.7 and -2.4 °C in spring at M,

R and B stations, and in summer Tmin will decrease up to -0.16 and -1.5 °C in M and R stations respectively. Overall SDSM predicted increasing range of Tmin between +1.4 and +3.9 °C for cold seasons and reducing of Tmin between (-0.16) and (-2.4) °C for warm seasons at all climate stations which revealed that future winter seasons precipitate less rainfall and warm periods are going to be cooler and it potentially reduces the evapotranspiration rate in the future period. LARS-WG Model similar to SDSM model predicted increasing and decreasing trends for Tmin in cold and warm months respectively, but range of

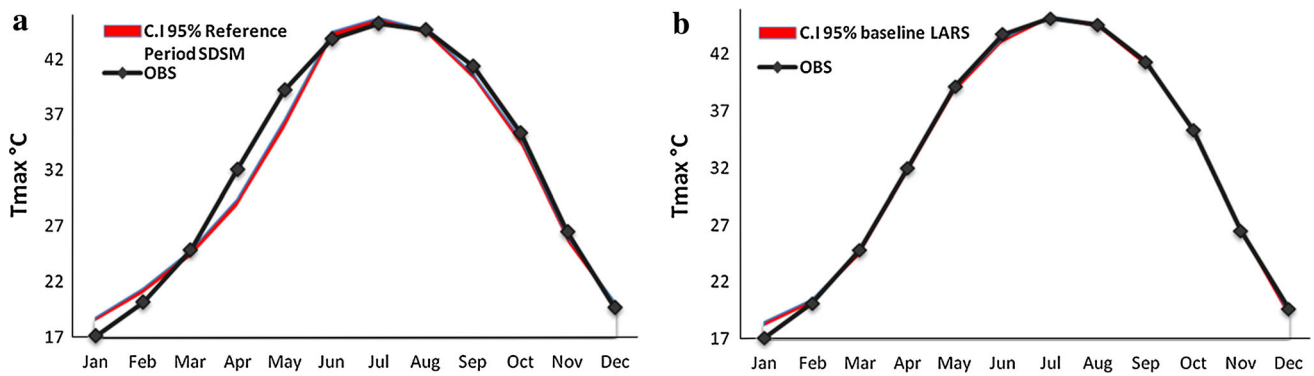


Fig. 9 Monthly bootstrap means of observed and modeled Tmax at 95 % CI in SDSM (a) and LARS-WGS (b) model in Mahshahr station respectively

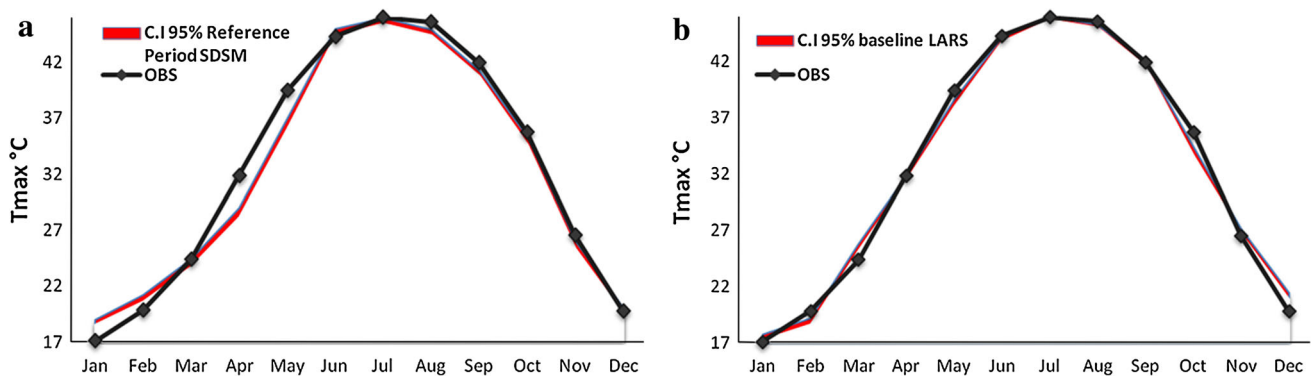


Fig. 10 Monthly bootstrap means of observed and modeled Tmax at 95 % CI in SDSM (a) and LARS-WGS (b) model in Ramhormoz station respectively

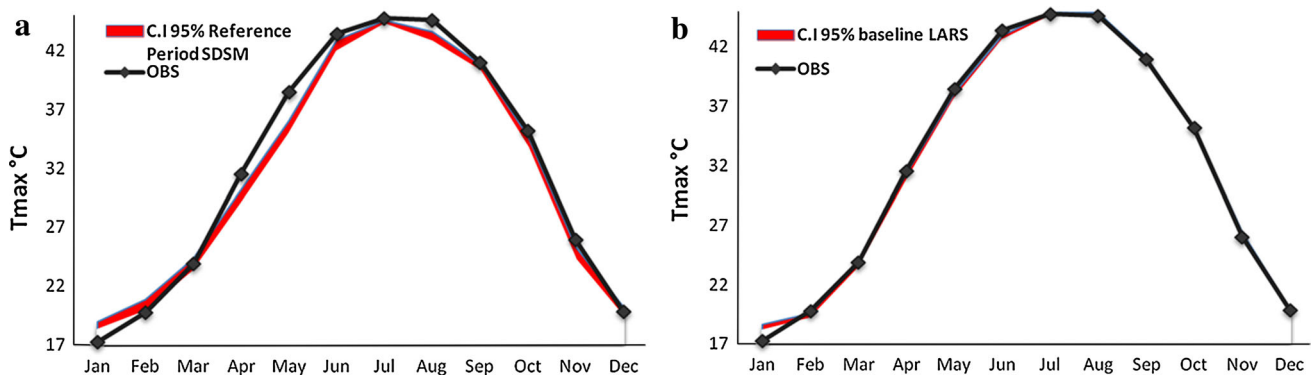


Fig. 11 Monthly bootstrap means of observed and modeled Tmax at 95 % CI in SDSM (a) and LARS-WGS (b) model in Behbahan station respectively

increasing and decreasing values generated by LARS-WG was less than SDSM model additionally. Maximum increasing (+2.9 °C) has been observed at B station in February while maximum reduction of -1.21 was happened in R station in October. Downscaling result of Tmin using LARS-WG method indicated that future Tmin will raise +0.56, +0.45 and +1.4 °C in the winter at M, R and B stations respectively. Moreover it increases up to +0.24

and +0.12 °C in autumn at R and B stations, also future spring and summer Tmin will reduce up to -0.17 , -0.37 , -0.3 , -0.3 , -0.31 and -0.25 °C in all stations respectively. Generated Tmin with LARS-WG model increased between +0.12 and +1.4 °C in cold season and decreased between -0.17 and -0.37 °C in warm season totally. Both downscaling methods suggested increasing in Tmin for cold season and decreasing for warm season in 2010–2039

periods respectively. Totally the magnitude of the Tmin changes varies in each model, ranging between +0.12 and +3.9 °C and between -0.16 and -2.4° C in cold and warm seasons respectively.

Comparison between monthly bootstrap means daily Tmax of observed and future downscaled scenario using SDSM and LARS-WG is presented in Table 7. SDSM model predicted distinct warming trend in Tmax in January, February, March, November and December and cooling trend in the rest of year (April to October at all tree stations). In fact Tmax will rise up to +1.5, +4.2 and +1.9 °C in winter, and +2.0, +1.2 and +1.2 °C in autumn at M, R and B stations respectively. Beside Tmax will decrease up to -1.6, -1.1 and -5.3 °C in spring and Tmax will reduce up to -5.4, -7.3 and -1.9 °C in summer at all locations respectively. Increasing and decreasing Tmax in cold season and warm season varies ranging between +1.2 to +4.2 °C and -1.1 to -7.3 °C overall. Future climate projection using LARS-WG model indicated that Tmax will reduce in April, May, Jun, July, August, September and October at all three stations and the rest of year will raise in the future period. Maximum increasing is up to +1.5 °C in January at B station and maximum decreasing is up to -5.7 °C in September at R station additionally. Future spring and summer Tmax reduce up to -0.42, -0.67 and -0.45 and up to -0.46, -5.53, -0.20 °C at three stations respectively. Also Tmax will rise up to +0.73, +0.67 and +0.70 °C in winter at all stations, it also increases up to +0.01 and +0.18 °C in autumn at M and R stations. A comparison of two downscaling methods demonstrated that in both models Tmax rises in cold seasons and reduces in warm seasons in 2010–2039 period and overall the major changes varies in each month/model/station respectively, furthermore Tmin ranges between

+0.01 and +4.2 °C for cold seasons and between -1.1 and -7.3° C for warm season in the future period.

4.2.4 Precipitation

Review of literature stressed on abnormal distribution of precipitation especially in low precipitation region, like arid and semi-arid areas (see Samadi et al. 2013b). In fact, precipitation is mostly distributed uneven and known as non-normal variable particularly in an arid climate with less and spare rainfall events. Beside precipitation is related to some local factors like topography which was disregarded in GCM simulation, so it may enter uncertainty during prediction processes. Also this reveals the inability of the GCM model to resolve sub-grid scale atmospheric processes (Samadi et al. 2013a) such as uncertainty associated of GCMs models in the boundaries as well as uncertainty propagation of the area between GCM and atmospheric ocean general circulation model (AOGCM) like this study area where is close to Persian Gulf, in such a location uncertainty associated to GCM models and prediction can raise as a sequence. The bootstrap means result of observed and modeled precipitation data sets at 95 % CI presented in Figs. 12, 13 and 14. Monthly bootstrap means of observed and LARS-WG precipitation datasets were precisely at CI 95 % baseline period, except in March for R station, where model underestimated precipitation values. Model also over predicted and under predicted precipitation data for January and February in Behbahan station respectively.

Overall uncertainty analysis of observed and down-scaled daily precipitation indicated that LARS-WG model is most profit to predict precipitation data in this arid basin. In fact uncertainty analysis of SDSM presented that

Table 6 Monthly bootstrap means daily Tmin of observed and future (2010–2039) scenario using SDSM and LARS models

Station	Mahshahr			Ramhormoz			Behbahan		
	OBS	SDSM	LARS	OBS	SDSM	LARS	OBS	SDSM	LARS
January	8.12	13.07	8.738	8.369	10.25	8.473	7.034	12.42	7.871
February	9.413	10.10	10.38	9.451	10.03	9.481	7.565	11.92	10.49
March	13.32	17.73	13.42	12.93	14.80	14.17	10.68	10.41	11.12
April	18.95	15.58	18.28	18.43	14.84	18.32	16.36	15.53	15.82
May	23.45	19.88	23.04	24.28	22.00	23.26	21.77	17.24	21.38
June	25.83	27.32	26.38	27.74	28.30	27.76	25.42	23.42	25.43
July	28.41	32.16	27.6	30.24	29.86	29.71	28.20	27.84	27.52
August	27.84	22.36	27.01	29.77	26.12	29.12	27.32	31.17	26.69
September	23.48	24.70	24.2	25.95	25.24	26.18	22.52	26.05	23.07
October	19.62	22.25	19.13	21.47	22.21	20.26	17.71	22.00	17.63
November	13.38	17.97	13.98	14.62	16.50	14.86	12.07	19.37	12.03
December	9.644	14.18	9.365	10.35	12.53	12.06	8.538	9.61	9.027

Table 7 Monthly bootstrap means daily Tmax of observed and future (2010–2039) scenario using SDSM and LARS models

Station	Mahshahr			Ramhormoz			Behbahan		
	OBS	SDSM	LARS	OBS	SDSM	LARS	OBS	SDSM	LARS
January	17.11	20.31	18.47	17.09	21.17	17.62	17.27	20.99	18.82
February	20.12	19.12	20.89	19.84	23.84	19.73	19.77	21.47	20.39
March	24.83	27.18	24.90	24.4	29.16	26	23.9	24.47	23.85
April	32.05	32.03	31.55	31.89	32.01	31.45	31.56	27.79	31.36
May	39.22	36.53	38.71	39.44	37.69	38.27	38.48	30.92	38.01
June	43.78	41.40	43.51	44.31	42.36	43.91	43.43	39.07	42.75
July	45.19	40.31	44.58	45.98	41.15	45.73	44.77	39.26	44.75
August	44.6	40.80	44.11	45.61	38.31	45.03	44.62	43.62	44.02
September	41.33	33.53	41.03	41.96	31.93	26.18	40.99	41.62	41
October	35.35	33.77	35.35	35.72	33.48	33.99	35.17	35.76	34.82
November	26.49	29.27	27.03	26.56	28.73	26.71	26	29.92	26.14
December	19.65	24.53	19.15	19.78	23.69	21.92	19.84	19.15	19.94

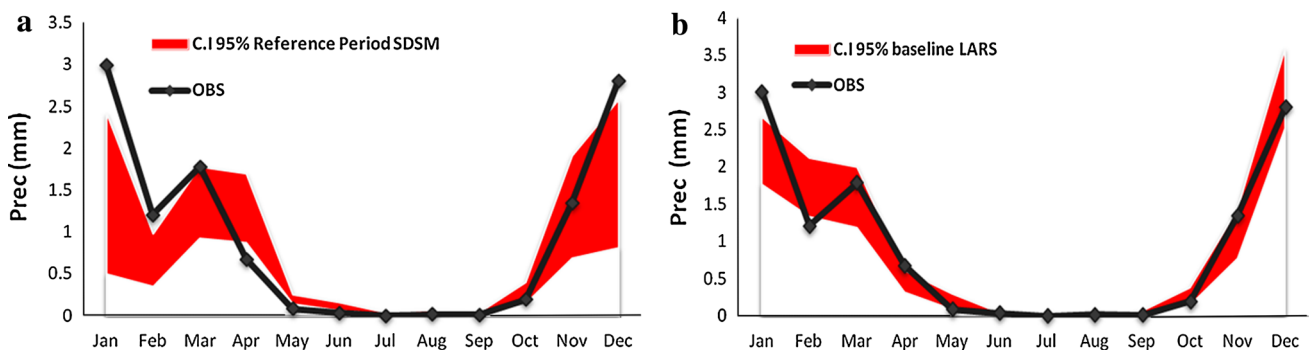


Fig. 12 Monthly bootstrap means of observed and downscaled precipitation data at 95 % CI using SDSM (a) and LARS-WGS (b) models in Behbahan station

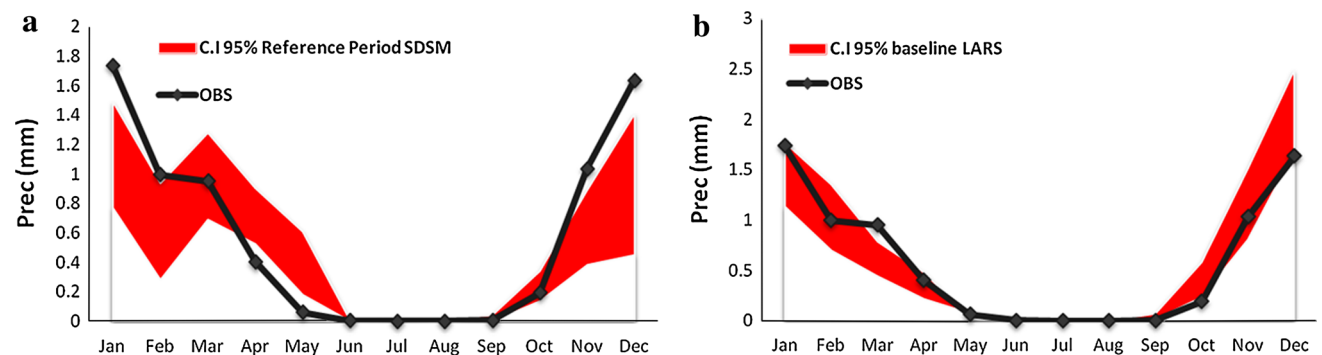


Fig. 13 Monthly bootstrap means of observed and downscaled precipitation data at 95 % CI using SDSM (a) and LARS-WGS (b) models in Ramhormoz station

uncertainty and error associated to daily precipitation is high in the most of a year (January, February, April, May, Jun, November and December) with high probable rate of precipitation amount. In the other hands, uncertainty associated with downscaled climatic variables is depicted as a uniform distribution in LARS-WG model, while

SDSM outputs are not quantified at the 95 % CI comparatively. Consequently it can be concluded that, the LARS-WG method is the most proficient model at reproducing various statistical characteristics of observed data at a 95 % confidence level while the SDSM model is the least capable in this respect.

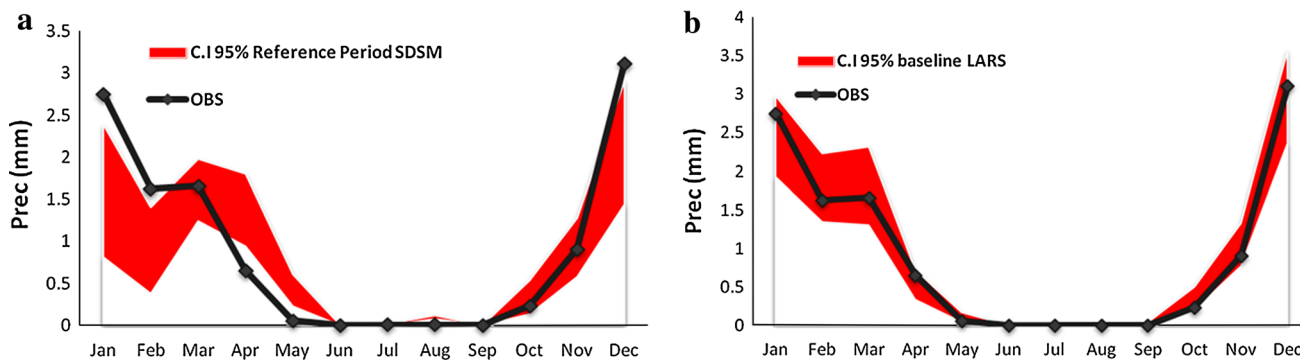


Fig. 14 Monthly bootstrap means of observed and downscaled precipitation data at 95 % CI using SDSM (a) and LARS-WGS (b) models in Mahshahr station

4.2.5 Monthly dry and wet days

A wet day is defined as a day with rainfall more than 0.3 mm (Khan et al. 2006), so in this research we considered a day with more than 0.3 mm rainfall amount as a wet day. Figures 15, 16 and 17 exhibited the monthly means dry and wet spells of both models and observed data based on bootstrap analysis at three stations respectively. It was found that the LARS-WG model estimated dry-spell days closer to the observed data except in September and November in Mahshahr station. Besides LARS-WG model under predicted dry spells in September at Behbahan station. Also the LARS-WG model overestimated in April at both Behbahan and Ramhormoz stations and over predicted in May at Ramhormoz station as well. Overall, the LARS-WG model showed that it is capable to predict wet-spell days closely to the observed data for the most of a year at three stations. Nevertheless downscaled dry and wet spell by SDSM model overestimated/underestimated in the most of a year at all stations totally. Estimation of dry spells is a significant indicator in an arid region especially in wetland hydrology studies and it indicated how many days this area will experience dry stress in the future.

4.3 Uncertainty analysis of variance for daily minimum and maximum temperatures and daily precipitation

Uncertainty can also be estimate by evaluating CI for variance. In this study the non-parametric bootstrap technique has been used in estimating 95 % CI for modeled and observed variances. Minimum and maximum temperatures and precipitation presented in Figs. 18, 19, 20, 21, 22, 23, 24, 25 and 26 for all stations. Larger CIs bands demonstrated higher uncertainty and the smaller bands showed less uncertainty as well. In the case of Tmin, comparison of monthly observed and modeled variances indicates that the LARS-WG model variability is close to the observed data in 8 months in all stations. But the variance represented by SDSM model, either overestimated or underestimated in January, February, April, June, November and December at three locations respectively. In addition these results indicated a high capability of LARS-WG model to predict the exact sequence of observed data in minimum or Tmax but not at a same level for precipitation data furthermore. Figures 21, 22 and 23 exhibited uncertainty associated to Tmax variance at 95 % CI in LARS-WG model. It also

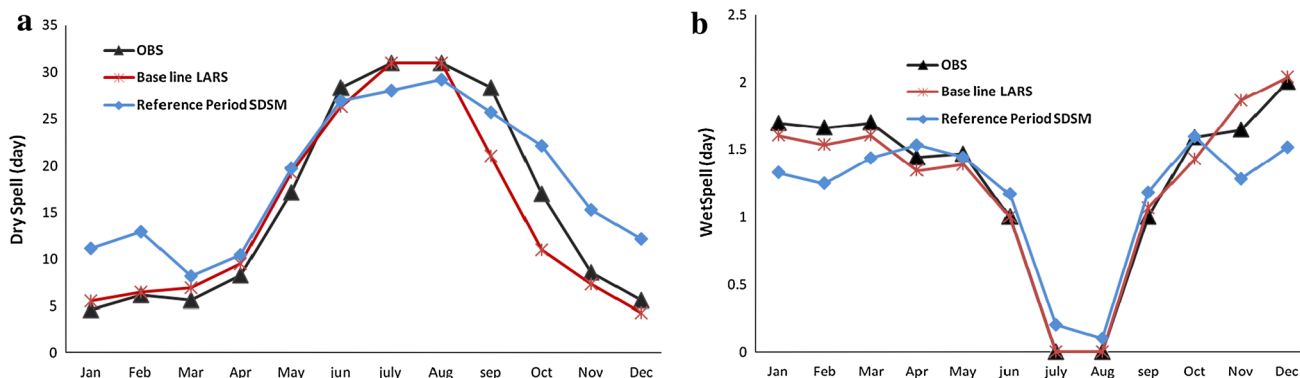


Fig. 15 Comparison of monthly bootstrap means of (a) Dry spell and (b) Wet spell for precipitation downscaled data using SDSM, LARS and observe datasets in Mahshahr station

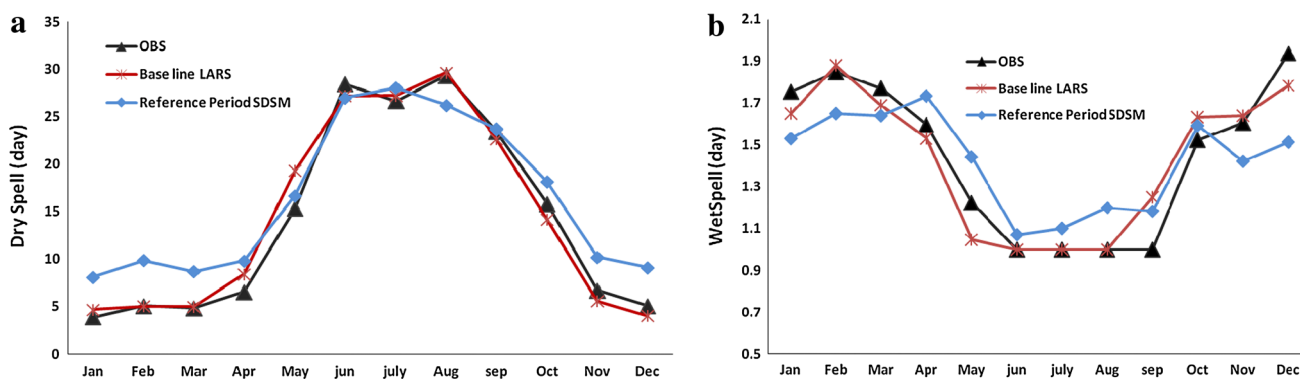


Fig. 16 Comparison of monthly bootstrap means of (a) Dry spell and (b) wet spell for precipitation downscaled data using SDSM, LARS and observe datasets in Ramhormoz station

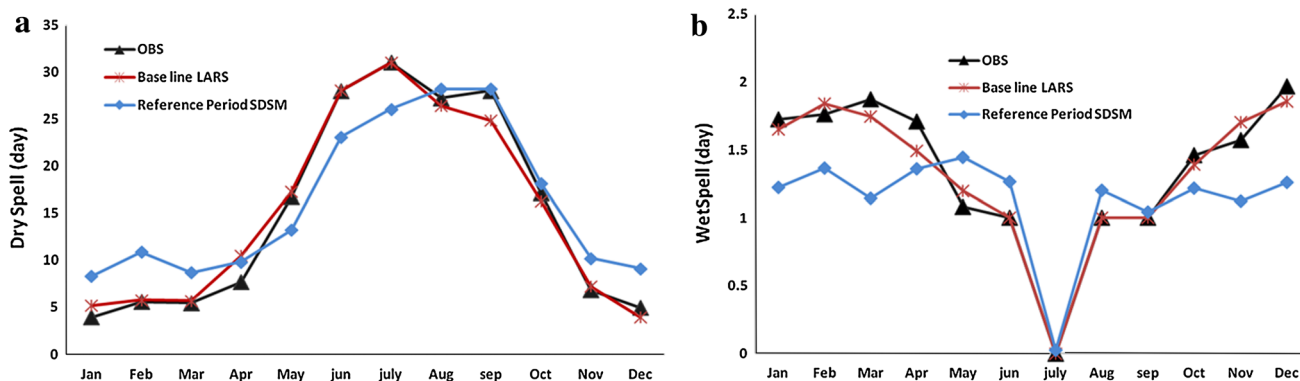


Fig. 17 Comparison of monthly bootstrap means of (a) Dry spell and (b) wet spell for precipitation downscaled data using SDSM, LARS and observe datasets in Behbahan station

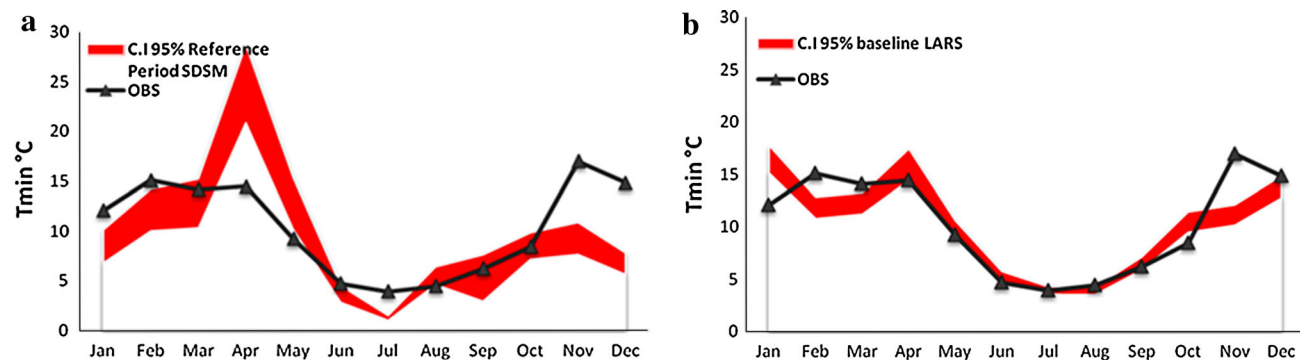


Fig. 18 Monthly bootstrap variance of observed and downscaled Tmin data at 95 % CI using SDSM (a) and LARS-WGS (b) model in Behbahan station

revealed that the least uncertainty for most of a year in Behbahan, Mahshahr and Ramhormoz stations while the SDSM model represented the least uncertainty for overall 6, 4, 2 months of a year in Behbahan, Mahshahr and Ramhormoz stations respectively. This result indicated that uncertainty propagation to LARS-WG method is significant at 95 % prediction bounds in most of a year. Figures 24, 25 and 26 exhibited the uncertainty bounds for

precipitation variance at 95 % CI, LARS-WG model also presented the least uncertainty at Ramhormoz and Mahshahr stations while exhibited more uncertainty propagation in 10 months at Behbahan station overall. Beside the SDSM model represented the least uncertainty for 7 months (April, June, July, August, September, October and November), 4 months (May, July, August and December) and 3 months (July, August, September) of a

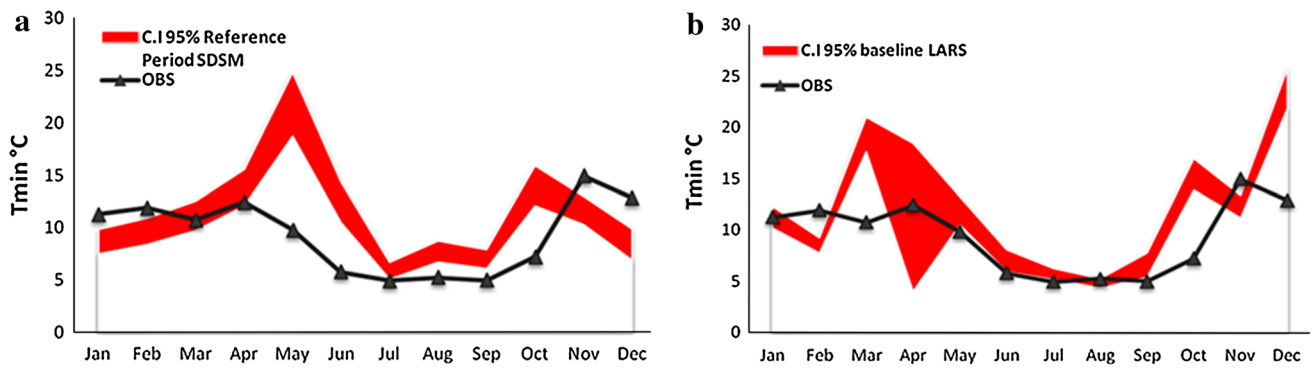


Fig. 19 Monthly bootstrap variance of observed and downscaled Tmin data at 95 % CI using SDSM (a) and LARS-WGS (b) model in Ramhormoz station

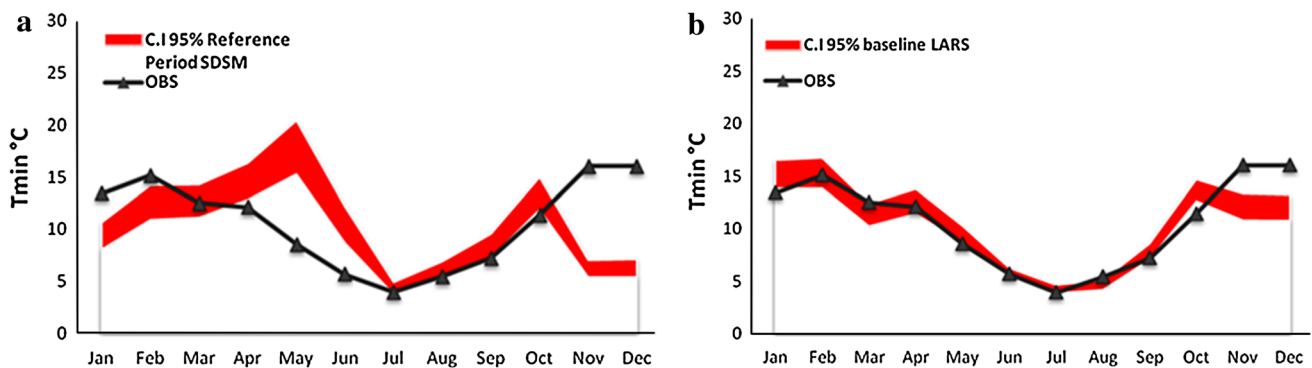


Fig. 20 Monthly bootstrap variance of observed and downscaled Tmin data at 95 % CI using SDSM (a) and LARS-WGS (b) model in Mahshahr station

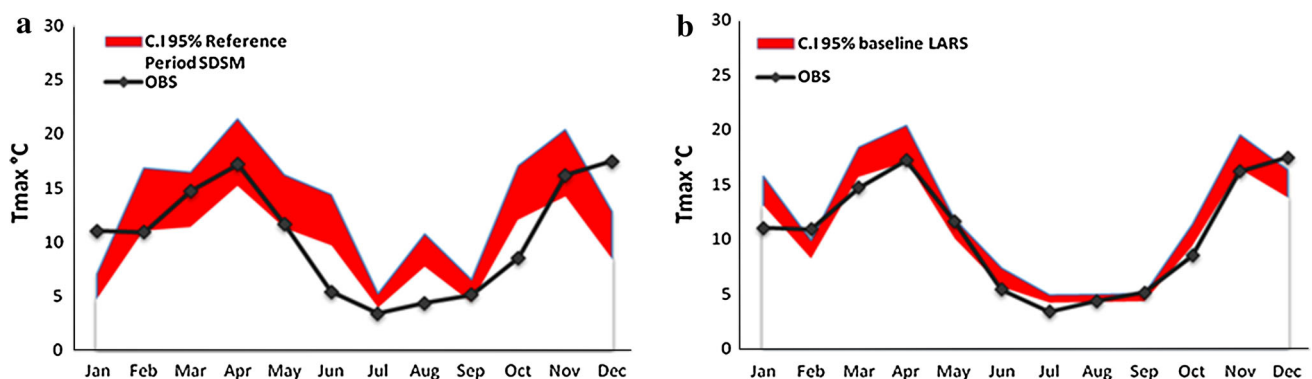


Fig. 21 Monthly bootstrap variance of observed and downscaled Tmax data at 95 % CI using SDSM (a) and LARS-WGS (b) model in Behbahan station

year in Behbahan, Ramhormoz and Mahshahr stations respectively. Finally by comparing variance of monthly precipitation for each month, the LARS-WG errors were significant for most of a year at a 95 % confidence level, but the SDSM model errors found to be insignificant for most of the months in a year, they were significant in some months and insignificant in the rest of a year as well.

5 Summery and discussion

Wetlands are one of the most important ecosystems with the highest ecological value in the world. Nowadays, there is growing concern about the importance of wetland ecosystems and the broad diversity of goods and services provided by them for instance biodiversity and freshwater

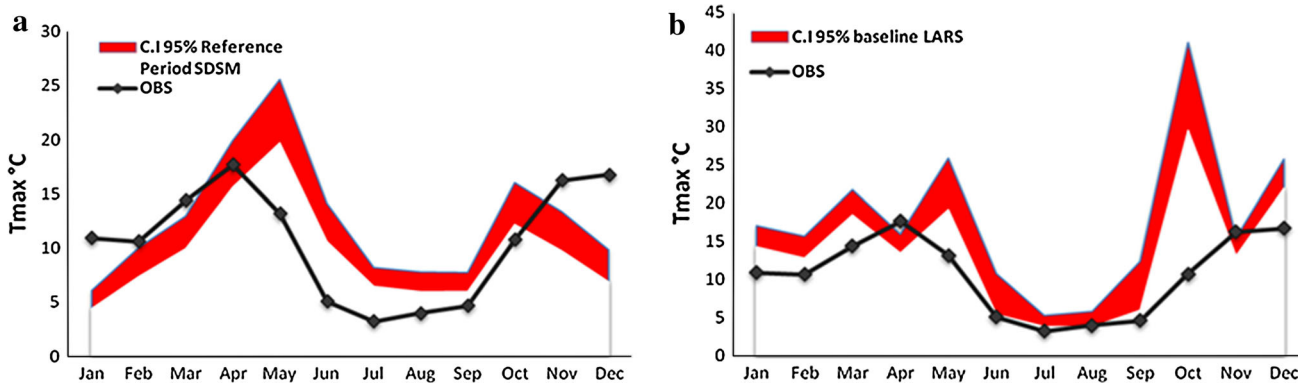


Fig. 22 Monthly bootstrap variance of observed and downscaled Tmax data at 95 % CI using SDSM (a) and LARS-WGS (b) model in Ramhormoz station

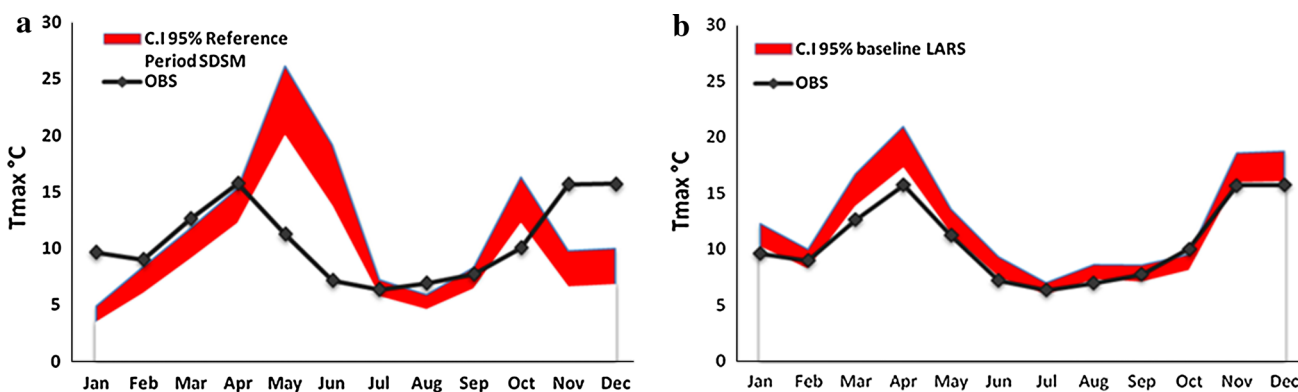


Fig. 23 Monthly bootstrap variance of observed and downscaled Tmax data at 95 % CI using SDSM (a) and LARS-WGS (b) model in Mahshahr station

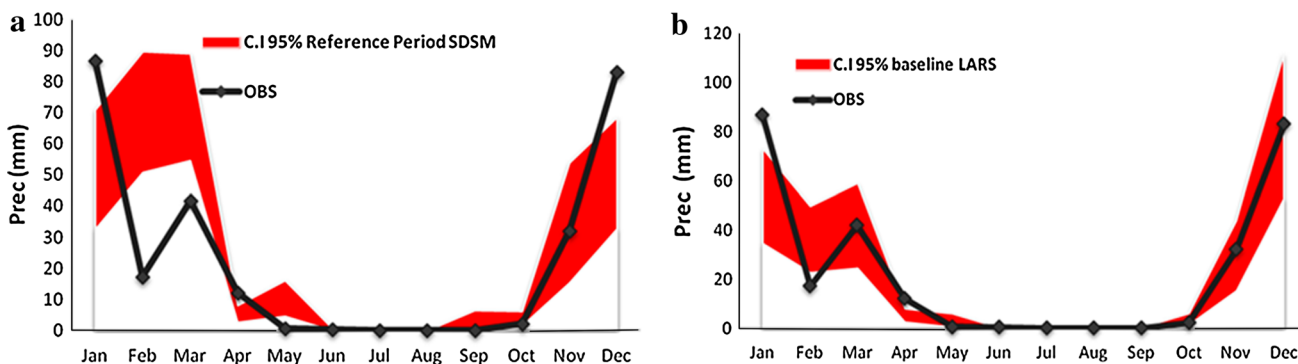


Fig. 24 Monthly bootstrap variance of observed and downscaled precipitation data at 95 % CI using SDSM (a) and LARS-WGS (b) model in Behbahan station

in human welfare (Ramsar convention bureau 2010). In this research, HadCM3 model data used to downscale climatic variables by a regression based method called SDSM model and ECHO-G model data applied in a stochastic weather generator method called LARS-WG model to investigate the uncertainty and errors associated with downscaled data at 95 % CI in an international wetland. The downscaling methods initially validated based on five

different criteria recommended for goodness of fit evaluation and analysis worldwide. Overall the results of validation models presented that, predicted climatic variables by both downscaling methods are very close to the observed data except in downscaled precipitation by SDSM model which the downscaling outputs wasn't satisfied at 95 % CI level. In the other hands, the results of this research indicated that the uncertainty and error based on

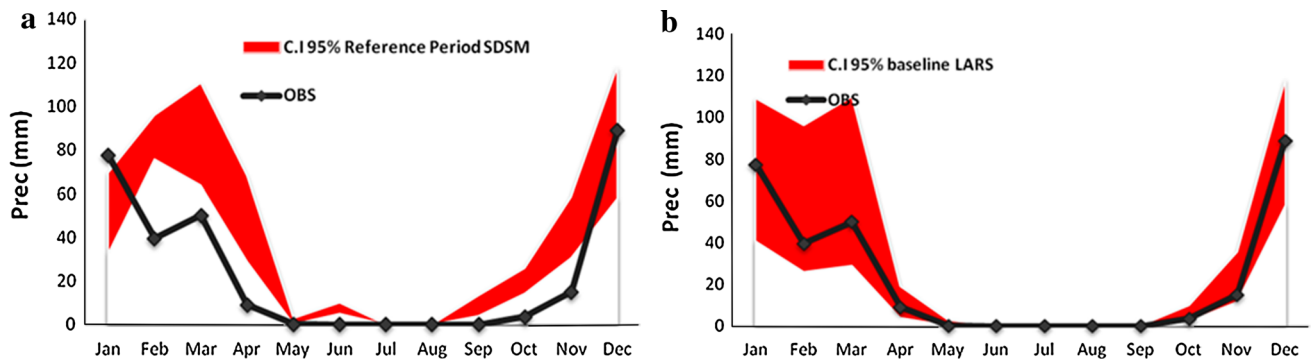


Fig. 25 Monthly bootstrap variance of observed and downscaled precipitation data at 95 % CI using SDSM (a) and LARS-WGS (b) model in Ramhormoz station

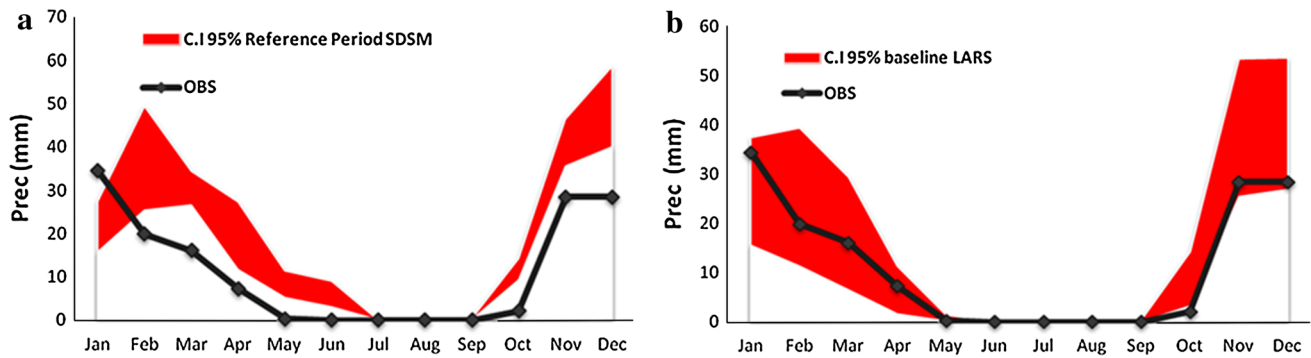


Fig. 26 Monthly bootstrap variance of observed and downscaled precipitation data at 95 % CI using SDSM (a) and LARS-WGS (b) model in Mahshahr station

LARS-WG downscaling method is significant at 95 % CI in all three stations as well.

As a result, LARS-WG model showed a superlative reliability than SDSM model in downscaling of T_{min} and T_{max} in an aquatic ecosystem. Downscaled T_{min} using SDSM overestimated in cold months (January, February, November and December) while LARS-WG uncertainty and error were significant at 95 % CI in T_{min} downscaling results. Results indicated that LARS-WG has high capability to estimate T_{max} in the future and the downscaled data can be use with reliability for future ecohydrological studies of this arid region. SDSM uncertainty and errors associated with downscaled climatic data over an aquatic ecosystem is high in compare with outputs from LARS-WG model. In the other hands, the SDSM is capable to reproduce statistical characteristics of the observed data in its downscaled minimum and T_{max} values but not at the same level as the LARS-WG model.

In this study, LARS-WG was the sophistic method to estimate monthly bootstrap means of precipitation and wet-dry spell lengths for base period as closely as to observed data. Furthermore SDSM approach showed high uncertainty propagation in this research. This study suggested that future climate change impact studies follows by the results of LARS-WG method than multi-linear regression

method in this arid area. It is worth to note that GCM model is unable to predict climate data as same as observed sequence and replicate the exact daily sequences found in observations particularly in an arid area where data are too sparse and climate condition is affected by high temperature values. Moreover large scale data for regions between GCM and AOGCM contribute more uncertainty and error propagations in their prediction processes. Therefore this complexity needs to be addressed in the future studies and more accurate GCMs or regional circulation model should apply for this type of regions.

According to the output of this research, climate change is going to affect on Iranian international wetland according to LARS-WG model analysis and this impact are predicted to become more noticeable in coming decade significantly. Indeed, with drier future conditions, the wetland will shrink and loss without proper conservation practice. In order to conserve the biodiversity value of these wetlands, special efforts should be undertaken to protect the most affected areas and ecoregions of the wetlands. This study presented a basis for uncertainty analysis of different downscaling techniques in an arid area with emphasis on wetland climate change study. However the focus of most literatures are on the uncertainty of GCMs models and other sources of uncertainty, such as the choice of downscaling method on

river hydrology and study the uncertainty associated to downscaling techniques on wetland climate condition have been given much less attention before. Therefore this study provided a basis for future uncertainty analysis associated with traditional SDSMs over an international aquatic ecosystem in south Iran. The study area characterized as an arid region where the climate is under serious drought stress even without climate change consideration. Shadegan wetland is participated as an aquatic portion of this region; therefore climate change studies and indeed uncertainty analysis of downscaling methods are vital to address the water stress and any water resource management and planning of this stressful ecological habitat in the future.

Consistent with previous studies (see LARS-WGon 1995; Poiani and Johnson 1991; Withey and Kooten 2011), wetlands are more sensitive to temperature changes rather than precipitation. However it is quite obviously that the selection of a downscaling method is critical for any climate change impact study on the wetland water quantity. But in such cases, LARS-WG based approaches may be more successful in resolving extremes events with high dry spells and high temperature dataset. This would especially be the case for arid and semi-arid areas where the selection of a downscaling method and uncertainty associated to downscaled data is very significant for future water resource studies, therefore one or more downscaling and uncertainty methods should apply and evaluate with respect to the sensitivity of this type of region and indeed goals and objectives of climate change impact projects.

Finally this study predicted a reduction in precipitation amount in the future; therefore reductions in river flow and water table are largely in proportion to changes in precipitation value. These may also be influenced by rising temperatures through changes in potential evapotranspiration rate actively. As the former mention, changes in precipitation will alter water level, and in contrast wetland ecosystems depend on water levels, precipitation changing and variability during a year, is likely to have a significant impact on habitat species like marble duck (*Marmaronetta angustirostris*). In the other hands, according to future climate condition in this area, the biggest marble duck habitat would shift under a drier climate scenario in the future (see Etemadi et al. 2012). The majority of this wetland in these areas has already been drained. Restoration and protection of these habitats is a priority as insurance for biodiversity against the effects of climate change. Consequently understanding the relationships among the climate variables, and anthropogenic effects are important for the sustainable management of environmental resources in these regions. Finally the findings of this study can be benefit for assessment of long-term events such as drought and drought stress on the wetlands, aquatic habitat and agriculture sector as well.

6 Conclusion and future work

Wetlands and aquatic ecosystems will be highly vulnerable to climate variability and change and this research outputs addressed the susceptible to this change. In this study, the climate change assisted using two downscaling models and their uncertainty analysis in predictions processes at 95 % CI. This research indicated that uncertainty analysis of downscaling techniques is an important step in climate change impact studies. Furthermore uncertainty associate with precipitation prediction is more than temperature data.

Since in the future Shadegan wetland will be under water stress, therefore local flow reducing actions could be minimized to avoid water shortage in the wetland. Besides upstream agricultural water abstractions can also be mitigated by the installation of efficient modern irrigation schemes. Such efforts could be coupled with international measures of subsidizing adaptation to climate change, and payments for ecological services such as the contribution of the Shadegan wetland to the global biodiversity database. Also the pressure of human activity on Shadegan wetland like the construction of Maroon dam as well as petroleum activities reduce water quality and quantity, and therefore change natural and hydrological regime. On the other hands, the entrance of waste water from sugar cone factories, changing in land use and construction of gas powerplant sites have severity damaged to the environment of this international wetland, so appropriate management and plan can reduce enforceable climate change impacts to Shadegan ecosystem. However Department of Environment of Iran has been unable to resist major development projects, or control destructive activities outside protected areas' boundaries (Pandam Consulting Engineer 2002). But where the country failed to conserve it, some foreign aids and potential grantor such as NGOs can help to better conservation of vulnerable area.

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