Projection of important climate variables in large cities under the CMIP5–RCP scenarios using SDSM and fuzzy downscaling models

Hossein Shakeri, Homayoun Motiee and Edward McBean

ABSTRACT

Climate change impacts are among the many challenges facing management of large cities. This study assesses the important climate variables under climate change impacts in Tehran, Iran, for 2021–2040. Eight Coupled Model Intercomparison Project, Phase 5 (CMIP5) models under the scenarios of Representative Concentration Pathway 2.6 (RCP2.6), RCP4.5, and RCP8.5 were used, and seven climate variables were projected utilizing the Fuzzy DownScaling Model (FDSM) and the Statistical DownScaling Model (SDSM). The FDSM and SDSM results underline the high performance of both models and the important capability of the FDSM, showing the increasing trend of annual changes in mean temperature ($T_{\text{mean}}$) and maximum temperature ($T_{\text{max}}$), precipitation, and the mean wind speed ($W_{\text{mean}}$). The maximum increase of annual average in $T_{\text{mean}}$ and $T_{\text{max}}$ and the $W_{\text{mean}}$ among all scenarios will be in the order of 1.29°C, 1.57°C, and 0.8 m/s (for RCP8.5), and also the maximum increases of annual average precipitation will be 10 mm (for RCP2.6). Furthermore, the monthly long-term averages of $T_{\text{mean}}$ and $T_{\text{max}}$ in all three scenarios show significant increases in summer. For precipitation, relative stability in summer, and increases in winter and early spring are predicted, but the changes in minimum temperature, relative humidity, and sunshine hours indicate relative stability.

Key words | climate change, CMIP5, Fuzzy Downscaling, RCP, SDSM, Tehran

HIGHLIGHTS

- Projection of seven Tehran climate variables by eight CMIP5 models under RCP2.6, RCP4.5 and RCP8.5 in 2021–2040.
- Downscaling by both SDSM and FDSM demonstrate there is no single model better than all other models, for all climate variables.
- The performance of FDSM in downscaling of the temperature was shown to be the best model for Tehran.
- FDSM in this research proved to be innovative and superior to other downscaling models which use the Sugeno system.
- Predicted increases in annual temperature, precipitation, mean wind speed and relative stability in changes of relative humidity and sunshine for Tehran in 2021–2040 are provided.
INTRODUCTION

Predictions of climate change and their impacts on meteorological and hydrologic variables are among the challenges being faced for urban water management in large cities. Studies are underlining the impacts of climate change on the frequency of floods and droughts as well as increases in water consumption and the generation of urban wastewater in different regions of the world (IPCC 2014; Noi & Nitivattananon 2015; Nasseri et al. 2017; Ahmadi et al. 2019). Various studies are predicting increasing trends in temperature in most cities of Iran which, coupled with the increases in population and droughts in recent decades, have intensified the shortages of water (Najafi & Hessami Kermani 2017; Mansouri et al. 2018; Mirakbari et al. 2018). In this respect, assessment and projection of the climate variables affected by climate change constitute essential steps toward water-related management for large cities (UNISDR 2015); to this end, Tehran, Iran was the focus in this research.

In the above context, general circulation models (GCMs) are among the most reliable tools for simulation and projection of the future climate variables on the basis of the past climate. GCMs are capable of modeling the atmospheric and oceanic parameters for lengthy periods using the scenarios approved by the Intergovernmental Panel on Climate Change (IPCC); (Geoffroy et al. 2013; Shimura et al. 2017; Asmat et al. 2018; Mehrazar et al. 2018). In its 5th assessment report (AR5) on climate change, IPCC has applied the Coupled Model Intercomparison Project, Phase 5 (CMIP5) models, due to their lower uncertainty and higher resolution than previous models.
(Mirakbari et al. 2018), and are relied upon herein. These models use scenarios called Representative Concentration Pathway (RCP). The RCP emission scenarios include the optimistic scenarios (RCP2.6: the lowest rates of greenhouse gas emission and the resulting radiative forcing), the two intermediate scenarios (RCP4.5: intermediate inclined toward optimistic scenario and RCP6: intermediate inclined toward pessimistic scenario), and the pessimistic scenario (RCP8.5: the highest rates of greenhouse gas emissions and the resulting radiative forcing), all of which were named according to radiative forcing (W/m²) resulting from projected increases of greenhouse emissions for year 2100 (IPCC 2014). The outputs of CMIP5 are dealing with geographically large-scale limits, hence not projecting directly the downscaled local and regional climate changes (such as for Tehran). To transform the large-scale outputs to local downscaled values, downsampling methods are applied which are primarily statistical and dynamic. The dynamic methods are related to a regional high-resolution climate model, but these methods have limitations (dependent on the realism of GCM boundary forcing, placing constraints on the feasible domain size, number of experiments and duration of simulations) (Wilby et al. 2002). Some researchers have studied the dynamic models in downsampling the Iran climate variables (e.g. Sodoudi et al. 2013 and Alizadeh-Choobari 2019). In statistical methods, an empirical-statistical relation is established between the large-scale and local variables, and therefore follows more rapid calculation processes (Shrestha et al. 2016). Given the suitable capabilities of statistical methods, this research used the Statistical DownScaling Model (SDSM) as well as fuzzy logic to downscale the Tehran climate variables.

Some researchers have studied the capability of SDSM in downsampling the climate variables (especially temperature and precipitation). Shivam & Sarma (2017) analyzed the changes in temperature in the Subansiri River catchment in India using the CMIP5 models and the SDSM, reporting minimum and maximum temperatures increases of 0.002–0.013 °C in the RCP2.6, RCP6.0, and RCP8.5 scenarios during the period 2011–2100. Aref & Alijani (2018) reviewed the changes in the temperature and precipitation of Yazd–Ardekan Catchment Basin in Iran under the RCP scenarios using the SDSM, indicating a 0.5 °C increase in temperature and an 8.8% decrease in precipitation in the period of 2016–2045 at RCP4.5 scenario. Mirakbari et al. (2018) used the SDSM to evaluate the efficiency of the CanESM2 Model in simulation and projection of the mean temperature, precipitation, and wind speed in Yazd, Iran, indicating mean temperatures, precipitation, and wind speed increases for RCP2.6 and RCP8.5 scenarios. Ahmadi et al. (2019) analyzed climate changes in the Kan Basin in Iran using the SDSM for RCP2.6, RCP4.5, and RCP8.5 scenarios, using the CanESM2 model, and reported increases in the mean temperature of between 0.8 and 5.6 °C as well as a 4% increase in precipitation for the period 2006–2100. Fallah Ghalhari et al. (2019) assessed the climate change at Bojnoord Station in Iran under the RCP scenarios using the SDSM, showing predicted increases in precipitation and minimum temperature for RCP2.6, RCP4.5, and RCP8.5 scenarios for the period 2016–2050, and at the highest elevation, the precipitation increases by 273 mm at the scenario of RCP4.5. Goodarzi & Fatehifar (2019) assessed climate change at Azarshahr Chai Basin, Iran, under the RCP8.5 scenario using the CanESM2 model with SDSM downscaling, indicating increases of 0.23 °C in mean temperature and a 4.53% increase in precipitation for the period 2030–2059.

Tavakol-Davani et al. (2013) developed the Data-Mining Downscaling Model (DMDM) based on the SDSM structure to estimate precipitation in different regions of Iran. In this regard, they developed the DMDM toolbox which has the ability to use a combination of four linear methods. The results using this method improve downscaling for reproducing monthly standard deviation for calibration and validation datasets. In addition, some researchers have processed the downscaling of climate variables by artificial intelligence (AI) methods and systems. Bardossy et al. (2005) developed a fuzzy methodology for downsampling daily precipitation based on 700 hpa geopotential height in Ruhr catchment, Germany. In this methodology, 10 years of precipitation data (1970–1979) were used for training, using probability distributions showing that this downscaling method is able to capture the relationship between daily local and large-scale precipitation data. Valverde et al. (2014) compared the artificial neural network (ANN) and the Takagi-Sugeno fuzzy system for downsampling daily precipitation data.
in 12 major urban centers all over the state of São Paulo, Brazil, demonstrating suitable performance of approaches in projecting daily precipitation and an increasing trend in extreme precipitation. Das & Umamahesh (2016) projected the future monsoon precipitation in Godavari River basin, India, using regression modeling based on a combination of fuzzy clustering and multiple regression. The results demonstrated good performance of models in projecting the increases in precipitation for the RCP8.5 scenario for 2070–2100. Hosseini et al. (2020) compared the performance of the Adaptive Neuro-Fuzzy Inference System (ANFIS) and the ANN in simulation of precipitation data at Emameh Station in the Latian Dam basin northeast of Tehran. To this end, the outputs of HadCM3 and CanESM2 models were used on the bases of AR4 and AR5 scenarios, respectively. The results demonstrate the acceptable performance of both methods in downscaling precipitation. In addition to these studies, Vu et al. (2016) analyzed the downscaling of precipitation in Bangkok, Thailand, using ANN and SDSM. The results of simulation of the baseline period by ANN based on the National Center for Environmental Prediction (NCEP)’s data show the values of correlation coefficient and Nash–Sutcliffe Efficiency (NSE) indicators to be equal to 0.8 and 0.65, respectively. Sobhani et al. (2017) compared the SDSM and ANN downscaling the daily precipitation and the minimum and maximum temperatures northwest of Iran. By assessing the variables at 12 meteorological stations, the study compared the different models using RMSE, with the results showing ANN to be superior as far as the minimum and maximum temperatures are concerned, while SDSM showed better performance for daily precipitation. Dorji et al. (2017) analyzed the climate change in Colombo, Sri Lanka under the RCP8.5 scenario, with outputs of CanESM2 model, and downscaled using both the ANN and the SDSM methods, with the results showing a 2.83 °C increase in the mean temperature and a 33% increase in precipitation scenario for 2006–2100.

Studies on climate change in Tehran have mostly been undertaken using the scenarios of IPCC’s 4th assessment report (AR4). Eskandari et al. (2016) assessed the changes in temperature and precipitation at the Mehrabad Station in Tehran under the AR4 scenarios for 2000–2100. They used the HadCM3 model with SDSM downscaling, with the results showing an intense increase in precipitation and a gradual increase in the mean temperature in the future. Najafi & Hessami Kermani (2017) projected the temperature and precipitation at Mehrabad Station for the period 2011–2100 using the SDSM. After calibration using 1961–1990, the outputs of CGCM3 and HadCM3 models were downscaled for the AR4 scenario, showing the performance of SDSM in simulating the baseline period with $R^2$ and RMSE indicators being acceptable, and the results showing increases in temperature and the relative stability of precipitation at this station for future periods.

The preceding studies for Tehran show that due to the use of CMIP3, they need to be updated with newer scenarios and models. In addition, due to the planning of various water and environmental projects in Tehran for the next 20 years, there is a need to update the assessment of the impacts of climate change on climate variables under CMIP5-RCP scenarios. The results also indicate the utility of assessing the application of other methods for downscaling the Tehran climate variables, and there is merit in using more synoptic stations due to the vastness of Tehran. Given these findings, the objective of the current research is to assess the important climate variables in Tehran under the RCP scenarios in the future. To this end, the outputs of eight CMIP5 models were used. Accordingly, seven Tehran climate variables, namely mean temperature ($T_{\text{mean}}$), maximum temperature ($T_{\text{max}}$), minimum temperature ($T_{\text{min}}$), precipitation, relative humidity, mean wind speed, and the sunshine hours were reviewed for a 30-year baseline period from 1989 to 2018 and then projected and assessed for a 20-year future period from 2021 to 2040 using scenarios of RCP2.6, RCP4.5, and RCP8.5. According to previous studies, these variables play an important role in assessing climate change impacts of large cities and are available for Tehran (Noi & Nitivattananon 2015; Eskandari et al. 2016; Najafi & Hessami Kermani 2017; Nasseri et al. 2017). In this context, in addition to use of the SDSM, Fuzzy logic was also applied for downscaling using the Fuzzy DownScaling Model (FDSM) for compilation and then the performances of FDSM and SDSM in simulation and projection of climate change in Tehran were compared and analyzed as described below.
MATERIALS AND METHODS

Case study

Extended over an area of 730 km², Tehran is located between longitudes 51°5’ to 51°37’ east and latitudes 35°34’ to 35°50’ north. Its altitude above sea level varies from 1,800 m in the north to 1,000 m in the south. To assess and project the Tehran climate variables, the daily data of $T_{\text{mean}}$, $T_{\text{max}}$, $T_{\text{min}}$, percentages of relative humidity, precipitation, mean wind speed, and the sunshine hours in the years 1989–2018 were obtained from the Meteorological Organization of Iran. Given the geographical expanse of Tehran and the large differences in altitude from the north to the south, the data from the three synoptic stations of Mehrabad, Geophysics, and Doshan–Tappeh (in the light of their appropriate geographical dispersion and their extensive available data) were used. The geological locations of these stations are shown in Figure 1. The station weights were determined using the Thiessen Polygon method and then the weighted mean of each climate variable of Tehran was calculated. In the current research, this operation was undertaken using the ArcGIS software. Accordingly, the weights of Mehrabad, Geophysics, and Doshan–Tappeh synoptic stations were in the order 0.48, 0.20, and 0.32. Based on these results, the annual mean of the $T_{\text{mean}}$, $T_{\text{max}}$, and $T_{\text{min}}$; relative humidity, mean wind speed, and the hours of sunshine from 1989 to 2018 were equal to 18.26 °C, 23.01 °C, 13.40 °C; 39.04%; 2.6 m/s, and 3,039.08 h, respectively.

Methodology

To assess the magnitudes of projected climate change for Tehran, this study applied the upgraded and efficient multi-model ensemble to reduce the uncertainties of the CMIP5 models. Accordingly, the outputs of the eight CMIP5 models for RCP scenarios were collected from the Earth System Grid Federation (ESGF) (www.esgf-node.ipsl.upmc.fr/search/cmip5-ipsl/) and applied. The specifications of these models are listed in Table 1.

To reduce the uncertainty caused by the different outputs of the eight CMIP5 models, the weighted means of the models’ outputs were used to project the future. On this basis, first, the outputs of the eight CMIP5 models were downscaled. Then the weight of each model in the 12 months of the baseline long-term (January, February, … and December) was determined according to the capability of the models in simulating the period and using (1). According to (1), the weights for each CMIP5 model in each month were calculated based on the deviation of the long-term mean of climate variable simulated in the baseline period from the long-term mean values observed (Ahmadzadeh Araji et al. 2018;
Table 1 | The specifications of the selected CMIP5 models in this study

<table>
<thead>
<tr>
<th>Model name</th>
<th>Group founder</th>
<th>Spatial resolution (longitude × latitude)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CanESM2</td>
<td>CCCMA (Canadian Center for Climate Modelling and Analysis, Canada)</td>
<td>2.8° × 2.8°</td>
</tr>
<tr>
<td>CNRM-CM5</td>
<td>CNRM-CERFACS (Centre National de Recherches Météorologiques, Centre Européen de Recherche et de Formation Avancée en Calcul Scientifique, France)</td>
<td>1.4° × 1.4°</td>
</tr>
<tr>
<td>CSIRO-Mk3.6</td>
<td>CSIRO (Commonwealth Scientific and Industrial Research Organization, Australia)</td>
<td>1.9° × 1.9°</td>
</tr>
<tr>
<td>FGOALS-g2</td>
<td>LASG-CESS (Institute of Atmospheric Physics, Chinese Academy of Sciences and CESS, Tsinghua University, Chinese)</td>
<td>2.8° × 2.8°</td>
</tr>
<tr>
<td>GFDL-CM3</td>
<td>NOAA-GFDL (Geophysical Fluid Dynamics Laboratory, USA)</td>
<td>2.5° × 2.0°</td>
</tr>
<tr>
<td>HadGEM2-ES</td>
<td>MOHC (Met Office Hadley Center, UK)</td>
<td>1.9° × 1.3°</td>
</tr>
<tr>
<td>MIROC-ESM-CHEM</td>
<td>MIROC (Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies, Japan)</td>
<td>2.8° × 2.8°</td>
</tr>
<tr>
<td>MPI-ESM-MR</td>
<td>MPI-M (Max Planck Institute for Meteorology, Germany)</td>
<td>1.9° × 1.9°</td>
</tr>
</tbody>
</table>

Mehrazar et al. 2018).

\[ W_j = \frac{1}{\Delta C_{ij}} \left( \sum_{i=1}^{n} \frac{1}{\Delta C_{ij}} \right) \]  \hspace{1cm} (1)

Based on (1), 12 weighted parameters corresponding to the 12 months were calculated for each CMIP5 model (for each climate variable). In (1), \( W_j \) is the weight for the \( j \)th climate change model in the \( i \)th month \((1 \leq i \leq 12, \ 1 \leq j \leq n)\), with \( n \) representing the number of models. Moreover, \( \Delta C_{ij} = C_{ij}^\text{observed} - C_{ij} \), wherein \( C_{ij} \) represents the long-term mean of climate variable simulated by the \( j \)th climate change model in the \( i \)th month of the baseline period, and \( C_{ij}^\text{observed} \) represents the long-term mean of the climate variable observed in the \( i \)th month for the baseline period. After specifying the weights of all eight CMIP5 models in the baseline period, the daily weighted means of climate variable were calculated for each RCP2.6, RCP4.5, and RCP8.5 scenario for future period using (2).

\[ M = \frac{\sum_{i=1}^{n} (C_{ij}W_j)}{\sum_{j=1}^{n} W_j} \]  \hspace{1cm} (2)

Based on (2), \( M \) represents the daily weighted mean of climate variables as projected by CMIP5 models for an RCP scenario; \( n \) represents the number of models and \( C_j \) represents the daily amount of the climate variables projected by the \( j \)th climate change model in future periods. Furthermore, \( W_j \) is the weight for each model (1) which, for instance, for all the days of January in the years of future period (2021, 2022, ... and 2040) is equal to \( W_{1j} \), i.e. the weight of January for the \( j \)th model.

**Statistical DownScaling Model**

The SDSM is a combination of multivariable regression methods and random generation of artificial climate data for downscaling proposed by Wilby et al. (2002). Through SDSM, and based on the establishment of a suitable statistical link between large-scale geographical predictors and predictands (observed data) within the baseline period, resulting in an appropriate equation to project the climate variables under the effects of climate change in future period being obtained (Goodarzi et al. 2016). In the SDSM software, there is scope for infilling and hind-casting missing data using identified relationships between large-scale geographical predictors and local predictands (Wilby & Dawson 2013). Accordingly, the software compensates for missing data by producing artificial data in the baseline period (Wilby et al. 2002). The SDSM used in this study, version 5.3.5, was developed for CMIP5 (www.sdsm.org.uk/software.html). The relevant equations were proposed by Wilby & Dawson (2013). However, for use in this software, reference is made to the user's manual.
As per the SDSM software developers’ recommendations on the calibration and validation of the downscaling model at the baseline period, the predictors must be selected from the data bank of the National Center for Environmental Prediction (NCEP); (Wilby et al. 2002). The large-scale NCEP predictor variables included 26 atmospheric variables defined using a $2.5^\circ \times 2.5^\circ$ grid measuring $\sim 250$ by $250$ km. The data have equal values for all points within a single cell of NCEP grid (Rezaee et al. 2015). The complete list of NCEP predictor variables is listed in Table 2.

Among the NCEP predictors, those with a high correlation with the observed predictands (temperature, precipitation, etc.) were selected as future climate predictors (Ghermezcheshmeh et al. 2014; Goodarzi et al. 2016). To this end, different correlation tests were completed by screening the variables in SDSM software. In order to calibrate the SDSM, 70% of the baseline period’s data were selected for model building, and the remaining 30% for SDSM validation (Dibike & Coulibaly 2005; Ahmadi et al. 2019). After assessing the performance of SDSM in simulating the baseline period, the Tehran climate variables for future periods on the CMIP5 models were downscaled and projected.

**Fuzzy DownScaling Model**

Fuzzy Set Theory (Zadeh 1965) can be applied to complex, vague, unspecified and poorly defined problems and, in general, with ambiguity due to inaccurate or inadequate data. In this research, by taking the fuzzy approach, and based on the establishment of a suitable link between predictors and predictands during the baseline period, this provides a reliable model for downscaling and projection of the climate variables under the effects of climate change in future periods. For this research, the FDSM was calibrated (with 70% of data) and validated on the basis of the daily NCEP predictors and the daily observed climate variables for the baseline period. In this respect, the predictors for each climate variable were selected in the same manner as for the SDSM process. Then, the Fuzzy C-Means Clustering process (Bezdek 1981) was applied to determine the Fuzzy Membership Functions and the relevant Fuzzy Rules. In this process, each data with a special degree – determined by the Fuzzy Membership Degree – is attributed to a cluster, and on this basis, the method of data grouping is determined by the specific number of clusters. This method is based on minimizing the objective function (the objective function includes the distance between each data point to the cluster

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Description</th>
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<tbody>
<tr>
<td>p8_f</td>
<td>850 hpa Airflow strength</td>
<td>mslp</td>
<td>Mean sea level pressure</td>
</tr>
<tr>
<td>p8_u</td>
<td>850 hpa Zonal velocity</td>
<td>p_f</td>
<td>Surface airflow strength</td>
</tr>
<tr>
<td>p8_v</td>
<td>850 hpa Meridional velocity</td>
<td>p_u</td>
<td>Surface zonal velocity</td>
</tr>
<tr>
<td>p8_z</td>
<td>850 hpa Vorticity</td>
<td>p_v</td>
<td>Surface meridional velocity</td>
</tr>
<tr>
<td>p8th</td>
<td>850 hpa Wind direction</td>
<td>p_z</td>
<td>Surface vorticity</td>
</tr>
<tr>
<td>p8zh</td>
<td>850 hpa Divergence</td>
<td>p_th</td>
<td>Surface wind direction</td>
</tr>
<tr>
<td>p500</td>
<td>500 hpa Geopotential height</td>
<td>p_z</td>
<td>Surface divergence</td>
</tr>
<tr>
<td>p850</td>
<td>850 hpa Geopotential height</td>
<td>p5_f</td>
<td>500 hpa Airflow strength</td>
</tr>
<tr>
<td>r500</td>
<td>Relative humidity at 500 hpa</td>
<td>p5_u</td>
<td>500 hpa Zonal velocity</td>
</tr>
<tr>
<td>r850</td>
<td>Relative humidity at 850 hpa</td>
<td>p5_v</td>
<td>500 hpa Meridional velocity</td>
</tr>
<tr>
<td>rhum</td>
<td>Near surface relative humidity</td>
<td>p5_z</td>
<td>500 hpa Vorticity</td>
</tr>
<tr>
<td>shum</td>
<td>Near surface specific humidity</td>
<td>p5th</td>
<td>500 hpa Wind direction</td>
</tr>
<tr>
<td>temp</td>
<td>Near surface air temperature</td>
<td>p5zh</td>
<td>500 hpa Divergence</td>
</tr>
</tbody>
</table>
center, based on their membership degree), defined according to (3) (Bezdek 1981):

\[ J_m(U, v, X) = \sum_{i=1}^{c} \sum_{k=1}^{n} (u_{ik})^m d^2(x_k, v_i) \]  

(3)

In the above equation, \( d^2(x_k, v_i) \) represents the squared Euclidean distance between \( v_i \) (the center of \( i \)th cluster) and \( x_k \) (\( k \)th data), \( u_{ik} \) represents the membership degree of the \( k \)th data at \( i \)th cluster; moreover, \( c \) and \( n \) are the number of clusters and number of data points, respectively; \( m \) is user-defined parameter (the real number) which determines the amount of ‘fuzziness’ of the cluster \( (m \geq 1) \). Minimization of \( J_m \) is based on suitable selection of \( U \) (membership degree matrix) and \( v \) (cluster center matrix) using an iterative process (Bezdek 1981). For the input–output pair, the process of clustering is realized by accounting for the relation between the two groups of input and output data, and in this process, the clusters of input and output data are linked together through fuzzy rules. In this method, the numbers of input and output data clusters are equal, and the number of fuzzy rules is limited to the number of clusters. In this study, this process was undertaken using the clustering toolbox of MATLAB software and by trial-and-error.

By using the structure obtained by clustering, the FDSM was built as a Mamdani Fuzzy Inference System. This system is a computational-based framework on the If-Then rules and fuzzy inference in which both sections of condition and result of the rule are fuzzy (Mamdani & Assilian 1975). The maximum–minimum combination is used in the Mamdani systems for combination and inference of rules and to calculate the final result. The combination of the \( r \) Fuzzy rules of the system with the two inputs of \( X \) and \( Y \) is calculated according to (4) (Monjezi & Rezaei 2011):

\[ \mu_C(Z) = \max_{K=1,2,\ldots,r} \min[\mu_{\lambda_k}(\text{input}(X)), \mu_{B_k}(\text{input}(Y))] \]  

(4)

In (3), \( \mu_C \) represents the output membership function \( Z \) (the system’s final output), which is made up of the combination of outputs of \( r \) rules of the system. Moreover, \( \mu_{\lambda_k} \) and \( \mu_{B_k} \) are ordered input membership functions \( X \) and \( Y \) for the \( K \)th rule \( (K=1, 2, \ldots, r) \). The non-fuzzy value of the system’s final output \( z \) was obtained by the Centroid of Area Method (Jamshidi et al. 2015). Finally, after many repeated clustering efforts, modeling and assessment of the models’ results, the data were analyzed in MATLAB software, and the superior FDSM was obtained with the minimum number of membership functions and fuzzy rules and with the maximum accuracy of results. By entering the daily large-scale CMIP5 data in the FDSM, the studied downscaled variables were calculated for the future period.

### Performance assessment indicators of the models

To compare the performance of the models in this study, \( R^2 \), RMSE, NSE, and the mean absolute errors (MAEs) were applied according to (5) through (8). Each of these indicators express the correspondence or similarity between the observed values and the simulated ones (Ashofteh et al. 2015; Tiwari et al. 2020):

\[ R^2 = \frac{\sum_{i=1}^{n} (X_{\text{obs},i} - \bar{X}_{\text{obs}}) \times (X_{\text{model},i} - \bar{X}_{\text{model}})^2}{\sum_{i=1}^{n} (X_{\text{obs},i} - \bar{X}_{\text{obs}})^2 \times \sum_{i=1}^{n} (X_{\text{model},i} - \bar{X}_{\text{model}})^2} \]  

(5)

\[ \text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (X_{\text{obs},i} - X_{\text{model},i})^2}{n}} \]  

(6)

\[ \text{NSE} = 1 - \frac{\sum_{i=1}^{n} (X_{\text{obs},i} - X_{\text{model},i})^2}{\sum_{i=1}^{n} (X_{\text{obs},i} - \bar{X}_{\text{obs}})^2} \]  

(7)

\[ \text{MAE} = \frac{\sum_{i=1}^{n} |X_{\text{obs},i} - X_{\text{model},i}|}{n} \]  

(8)

In these equations, \( X_{\text{obs},i} \) and \( X_{\text{model},i} \) are, in order, the daily observed and the simulated values of variable \( X \) at the \( i \)th time step, \( \bar{X}_{\text{obs}} \) and \( \bar{X}_{\text{model}} \) represent the daily average observed and simulated values of climate variable \( X \) during the modeling period, and \( n \) is the number of time steps or the number of data. The best value for the indicator \( R^2 \) is equal to 1, which shows a complete one-to-one linear relationship between the model’s outputs and the observed values, and can indicate the relative capability of the model in predicting the observed values. RMSE is the criterion for the amount of deviation of the simulated results.
from the observed amounts. The value of this indicator varies from zero (representing the best state of simulation) to infinity. NSE represents the ratio of the variance of the observed values to the variance of values simulated by the model. The best value of this indicator is 1 and, overall, shows the complete correspondence of the observed values with the modeled ones. MAE also represents the model’s error, with its best value being equal to zero. In addition to the above indicators, there are other tests on credibility of statistical downscaling in a nonstationary climate, including for alternatives, see Salvi et al. (2016).

RESULTS AND DISCUSSION

By screening the variables in SDSM software, the predictors were selected for the SDSM and FDSM. In this regard, the predictors of p500 and temp were selected for $T_{\text{mean}}$, $T_{\text{max}}$, $T_{\text{min}}$, and the sunshine hours in Mehrabad synoptic station. Also, the predictors of mslp and r850 for precipitation, the predictors of mslp, r500 and r850 for relative humidity, and the predictors of $p_{zh}$ and $p_{8zh}$ were selected for the variable of mean wind speed in this synoptic station. Based on the same method, the predictors were selected for the Geophysics and Doshan–Tappeh synoptic stations. These predictors were quite similar to the predictors of Mehrabad station. In addition, the geographical locations of Tehran city and all three stations and even Tehran province are located in a single cell of the NCEP grid. Accordingly, the data of NCEP predictors have equal values for all three stations. Furthermore, all three stations were located in a single cell of the CMIP5 models’ grids in Table 1. Therefore, the large-scale variables of each model (Table 1) have equal values in all three stations. Although the spatial extent of atmospheric circulation responsible for climate may expand beyond a single cell (Kannan & Ghosh 2011; Salvi et al. 2013), due to the uniformity of the large-scale data (NCEP data as well as CMIP5 models’ data) at all three stations, the weighted mean of the observed data from the stations (daily data) was used.

The superior FDSMs for $T_{\text{mean}}$, $T_{\text{max}}$, $T_{\text{min}}$, relative humidity, precipitation, mean wind speed, and sunshine hours have in order 5, 5, 5, 7, 9, 8, and 5 fuzzy rules (and Gaussian fuzzy membership function). The fuzzy rules and the range of fuzzy membership function in superior FDSMs are different for each climate variable. The FDSM for each climate variable has its own specific structure. For instance, a fuzzy rule in the superior FDSM for $T_{\text{mean}}$ is: if the geopotential height at the level of 500 hpa is equal to Membership Function 1 for p500 and the near surface air temperature is equal to the Membership Function 1 for temp, then the mean daily temperature of Tehran would be equal to the Membership Function 1 for $T_{\text{mean}}$. This rule is expressed as the following equation:

$$\text{If } p500 \text{ is } \text{in1cluster1} \text{ and } \text{temp is } \text{in2cluster1} \text{ then } T_{\text{mean}} \text{ is } \text{out1cluster1}$$

In which, in1cluster1, in2cluster2 and out1cluster1 are the membership functions 1 for p500, membership function 1 for temp, and the membership function 1 for $T_{\text{mean}}$. For example, in Figure 2–4, the shape of fuzzy membership functions and the range of their definitions for the superior FDSM predictors of mean temperature, i.e. p500 and temp

![Figure 2](http://iwaponline.com/jwcc/article-pdf/12/5/1802/923697/jwc0121802.pdf) | The shape of Fuzzy Membership Functions for p500 (in the superior FDSM of $T_{\text{mean}}$).
as well as the predictands of the mean daily temperature of Tehran, are presented.

Furthermore, Figure 5 presents a schematic figure depicting how the downscaling of the daily $T_{\text{mean}}$ in the superior FDSM with five Fuzzy rules, and the daily predictors $p500$ and $\text{temp}$ were equal to $-0.564$ and $-0.443$, respectively, on the basis of which the daily (downscaled) $T_{\text{mean}}$ was calculated as $11.3 \, ^\circ\text{C}$.

According to the performance assessment indicators of the models, the SDSMs and FDSMs for this study had very good quality and performance for all the daily Tehran climate variables for the calibration and validation period, as shown by the results in Table 3. The results of FDSM’s performance assessment indicators were quite close to SDSM and even better than the latter $T_{\text{mean}}$, $T_{\text{max}}$, and $T_{\text{min}}$. Therefore, the FDSM developed in this study has very high performance and capability for simulating the daily climate data for the baseline period, with the quality of its results being at the level of the strong SDSM method.

In addition, to assess the performance of the models for the 12 months of the baseline period, the long-term mean of climate variables as simulated by the SDSM and the FDSM was compared with the observed values as shown in Figure 6. As seen in Figure 6, the long-term mean of climate variables as simulated by the SDSM and the FDSM as compared with the observed values of Tehran had a very high accuracy and correspondence for all 12 months, with only very small differences between the generated and the observed values. For example, the FDSM had a very slight overestimation for $T_{\text{mean}}$ in the months of January, February, April, and October (maximum $0.02 \, ^\circ\text{C}$ in October). Furthermore, in the case of precipitation, the SDSM had a slight overestimation in the months of January, April, May, November, and December (maximum $1.25 \, \text{mm}$ in December) and a negligible underestimation for October ($1.23 \, \text{mm}$). The results of FDSM and SDSM demonstrate that neither model has absolute superiority over the other in downscaling. However, it appears that with a slight margin, the FDSM had a better performance for $T_{\text{mean}}$.

**Figure 3** | The shape of Fuzzy Membership Functions for $\text{temp}$ (in the superior FDSM of $T_{\text{mean}}$).

**Figure 4** | The shape of Fuzzy Membership Functions for $T_{\text{mean}}$ (in the superior FDSM of $T_{\text{mean}}$).
$T_{\text{max}}$ and $T_{\text{min}}$, and also the SDSM had a better performance for precipitation, relative humidity, mean wind speed, and the sunshine hours. Accordingly, these models were chosen as the superior downscaling model for the Tehran climate variables in this study. In addition to using NCEP predictors, the historical data of the eight CMIP5 models were used as predictors in FDSM and SDSMs to simulate the climate variables in the baseline period. Based on the results of the superior FDSM and SDSMs, the long-term mean of the results was compared with observed data as shown in Figure 6. Accordingly, NCEP data-based simulations have higher quality and more acceptable performance than CMIP5 historical data-based simulations in the baseline period. Furthermore, the standard deviation of climate variables as simulated by the superior FDSM and SDSMs was compared with the observed values in the baseline period (based on NCEP data and CMIP5 historical data) as shown in Figure 7. According to Figure 7, NCEP data-based simulations have more appropriate performance than CMIP5 historical data-based simulations for all of the daily Tehran climate variables in the baseline period.

By entering the daily output of CMIP5 under the RCP scenarios (Table 1) for the superior FDSM and SDSMs, the downscaled values of the climate variables during the future period (2021–2040) were calculated. Given the downscaling of seven climate variables based on the outputs of eight CMIP5 models at three RCP scenarios by the superior FDSM and SDSMs in the present study, it is not possible to present all the results (21 charts) due to the limited space of this article. Therefore, as an example, Figure 8 shows the long-term mean of $T_{\text{mean}}$ of Tehran on the basis of the eight CMIP5 models for the RCP2.6, RCP4.5, and RCP8.5 scenarios at future period.

According to Figure 8, the long-term mean of $T_{\text{mean}}$ of Tehran at future period for the RCP2.6, RCP4.5, and RCP8.5 scenarios will have increasing trends. Of course, the amounts projected by the eight CMIP5 models had different quantities. These different quantities in the projected amounts existed also in other climate variables reviewed herein. To reduce the uncertainty resulting from the different outputs of the eight CMIP5 models in the final assessment of the climate variable of Tehran, a
weighting method on the basis of the capability of each model in simulating the baseline period, the weighted mean of the models was used. Therefore, the large-scale historical data of the eight CMIP5 models at the baseline period were downscaled by the superior FDSM and SDSM, and then the weights of each model in each of the 12 months of the baseline period were calculated using Equation (1). Using these weights separately in each of the RCP2.6, RCP4.5, and RCP8.5 scenarios, the weighted means of each climate variable of Tehran in the future period were calculated using Equation (2). According to these results, Figure 9 shows the comparison of long-term mean of the Tehran climate variables for RCP scenario (on the basis of the ensemble of all eight CMIP5 models) in the future periods.

As shown in Figure 9, the long-term mean of \( T_{\text{mean}} \) and \( T_{\text{max}} \) of Tehran in the future period of 2021–2040 in the three scenarios of RCP2.6, RCP4.5, and RCP8.5 showed an increase for all the months except April, May, and November. From the point of view of percentage of changes, the largest change in the long-term mean of \( T_{\text{mean}} \) occurred in January at RCP2.6 (36.9% increase) and in April at RCP8.5 (11.96% decrease). Moreover, the long-term mean of \( T_{\text{max}} \) of Tehran in a future period will increase by a maximum of 30.17% (in January at the scenario of RCP2.6) and will decrease by a maximum of 6.51% (in April at the scenario of RCP8.5). As for the \( T_{\text{min}} \) in Tehran, the projection for all the three scenarios consists of a decrease in the months of April, May, June, September, October, and November and an increase in the remaining months. In this context, there will be a maximum of 28.84% increase (in January for the scenario of RCP4.5) and a maximum of 24.39% decrease (in April for the scenario of RCP8.5). As for precipitation in the warm months of the future period, a relatively stable trend was observed \( \text{vis-a-vis} \) the baseline period. However, in the cold months of December, January, February, and especially March, for all three scenarios, the increase of precipitation is predicted. As for the percentage of changes, for the long-term mean of precipitation in Tehran in future periods there will be a maximum of 21.84% increase (in the month of May at the scenario of RCP8.5) and a maximum of 49.23% decrease (in August for the scenario of RCP2.6). The value of the projected relative humidity points to the increase of this variable for all

### Table 3

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<tr>
<th>Daily climate variable</th>
<th>SDSM Validation</th>
<th>FDSM Validation</th>
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Figure 6  The comparison of the long-term mean of climate variables as simulated by the superior SDSM and FDSM with the observed values (based on NCEP data and CMIP5 historical data).
Figure 7 | Comparison of standard deviation of climate variables as simulated by the superior SDSM and FDSM with the observed values (based on NCEP data and CMIP5 historical data).
three RCP scenarios in Tehran. In this context, it should be noted that the values of the long-term mean of the 12 months in future periods showed very slight differences from one another and the largest differences were observed during the cold months of the year. The magnitude of differences in the long-term mean of relative humidity in the
Figure 9 | Comparison of the long-term mean of the Tehran climate variables for three scenarios of RCP (on the basis of the ensemble of all eight CMIP5 models) in the future period (2021–2040).
future period was a maximum increase of 4.72% in January for the RCP4.5 scenario and a minimum increase of 0.13% in November for RCP2.6. As for mean wind speed, the increasing trend was dominant for all three scenarios. In this respect, the amount of increase in the mean wind speed was larger in spring, i.e. the months of April, May, and June. From the point of view of percentage of changes, the long-term mean of mean wind speed of Tehran will increase by a maximum of 10.96% (in the month of December at RCP4.5) in the future. The general trend of sunshine hours denotes a slight increase in the projected amounts. Of course in some months, including September and October for all three RCP scenarios, the number of sunshine hours will be slightly shorter. From the aspect of percentage of changes, the long-term mean of sunshine hours of Tehran in future will increase by a maximum of 7.43% (in December for the RCP8.5 scenario) and will decrease by a maximum of 6.98% (in September for the RCP2.6 scenario).

Furthermore, the trends of annual changes of Tehran climate variables from 1989 to 2040 can also be compared and analyzed. Accordingly, in Figure 10, the annual changes of climate variables at different RCP scenarios (on the basis of the ensemble of all eight CMIP5 models) in the future vis-a-vis the baseline period are shown. In addition, in Figure 10, the time series of climate variables based on the ensemble of CMIP5 models’ historical data and NCEP data are compared with observed data in the baseline period. Accordingly, NCEP data-based simulations have better performance than CMIP5 historical data-based simulations in the baseline period.

From Figure 10, the trend of annual changes of the mean $T_{\text{mean}}$ and the mean $T_{\text{max}}$ of Tehran at all three RCP scenarios as compared with the baseline period will be an increasing one. It is projected that the annual mean $T_{\text{mean}}$ throughout the future period for the scenarios of RCP2.6, RCP4.5, and RCP8.5 will reach 19.51, 19.47, and 19.55 °C (with a maximum of 1.29 °C increase at RCP8.5) and the annual mean $T_{\text{max}}$ to 24.56, 24.57, and 24.58 °C (with a maximum of 1.57 °C increase at RCP8.5). Regarding the mean $T_{\text{min}}$ for Tehran, the trend of annual changes at all three scenarios showed a relative stability. It is projected that for the scenarios of RCP2.6, RCP4.5, and RCP8.5, $T_{\text{min}}$ will reach 13.42, 13.35, and 13.40 °C (with a maximum of 0.02 °C increase for RCP2.6). The trend of annual changes in the precipitation in Tehran for all three scenarios showed an increase with a very slow gradient. It is projected to reach to 255.75, 248.50, and 252.14 mm for the scenarios of RCP2.6, RCP4.5, and RCP8.5 (with a maximum increase of 10 mm at RCP2.6). The trend of changes in the mean relative humidity of Tehran for all three scenarios denoted a lack of regular increases or decreases. It is projected that for the scenarios of RCP2.6, RCP4.5, and RCP8.5, it will, respectively, reach 39.00, 38.74, and 39.09%. Furthermore, the annual changes in the mean wind speed of Tehran for all three scenarios will have increasing trends. It is projected that for the scenarios of RCP2.6, RCP4.5, and RCP8.5, mean wind speeds will reach 3.32, 3.37, and 3.40 m/s (with a maximum increase of 0.8 m/s for RCP8.5). Regarding the sunshine hours in Tehran, the trend of annual changes for all three scenarios showed relative stability. It is projected that at the scenarios of RCP2.6, RCP4.5, and RCP8.5, sunshine hours will, respectively, reach 3,044.61, 3,052.22, and 3,043.50 h (with a maximum of 13 h increase for RCP4.5).

Finally, it should be noted that there were various limitations in this research. The most important limitations in this study include the following:

- **Sources of uncertainty:** There were various sources of uncertainty in the current study, including: (1) the GCM (due to incomplete knowledge about the underlying geophysical processes of climate change, the random essence of climate in nature, and the grid resolution), (2) the different outputs of the eight CMIP5 models, (3) the essence of downscaling and transforming large-scale geographical variables to local downscale variables, (4) the downscaling models, and (5) the accuracy of the local or large-scale climate data. In this regard, efforts were made to reduce uncertainties as much as possible, using different approaches, including using the multi-model ensemble to reduce the uncertainty (1). Also, to reduce the uncertainty (2), the weighted means of the eight CMIP5 models’ outputs were used to project the future. For the uncertainty for (3) and (5), efforts were made to reduce the uncertainty in downscaling, using the fuzzy approach (based on the essential concepts of the fuzzy sets theory, including the fuzzy membership function and the fuzzy membership
Figure 10 | The annual changes of Tehran climate variables from 1989 to 2040 (on the basis of the ensemble of all eight CMIP5 models).
degree). In addition, efforts were made to reduce the uncertainties of unclear link between the large-scale data and observed data (in the process of grouping the data and developing the fuzzy rules), using the fuzzy approach. Furthermore, different synoptic stations with extensive available data were used. Also, to reduce the uncertainty (4), two downscaling models (SDSM and FDSM) were used and their performance compared.

• **Predictors selection:** Predictor–predictand relationships are often nonstationary. The selection of the appropriate predictors from different large-scale geographical predictors plays a major role in avoiding non-stationarity (Salvi et al. 2016). This problem is very important in SDSM and FDSM modeling. To this end, by screening the variables in the SDSM (based on different correlation tests) as well as using the trial-and-error method, the appropriate predictors were selected.

• **Data clustering:** The determination of the accurate fuzzy membership functions and the relevant fuzzy rules are complex under non-stationarity and nonlinear conditions. In this regard, to identify the optimum and efficient FDSM, the Mamdani fuzzy inference system with fuzzy C-means clustering was used in this study.

• **Model calibration:** The credibility of the model depends on the amount and quality of meteorological data available for calibration. In this regard, the data from the three synoptic stations (in the light of their appropriate geographical dispersion and their extensive available data) were used. Increasing the number of these stations and their data may also be more appropriate.

• **Precipitation simulation:** Usually, precipitation simulation is problematic for all downscaling methods, and the SDSM and FDSM are no exception. In this regard, frequency estimation of extreme precipitation amounts, particularly in summer, is very difficult. In current research, the SDSM had a better performance than FDSM in precipitation simulation.

### CONCLUSIONS

In this research, seven Tehran climate variables were assessed under the scenarios of RCP2.6, RCP4.5, and RCP8.5 (based on the outputs of eight CMIP5 models). To this end, in addition to using the SDSM, the FDSM was also utilized. The results of FDSM and SDSM at baseline and future periods demonstrated the very high performance and capability of both models in simulating and downscaling the Tehran climate variables. Therefore, taking the fuzzy approach for downscaling has a technical justification. In this context, the application of the Mamdani system, instead of other fuzzy inference systems such as Sugeno, increases the accuracy and quality of the results at different conditions (given the use of a fixed mathematical or linear function at the section of the rules results, the quality of the Sugeno systems drops under non-natural or nonlinear conditions). For this reason, in the current research, FDSM proved to be innovative and superior to other downscaling models which use the Sugeno-based AI systems such as ANFIS. On the other hand, the number of predictors and predictands and the scope of their changes in this context could have led to increases in the number of fuzzy membership functions and fuzzy rules. Therefore, the application of Fuzzy C-Means Clustering, in addition to optimizing the structure of fuzzy membership functions and rules, simplified the general understanding of the model. Moreover, the application of NCEP data, which have a higher resolution than GCM, also had an impact on the accuracy and efficiency of FDSM and SDSM. The results of FDSM and SDSM demonstrate the lack of absolute superiority of one model over the other in downscaling. However, by a very slight margin, the FDSM had a better performance for $T_{\text{mean}}$, $T_{\text{max}}$, and $T_{\text{min}}$, and the SDSM had a better performance for precipitation, relative humidity, mean wind speed, and the sunshine hours in Tehran. Accordingly, these models were selected as the superior downscaling models for Tehran climate variables in the current study.

According to the results, the changes in the annual mean $T_{\text{mean}}$, $T_{\text{max}}$, and the mean wind speed at all the three RCP scenarios in relation to the baseline period will have an increasing trend, while the annual changes of the precipitation will also (marginally) increase. However, the annual changes of other variables studied showed a relative stability. From the point of view of monthly changes, there were noticeable increases in the long-term means of $T_{\text{mean}}$, and $T_{\text{max}}$ of Tehran in the future period during the months of July, August, and September (i.e. summer season). As
for the $T_{\text{min}}$, no significant increases were observed and in some months, $T_{\text{min}}$ will even be on the decline. As regards precipitation, a relatively stable trend was observed in comparison with the baseline during the warm months of the future period, but during winter, and in particular at the beginning of the spring of the 2021–2040 period, there will be more precipitation at different months of the year than the 1989–2020 period. Furthermore, the projections about the percentage of relative humidity and the mean wind speed are an increase in these variables at all three RCP scenarios in Tehran. However, the general trend of sunshine hours will involve only a very slight increase.

It should be noted that the increasing trend observed in this study in the annual changes of $T_{\text{mean}}$ and precipitation of Tehran is similar to the projection of the studies based on CMIP3, including Eskandari et al. (2016) and Najafi & Hessami Kermani (2017), but due to the application of CMIP5 in this research, and the resulting values of these two variables, the percentages of their changes, and the gradients of their increase are different. Furthermore, the results demonstrated that the mitigation scenario will increase the temperature for some years, even higher than the pessimistic scenario. This matter was also present in the previous Tehran studies based on the CMIP3 (e.g. Eskandari et al. 2016 and Najafi & Hessami Kermani 2017). In addition to previous Tehran studies, this matter was also observed in some regions of Iran (e.g. Dastranj et al. 2016; Kimiagar Keteklahijani et al. 2019; Fallah Ghalhari et al. 2019; and Francaviglia et al. 2020). In this regard, various explanations are possible, such as uncertainty due to incomplete knowledge about the underlying geophysical processes of climate change in scenarios and the GCMs, the random nature of climate in nature as well as the chain of atmospheric changes in different parts of the world and the integration of greenhouse gas emission around the world. Furthermore, the inherent uncertainty of downscaling process as well as the uncertainty of downscaling models may be effective. However, investigating the reasons for this matter can be the subject of future research.

The outcomes of projecting the climate variables in this study also play an essential role in analyzing the impacts of climate change in Tehran, such as changes in water consumption and wastewater generation. For this reason, the increase or decrease in climate variables effective in water consumption and wastewater generation in Tehran may lead to quantitative changes in water and wastewater. Particularly, in light of the increasing trends of $T_{\text{mean}}$ and $T_{\text{max}}$ throughout the entire future period as well as the relative increase of precipitation in some years, the results of this research can be used to predict the hazards and management of risks related to the impacts of climate change during future periods of Tehran.

**DATA AVAILABILITY STATEMENT**

All relevant data are included in the paper or its Supplementary Information.

**REFERENCES**


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