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Projection of temperature and precipitation for 2020-2100 using post-processing of general circulation models output and artificial neural network approach, case study: Tehran and Alborz provinces

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Abstract

Multi-model projections in climate studies are performed to quantify and narrow uncertainty and improve reliability in climate projections. The challenging issue is that there is no unique way to obtain performance metrics, nor is there any consensus about which method would be exactly the best method for combining models. The goal of this study was to investigate whether combining climate model projections using an artificial neural network approach could improve climate projections and therefore reduce the range of uncertainty. The equally-weighted model averaging (the mean model) and single climate model projections (the best model) were also considered as a reference of comparison for our artificial neural network combination approach. Simulations of historical climate and future projections from 15 General Circulation Models for temperature and precipitation were employed.Our results indicate that based on calculated performance indices combining General Circulation Models projections by using the artificial neural network approach significantly improves the simulations of temperature and precipitation for the historical period compared to the best model approach and the mean model approach. Our results also indicate that based on the calculated performance indices for the three approaches, projections based on single model simulation might not yield reliable results because the best model changed between temperature and precipitation, and also among stations that were studied. Therefore, there was no a unique model which could represent the best model for all climate variables and/or stations in the study region. The mean model was also not skillful enough in giving an accurate projection of historical climate compared to the other two approaches. Therefore, the ANN approach was used to estimate projections of future temperature and precipitation for the study region based on three different emission scenarios.Simulation of temperature indicated that the artificial neural network approach had the best skill at simulating monthly means of the historical period compared to other approaches in all stations. Simulation of precipitation in the historical period, however, indicated that the artificial neural network approach was not the best approach in all stations, although this modeling approach performed better than the mean model approach. Multi-model projections of future climate variables for this study region performed by the artificial neural network approach projected an increase in temperature and reduction in precipitation in all stations and for all scenarios.

The artificial neural network approach can benefit projections of the climate variables and has the potential to reduce the uncertainty aspects in constructing and combining metrics used for weighting the models. However, this approach is subject to some limitations which exist in similar skill-based performance studies of models and should be considered in future similar studies.

Keywords: Climate change, IPCC AR4, artificial neural networks (ANN), multi-model combination, Tehran province, Iran wave velocity profile, site effects

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1 Introduction

General Circulation Models (GCMs) are considered important tools for simulating future global climate. These models can simulate different components of the Earth system, such as the atmosphere and oceans. However, due to their coarse resolution, projections of these models have low confidence and high uncertainty. Furthermore, using the output of a single GCM in climate change projections does not yield realistic projections of future climate conditions. Intercomparison studies of GCMs indicate that each climate model has different skills in simulating certain aspects of the climate system mechanisms (Gleckler et al., 2008; Lambert and Boer, 2001). This means that climate variables are simulated with different degrees of accuracy by different models, and no single model delivers the best simulation for all variables and/or all regions. Therefore, in order to quantify the range of uncertainty in climate change projections, Intergovernmental Panel on Climate Change (IPCC) recommends using multiple GCMs in climate simulations (Parry et al., 2007).

Uncertainty in climate projections usually arises from three main sources: internal variability of the climate system, which stems from natural fluctuations of the climate without considering the effect of radiative forcing of the planet; emission scenarios, that stem from uncertainties in estimating future emissions of aerosols and greenhouse gases; and model errors, that stems from model formulations and structural uncertainties (Little et al., 2015). The domination of the three sources of uncertainty in climate change projections varies with spatial and temporal scales (Cox and Stephenson, 2007; Räisänen, 2001). For projections in the range of a decade or two, the dominant sources of uncertainty are model uncertainty and internal variability. In projections of longer time scales, such as climate change conditions until the end of the 21st century, model uncertainty and scenario uncertainty become the dominant sources (Frölicher et al., 2016; Giorgi, 2010). Hawkins and Sutton (2009) showed that the importance of internal variability would increase at smaller spatial scales, and it was generally the dominant source in short-time scale projections. Their study also indicated that the importance of internal variability would decline when the projection time increased. Moreover, scenario uncertainty made an important contribution to many regions of the world at the end of the 21st century. Based on their study, model uncertainty had an important role in both global and regional scales and made a significant contribution to all time scales.

Model uncertainty plays an important role in studying the climate change conditions for the next century. In order to address model uncertainty in climate change simulations, a multi-model combination has been adopted as a well-accepted approach which generally increases the reliability of model forecasts (Weigel et al., 2010). However, so far, no consensus has been reached about which method would be the best method of combining the outputs of several climate models. Generally, in climate change multi-model studies, a common practice is to use the concept of weighting the outputs of climate models (Tebaldi and Knutti, 2007). The approaches fall into two general categories of *equal weighting* and *skill-based weighting*. Equal weighting is the easiest approach, in which every model is given equal weight regardless of its magnitude of contribution to the combination. *Skill-based* weighting is a more sophisticated approach. In this approach, every individual model is given a different weight based on its contribution to projections. The weights are calculated based on the skill of every individual model in simulating the historical climate conditions and therefore are considered as skill-based weights. A study by Giorgi and Mearns

(2002) proposed the "Reliability Ensemble Averaging" (REA) approach to weight different models based on their contributions to historical climate simulations. They defined two reliability criteria in multi-model studies to evaluate the skills of GCMs in simulating climate variables in the present and future climates: "model performance" that indicated how well the models can simulate the baseline (historical) climate, and "model convergence" that investigated the convergence between the simulations of future climate across models. The underlying philosophy of the REA approach in a multi-model projection is to detect models with weak performance in simulating historical climate (the outliers) and to reduce their role in projections by assigning them less weight than models with small bias and good performance. However, it has been argued that because common weaknesses in the representation of certain climate processes may exist among a majority of models, outliers may not appear at random. Therefore, considering and analyzing a subset of models as the best guess, whose agreement is considered as their individual tendencies, may result in disregarding the possible range of uncertainty in the convergence criterion.

Multi-model combination based on model weighting has been the focus of multiple studies (Arzhanov et al., 2012; Christensen et al., 2010; Gleckler et al., 2008; Knutti et al., 2010; Lambert and Boer, 2001; Min and Hense, 2006; Tebaldi et al., 2005; Weigel et al., 2010). A study by Lambert and Boer (2001) indicated that no one model is best for all variables and/or all regions, and different variables are simulated with different levels of success by different models. They also concluded that the equally-weighted average or the "mean model" usually provides the best comparison to observations than the single models. A similar study was conducted by Gleckler et al. (2008) which emphasized the results of Lambert and Boer (2001). They ranked models based on simulating each variable that was considered in their study and concluded that the ranking of models varied from one variable to the other one. They also considered the mean model in their study and demonstrated that the mean model would outperform all single models in nearly every aspect. In a multi-model study based on model weighting, Weigel et al. (2010) suggested that equally weighted multi-model, on average, would outperform single-model projections. They also considered the weighting of models and demonstrated that if the optimum weighting of the models were accurately performed, projection errors would be reduced in simulations. On the other hand, if inappropriate weights were assigned, which did not represent the skill of the model, the weighted multi-model would perform on average worse than equally weighted models, and therefore more information would be lost than was supposed to be obtained from simulations. The task of assigning weights to models is performed by defining some metrics to quantify model performance. The difficulty in this procedure is that there is no unique way to obtain metrics, nor is there any consensus about which method would be the best method for combining models. This difficulty is highlighted by the fact that the choice of the metrics to weight models is a pragmatic and subjective task that may incorporate more uncertainty into projections (Christensen et al., 2010; Tebaldi and Knutti, 2007).

In this study, we investigate an alternative modeling approach to combine multiple climate change projections. We combined the outputs of several GCMs with an artificial neural network (ANN) model to obtain a multi-model combination. The purpose of the suggested approach is to investigate how much the combination of GCM projections by using our ANN approach would improve multi-model projections and, therefore, could reduce the uncertainty by obtaining an optimal model combination. In order to assess the results, projections from two common approaches, namely single climate models (the best model) and equal weighting of the models (the mean model), were compared with this approach. The ANN approach derives an optimal combination of multiple climate models by correlating the GCM simulations at the grid-scale to observations of climate variables at the local scale. This procedure can benefit climate projections because it reduces the subjectivity and complexity aspects in constructing and combining metrics used for weighting the models.

Climate change is projected to impact each component of the climate system with regional differences (Mejia et al., 2018; Mosadegh et al., 2018; Mosadegh and Nolin, 2020). A few studies have addressed the uncertainty of climate projections over the 21st century for the Tehran region (Mosadegh et al., 2013; Mosadegh and Babaeian, 2021a) and have investigated to what extent the projected changes in climate variables can affect other aspects of our environment such as air pollution (Mosadegh et al., 2021; Mosadegh and Babaeian, 2021b). In order to investigate the skill of the suggested ANN approach, we simulated temperature and precipitation for the study region. Moreover, we used the ANN approach to obtain a multi-model projection of temperature and precipitation for the future climate change conditions of the study region to the end of the 21st century. In this projection, the focus was mainly on the projection aspect rather than the model convergence criterion, and also to know to what extent this approach can reduce the uncertainty in projections. We also took two sources of uncertainty into consideration: model uncertainty and scenario uncertainty. Internal climate variability is often considered negligible on long time scales (Hawkins and Sutton, 2009).

This paper is structured as follows: Data, models, and scenarios used in the present study are described in section 2. The employed methodology is presented in section 3. The results are discussed in section 4, and conclusions are provided in section 5.

2 Data, models, and scenarios

2.1 Data

Observation datasets from four synoptic stations in Tehran and Alborz provinces were used in this study. In each station, available long-term observations of monthly surface temperature and precipitation until 2000 were used as the baseline period. For training the ANN, long-term observation datasets were necessary. Therefore, the baseline period for each station was selected based on the availability of observed data until the year 2000. Monthly surface temperature datasets for every station were obtained from daily observed values in each station. The precipitation datasets were obtained from daily observed values in each station and then were summed to get the total monthly precipitation in each station. The information on stations is given in Table 1. In the present study, calculations for handling large datasets and obtaining the indices were programmed in MATLAB.

Table 1. Information of station used in the present study.

Station	Latitude	Longitude	Elevation (m)	Baseline
Karaj	35 55 N	50 54 E	1312.5	1985-2000
Mehrabad	35 41 N	51 19 E	1190.8	1960-2000
Doshan Tappeh	35 42 N	51 20 E	1209.2	1972-2000
Abali	35 45 N	51 53 E	2465.2	1983-2000

2.2 Models

Uncertainty from Climate models is an important source of uncertainty in short-term and long-term climate change projections (Hawkins and Sutton, 2009; Räisänen, 2001). Every model is skillful in capturing some aspects of the climate system, and there is no one model that is skillful to simulate all variables and/or regions (Lambert and Boer, 2001). We focused our work on a multi-model combination analysis and used the maximum available number of climate models in order to consider the widest possible range of model projections. This enables us to consider the skills of all models together in projections. The GCM projections for both historical and future climate conditions were obtained from the Canadian Climate Data and Scenarios database (http://ccds-dscc.ec.gc.ca) for the study region. This database provides monthly simulations of a broad range of climate variables based on different emission scenarios (A1B, A2, B1) and geographical position of every location from 24 coupled atmosphere–ocean GCMs.The employed simulations were from a subset of GCMs which were used in the IPCC 4th assessment report/CMIP3. We only considered GCMs that would provide projections of all three emission scenarios for the study region in order to consider the uncertainty from emissions scenarios in projections. In order to use the maximum number of GCMs in our multi-model projections, we selected 15 models which provided all three simulations of A1B, A2, and B1 emission scenarios from the set of 24 GCMs. The list of employed GCMs is given in Table 2.
Table 2. Features of the GCMs from IPCC AR4 used in this study.

Table 2. Features of the GCMs from IPCC AR4 used in this study.

Country	Developer	GCM	Model acronym	Grid resolution	Emission scenarios
Australia	Commonwealth Scientific and Industrial Research Organization	CSIRO-MK3.0	CSMK3	1.9° × 1.9°	SRA1B, SRB1
Canada	Canadian Centre for Climate Modeling and Analysis	CGCM33.1 (T47)	CGMR	2.8° × 2.8°	SRA1B
China	Institute of Atmospheric Physics	FGOALS-g1.0	FGOALS	2.8° × 2.8°	SRA1B, SRB1
France	Centre National de Recherches Meteorologiques	CNRM-CM3	CNCM3	1.9° × 1.9°	SRA1B, SRA2
France	Institute Pierre Simon Laplace	IPSL-CM4	IPCM4	2.5° × 3.75°	SRA1B, SRB1, SRA2
Germany	Max-Planck Institute for Meteorology	ECHAM5-OM	MPEH5	1.9° × 1.9°	SRA1B, SRB1, SRA2
Japan	National Institute for Environmental Studies	MRI-CGCM2.3.2	MIHR	2.8° × 2.8°	SRA1B, SRB1
Norway	Bjerknes Centre for Climate Research	BCM2.0	BCM2	1.9° × 1.9°	SRA1B, SRB1
Russia	Institute for Numerical Mathematics	INM-CM3.0	INCM3	4° × 5°	SRA1B, SRB1, SRA2
UK	UK Meteorological Office	HadCM3	HADCM3	2.5° × 3.75°	SRA1B, SRB1, SRA2
UK	UK Meteorological Office	HadGEM1	HADGEM	1.3° × 1.9°	SRA1B, SRA2
USA	Geophysical Fluid Dynamics Lab	GFDL-CM2.1	GFCM21	2.0° × 2.5°	SRA1B, SRB1, SRA2
USA	Goddard Institute for Space Studies	GISS-AOM	GIAOM	3° × 4°	SRA1B, SRB1
USA	National Centre for Atmospheric Research	PCM	NCPCM	2.8° × 2.8°	SRA1B, SRB1
USA	University Corporation for Atmospheric Research (UCAR)	CCSM3	NCCCS	1.4° × 1.4°	SRA1B, SRB1, SRA2

main sources of uncertainty in climate change projections and become more pronounced at longer term projections that simulate climate change conditions at the end of the 21st century (Hawkins and Sutton, 2009; Stott and Kettleborough, 2002).

The goal of this study was to investigate an alternative modeling approach for combining outputs of several climate models in order to reduce uncertainty in projections. In order to investigate the role of scenario uncertainty in projections, we considered three emission scenarios: A1B, A2, and B1, which are equivalent to RCP4.5, RCP8.5, and RCP2.6, respectively. These scenarios were used in climate simulations by all selected 15 GCMs. Each scenario takes into account the dominant features of emissions of greenhouse gases, such as physical, societal, and economic factors. In the present study, we only made use of three scenarios briefly described as follows:

A1B: This scenario which is equivalent to RCP4.5, depicts a future world with balanced consumption across energy resources, a world with very rapid economic growth and rapid introduction of new and more efficient technologies, but with low population growth. Personal wealth is preferred over environmental quality in this world.

A2: This scenario which is equivalent to RCP8.5, depicts a differentiated world. In this scenario, high population growth, less concern for rapid economic development, and strengthening regional cultural identities, with an emphasis on family values and local traditions, are the underlying themes.

B1: This scenario which is equivalent to RCP2.6, depicts a convergent world. In this scenario, the introduction of clean technologies, rapid technology development, and movement towards achieving environmental and social sustainability are the underlying themes.

3 Methodology

3.1 Simulation of present climate

3.1.1 Single model simulations

In some situations, a user usually has to decide beforehand which single model to choose for the decision-making process. This single model usually has better performance than other models. In order to find the best single model for each variable in each station, we investigated which GCM would be more skillful in reproducing the variables in the historical climate for the study region.

We used some known indices to evaluate the performance of the single models together with equally–weighted averaging of the model and the ANN combination approach in historical climate. In order to assess the skill of every single model in simulating monthly means of temperature and precipitation in historical climate for the study region, we used three indices for each scenario: coefficient of determination (R^2) (Eq. 1), index of agreement (IA) (Eq. 2), and root mean square errors (RMSE) (Eq. 3). R^2 and IA indicate the skill of the models in simulating the monthly means of the variables, and the more they are close to 1, the more it indicates that the monthly means of the simulations agree with observations. RMSE was used to investigate the accuracy of simulations of monthly means of the variables. RMSE is an error-index and demonstrates the bias between simulations and observations. This index has the same scale as the variables and therefore provides a good judgment for us about the range of bias in simulations. Each of the three indices does not represent the skill of the models in simulations individually, but taking all three indices together into consideration can tell us how skillful a model would be in simulating the historical climate.

$$R^2 = \frac{\left[\sum_{i=1}^{n} (S_i - \underline{S})(O_i - \underline{O})\right]^2}{\sum_{i=1}^{n} (S_i - \underline{S})^2 \sum_{i=1}^{n} (O_i - \underline{O})^2}, \qquad (1)$$

$$IA = 1 - \left[\frac{\sum_{i=1}^{n} (S_i - O_i)^2}{\sum_{i=1}^{n} (|S'_i| + |O'_i|)^2}\right], \qquad (2)$$

$$RMSE = \left[\frac{1}{n}\left(\sum_{i}^{n} (Si - Oi)^2\right)\right]^{1/2}, \qquad (3)$$

where S_i and O_i are the *i*th simulation and observation, and $\underline{S}$ and $\underline{O}$ are the means of simulations (S_i) and (O_i), respectively, n is the total number of the evaluated samples. In Eq. (1-3) S'_i and O'_i are

$$S'_i = S_i - \underline{S} \qquad (4)$$

$$O'_i = O_i - \underline{O} \qquad (5)$$

In this section, the long-term monthly

means of each variable were initially calculated from observations and GCM simulations. Then, the indices were calculated to compare the monthly means of the GCM simulations with observations in each station. The precipitation calculated by GCMs was based on mm/day which was changed to total precipitation in a month, based on mm, to match the observations.

3.1.2 Equally–weighted model averaging

Averaging the equally-weighted models or so-called the “mean model” is the simplest approach to combine outputs of several climate models and therefore to quantify uncertainty in projections (Lambert and Boer, 2001; Tebaldi and Knutti, 2007). Compared to single model simulations, this approach provides a better comparison to observations and is more straightforward than the weighting models based on their skill. We adopted the mean model approach as a reference to the best model and ANN approaches, and to see how much the mean model, in comparison with the two mentioned approaches, can reduce uncertainty in future climate simulations.

Outputs of the 15 employed GCMs were obtained from the Canadian Climate Data and Scenarios database (http://ccds-dscc.ec.gc.ca) for the baseline period of each variable and for each station. The baseline period for each station was defined based on the availability of observations in that station. First, the long-term monthly means of the variables were calculated from observations in each station. Then, the long-term monthly means of simulations were obtained from each GCM and each station based on its observation baseline. Finally, the long-term monthly means of simulations in each station were compared with their corresponding observations in each month. The comparison was made by using Eq. (1-3) and calculating the performance indices for the baseline period in each station.

3.1.3 The ANN combination approach

The objective of the present study was to investigate an alternative modeling approach to combining outputs of several climate model projections. We adopted the ANN approach to obtain a multi-model combination of multiple GCM projections, and to investigate how much this approach was able to improve projections. ANNs have been used in several climate studies (Boulanger et al., 2006; 2007; Karl et al., 1990; Knutti et al., 2003; Mpelasoka et al., 2001; Sailor et al., 2000; Trigo and Palutikof, 1999). For instance, Boulanger et al. (2006) and Boulanger et al. (2007) used this approach to investigate future climate change conditions of temperature and precipitation over South America during the twenty-first century. They found that the ANN would underestimate the potential climate change projections simulated by the IPCC models.

The ANN has two main roles in this study. First, it obtains an optimal combination of several GCMs. The optimal combination in this method is calculated by the network itself based on the skill of climate models in simulating the historical climate for the study region. Therefore, this method reduces the subjectivity and uncertainty aspects in constructing and combining metrics used for weighting the models. Second, the ANN approach correlates the GCM outputs on grid-scale to sub-grid scale possesses that are captured in observations on the local scale. GCMs lack any representation of the local environment especially the urban environment which may impact observations. The ANN approach provides a multi-model GCM projection which has been corrected for local environments especially for urban environments.

A detailed description of ANNs and multi-layer perceptron (MLP) can be found in numerous documentations in the literature. Therefore, in the present study, we will only focus on a brief summary of the methodology. The basic structure of every neural network involves inter-connected nodes that are arranged in layers. The architecture of every neural network is composed of an input layer, one or more hidden layers, and an output layer. Every node in the hidden and output layers consists of activation and transfer functions. Initially, in each node, the activation function value is calculated. Then the calculated value passes through a transfer function. This process is identical for all nodes in hidden and output layers. The input layer, however, does not contain any activation or transfer function and serves merely to transfer the inputs to the network. Finally, the output of the system is compared with the target value, and the output error of the modeling system is calculated. The objective of the training phase is to reduce the output error of the modeling system to its minimum. In the back-propagation training algorithm, this task is accomplished by distributing the output error back into the system among network weights and adjusting the weights so that the final output error approximates the target value with a selected error goal.

Figure 1 shows a schematic diagram of the ANN architecture that has been used. In the present study, a three-layered feed-forward MLP with a 15-30-1 network structure was used. The input layer consisted of 15 inputs which represented the monthly means of each GCM in the baseline period. Monthly means of the observations in each station were considered as the output of the network in the training phase. The historical simulated monthly means of each GCM were obtained from the Canadian Climate Data and Scenarios database (http://ccds-dscc.ec.gc.ca) for every station. A network with 15-30-1 node architecture was selected by trial and error and by considering the performance of each model architecture. Finally, 30 neurons were selected for the hidden layer because this number of nodes demonstrated the best performance in simulations. The dataset was divided into three subsets of the training set, test set, and validation set, each having 70%, 15%, and 15% of the total dataset, respectively. To evaluate the skill of each trained ANN, long-term monthly means of GCM simulations were given to the network, and ANN values were obtained for each month. Then, the long-term monthly means simulated by the ANN were compared with their corresponding monthly observations by using Eq. (1-3). Finally, the skill of each trained ANN was evaluated by indices such as R^2, RMSE, and IA.

3.2 21st-century simulations

Simulation of the climate variables for the 21st century was conducted by using the trained ANNs that were developed for every station based on section 3.1.3. Projections of future monthly means of temperature and precipitation from each GCM for the stations in the study region were obtained from the Canadian Climate Data and Scenarios database (http://ccds-dscc.ec.gc.ca) database for the 2020–2100 period. The projections were based on A1B, A2, and B1 emission scenarios which were regarded as the input to the developed ANNs. The GCM monthly simulations for every station were given to the ANNs as their inputs, and future monthly means of temperature and precipitation were projected by the developed ANNs in each station for the 2020–2100 period. Then, the simulated monthly means were averaged over every 20 years for four periods of 2020–2039, 2040–2059, 2060–2079, and 2080–2099 to demonstrate a better view of future changing trends in every station.

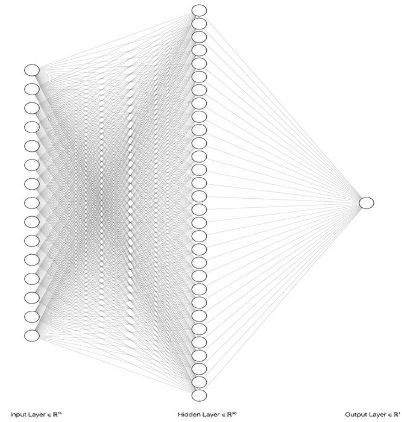

Figure 1. Schematic diagram of the used ANN architecture.

Table 3. Calculated performance metrics for the developed ANNs in the test phase.

Variable	Stations	No. of neurons	R	MAE	RMSE
Precipitation	Karaj	30	0.56	14.92	24.02
	Mehrabad	30	0.56	16.93	27.66
	Doshan Tappeh	30	0.62	13.58	18.14
	Abali	30	0.68	22.33	28.33
Temperature	Karaj	30	0.96	2.204	2.885
	Mehrabad	30	0.98	1.382	1.721
	Doshan Tappeh	30	0.98	1.303	1.644
	Abali	30	0.98	1.773	2.128

Table 4. Validation of temperature simulated by single models.

	Abali- A1B			Doshan Tappeh-A1B			Karaj- A1B			Mehrabad- A1B		
Models	R^2	IA	RMSE	R^2	IA	RMSE	R^2	IA	RMSE	R^2	IA	RMSE
BCM2.0	***0.993***	***0.998***	***0.900***	0.980	0.746	9.206	0.982	0.876	6.237	0.975	0.747	9.151
CGCM3T63	0.978	0.989	2.032	0.975	0.768	9.433	0.971	0.889	6.334	0.975	0.758	9.554
CNRMCM3	0.978	0.972	2.988	0.990	0.853	7.138	0.983	0.949	4.050	0.989	0.845	7.230
CSIROMk3.5	0.942	0.510	11.550	0.979	0.974	2.641	0.969	0.941	3.842	0.980	0.975	2.600
ECHAM5OM	0.977	0.748	8.674	0.997	0.933	4.420	0.993	0.990	1.636	0.998	0.935	4.349
ECHO-G	0.995	0.927	4.917	0.995	0.936	4.763	0.995	0.990	1.789	0.995	0.935	4.750
GFDLCM2.1	0.979	0.901	5.409	0.988	0.935	4.486	0.981	0.989	1.792	0.987	0.937	4.384
GISS-ER	0.957	0.875	6.860	0.961	0.959	4.024	0.949	0.978	2.873	0.959	0.955	4.198
HADCM3	0.943	0.932	4.566	0.975	0.899	5.734	0.963	0.971	2.974	0.979	0.900	5.670
INMCM3.0	0.953	0.942	3.641	0.978	0.734	8.116	0.968	0.881	5.238	0.979	0.731	8.113
IPSLCM4	0.995	0.875	5.871	0.984	0.938	4.249	***0.987***	***0.991***	***1.608***	0.984	0.937	4.244
MIROC3.2 medres	0.978	0.781	8.555	***0.987***	***0.993***	***1.551***	0.982	0.984	2.331	***0.987***	***0.993***	***1.578***
MRI CGCM2.3.2a	0.980	0.921	5.166	0.989	0.939	4.693	0.984	0.987	2.060	0.990	0.938	4.690
NCARCCSM3	0.981	0.904	5.295	0.987	0.928	4.704	0.983	0.966	3.204	0.986	0.877	6.236
NCARPCM	0.972	0.991	1.590	0.991	0.680	10.050	0.984	0.833	7.021	0.991	0.675	10.078

4 Results and discussion

4.1 historical climate simulations

As described in section 3.1.3, an ANN was developed for every variable and station. The statistics of the test phase of the developed ANNs are given in Table 3. Moreover, the calculated performance indices of every single GCM are given in Tables 4–7 for only the A1B emission scenario. A model that has the highest R^2 and D and the lowest RMSE can be considered as the best GCM for the study region. Among the 15 models, calculated R^2 and D are almost in the same range, and therefore RMSE could be regarded as the best index to distinguish the skilled GCM among the other models.

Table 4 gives the calculated performance indices for temperature for every 15 GCM in this study. As Table 4 indicates, there was not a unique single model that could be skillful over all four stations. Calculated indices indicate that at Doshan Tappeh and Mehrabad stations, located in Tehran megacity, the MIROC3.2 medium resolution GCM had the best agreement between simulations and observations, and, therefore the lowest uncertainty among the 15 models for Tehran megacity. Although this model did not have the highest R^2, it had the lowest RMSE among the single models, which made it the best model for simulating temperature in the area. At Doshan Tappeh station, CSIROM and IPSL, and at Mehrabad station, CSIRO and GISS GCMs were the second and third models that had better skills in simulating the historical climate over the other models in the area, respectively. At Abali station, BCM2, and at Karaj station, the IPSLCM4 GCMs had the best agreement between simulations and observations, respectively. Therefore, these GCMs were considered as the best models for simulating temperature in these stations. At Abali station, NCAR and CGCM3T, and at Karaj station, IPSL and ECHOG were the second and third models that had better skills in simulating the historical climate over the other models in the area, respectively.

Table 5 compares the calculated indices between the mean model and the ANN approach for temperature. As Table 5 indicates, the mean model did not improve the simulations. The indices indicated that there were some single models that had better skills in simulating historical climate than the mean model. However, there was a significant improvement in temperature simulations with the ANN approach. This approach considerably reduced RMSE and improved the temperature simulations by demonstrating the best skill compared to both the mean model and single models simulations.

Table 6 gives the calculated indices for every 15 GCM for precipitation. As Table 6 indicates, similar to temperature simulations, there was not a single model that could be skillful over all four stations. At Mehrabad and Doshan Tappeh stations located in the Tehran metropolis, MRI-CGCM2.3.2a and IPSL CM4 had the best agreement between simulations and observations, respectively. At Karaj and Abali stations, located near Tehran megacity, MRI and ECHO-G models had the best skill in simulating historical climate, respectively.

Table 7 compares the calculated indices between the mean model and the ANN approach for precipitation. As Table 7 indicates, the ANN approach did not have a satisfactory skill in simulating the historical period precipitation in all four stations. The ANN approach outperformed the single models in Abali and Mehrabad stations. However, in Doshan Tappeh and Karaj

Different calculated ranges of the indices, such as RMSE and $R^{2,}$ in the simulation of temperature and precipitation by single models indicate that the models can simulate temperature with higher confidence than precipitation in the historical climate. Moreover, there is a substantial difference among single models in simulating the historical precipitation. Unlike precipitation, the temperature has a narrower range of indices, especially RMSE, in simulations of historical climate. These results are compatible with several studies such as Hawkins and Sutton (2009), which have indicated this issue. A wider range of RMSE and R^2 in simulating baseline precipitation compared to temperature highlights the fact that models simulate historical precipitation with lower confidence than temperature. The low confidence in the simulation of precipitation is due to the fact that models are not able to correctly project some underlying subgrid processes that influence precipitation change. Moreover, precipitation is strongly influenced by some local or regional geographic features, such as mountainous terrain. These features are not usually well presented in current GCMs.

Table 5. Validation of temperature simulated by the mean model and the ANN approach.

Method	R^2	IA	RMSE	R^2	IA	RMSE	R^2	IA	RMSE	R^2	IA	RMSE
SIMPLE AVE.	0.984	0.915	5.127	0.992	0.919	5.104	0.987	0.985	2.142	0.992	0.918	5.122
ANN	***0.992***	***0.998***	***0.892***	***0.999***	***1.000***	***0.345***	***0.981***	***0.995***	***1.262***	***0.998***	***0.999***	***0.459***

Table 6. Validation of precipitation simulated by single models.

	Abali- A1B			Doshan Tappeh-A1B			Karaj- A1B			Mehrabad- A1B		
Models	R^2	IA	RMSE	R^2	IA	RMSE	R^2	IA	RMSE	R^2	IA	RMSE
BCM2.0	0.30	0.65	37.73	0.21	0.00	50.51	0.36	0.00	50.51	0.25	0.00	55.21
CGCM3T63	0.49	0.74	25.58	0.34	0.65	20.97	0.46	0.68	19.60	0.35	0.57	23.26
CNRMCM3	0.04	0.51	33.26	0.01	0.02	34.25	0.04	0.00	35.28	0.00	0.00	38.02
CSIROMk3.5	0.90	0.00	40.14	0.75	0.88	9.48	0.82	0.91	7.73	0.76	0.92	7.32
ECHAM5OM	0.75	0.06	37.84	0.46	0.70	12.54	0.60	0.77	10.76	0.49	0.69	11.85
ECHO-G	***0.75***	***0.77***	***22.31***	0.64	0.81	13.59	0.77	0.82	13.01	0.63	0.74	15.13
GFDLCM2.1	0.70	0.61	28.98	0.59	0.87	11.12	0.75	0.92	8.67	0.66	0.90	9.16
GISS-ER	0.54	0.65	27.63	0.53	0.82	14.36	0.63	0.84	12.92	0.53	0.76	16.09
HADCM3	0.75	0.29	34.52	0.61	0.80	11.52	0.80	0.92	7.51	0.70	0.88	8.43
INMCM3.0	0.27	0.00	35.13	0.19	0.51	14.74	0.26	0.54	13.31	0.15	0.49	14.82
IPSLCM4	0.85	0.57	29.09	***0.91***	***0.97***	***4.99***	0.83	0.95	6.27	0.93	0.97	5.46
MIROC3.2 medres	0.61	0.30	33.57	0.49	0.80	11.71	0.66	0.88	8.75	0.51	0.83	10.39
MRI CGCM2.3.2a	0.94	0.72	25.74	**0.93**	**0.98**	**5.17**	***0.95***	***0.97***	***5.29***	***0.97***	***0.97***	***5.39***
NCAR-CCSM3	0.75	0.69	25.43	0.87	0.94	7.59	0.74	0.86	10.87	0.85	0.88	10.20
NCARPCM	0.69	0.00	41.03	0.59	0.53	15.77	0.74	0.65	13.15	0.63	0.67	12.56

Table 7. Validation of precipitation simulated by the mean model and the ANN approach.

Method	R^2	IA	RMSE	R^2	IA	RMSE	R^2	IA	RMSE	R^2	IA	RMSE
SIMPLE AVE.	0.62	0.59	27.39	0.49	0.78	13.53	0.66	0.82	11.94	0.51	0.72	14.79
ANN	***0.65***	***0.82***	***20.99***	0.87	0.86	9.47	0.82	0.95	6.36	***0.93***	***0.98***	***3.94***

Furthermore, the identity of models and their ranking based on their skill changed between the two variables and among stations, i.e., there was not a unique model which could represent the best model for all variables and/or stations over the region. These results are similar to results from studies such as Hagedorn et al. (2005) and Gleckler et al. (2008) which indicated that the models that were best for temperature were not necessarily best for other variables such as precipitation. The mean model, which was calculated by simple averaging the outputs of the single models, was also considered in this study as a reference method for the ANN combination approach. As the calculated indices indicated, the mean model only provided the mean state of a variable and did not agree well with the historical climate compared to some single model simulations and the ANN combination approach.

Compared to the mean model, the indices indicated that the ANN combination approach significantly improved the simulations of historical climate. The ANN combination approach improved the IA and R^2 and considerably reduced the RMSE, especially in temperature simulations. In simulating temperature, the ANN approach demonstrated to have the best skill at simulating historical monthly means of the variables than the mean model and the best model in all 4 stations. In simulating the historical precipitation, however, the ANN approach was not the best approach in all stations, although it performed better than the mean model. In Abali and Mehrabad stations, the ANN had the best skill in simulating the historical precipitation. In Doshan Tappeh and Karaj stations, however, single GCMs had better skills than the other two approaches and were the best single models for simulating the precipitation. The reason for the better performance of some single models over the ANN combination approach in simulating the historical precipitation in some stations may be because some single models may resolve the sub-grid processes in simulating the precipitation, such as the geographical features of the study location better than other GCMs do. Moreover, we used all available models to incorporate all skills of the models into multi-model simulations. In a multi-model approach based on the historical skills of models, due to the low skill of some models in simulating a variable, some models affect the outcome of a multi-model projection by reducing the accuracy of simulations (Giorgi and Mearns, 2002; Tebaldi and Knutti, 2007). In addition, a study by Hagedorn et al. (2005) showed that for some variables, the multi-model combination might not be significantly better than the best single model. He concluded that the performance of a multi-model combination approach must be evaluated when considering its overall performance over all aspects of predictions.

To sum up, the results indicated that the proposed ANN combination approach to combining GCM simulations is able to reduce uncertainties and, therefore to improve reliability in climate projections, especially for temperature, compared to the best single model and the simple averaging approach. Therefore, based on its performance in historical climate, the ANN approach was adopted to produce a multi-model projection of temperature and precipitation for the study region.

4.2 21st century projections

The performance of the ANN combination approach based on simulating temperature and precipitation for the historical climate was investigated in section 4.1. The ANN combination approach demonstrated to have a better skill over the mean model and the best single model in combining outputs of historical climate models and delivering more reliable results in all stations. Therefore, in order to investigate the future changes in temperature and precipitation in the study region, we used the ANN approach to provide a multi-model projection of the variables by combining projections from 15 GCMs for the 21st century for the study region.

Figure 2 illustrates the projected temperature change for every station. Mehrabad and Doshan Tapeh stations are located in Tehran megacity and usually have higher temperatures. Karaj station is located in the Karaj urban area on the west side of Tehran megacity, and Abali station is located on the heights of Abali in Alborz Mountain Range with usually lower temperatures and higher precipitation than the other three stations. Projections of future climate conditions by the ANN multi-model approach indicated an increase in temperature in all stations and for all scenarios, even in Abali station, which usually has lower temperatures due to its higher altitude. Comparing the three scenarios (A2, A1, B, and B1) showed that the projected patterns were similar in all stations and differed mainly in their amplitude. Among the stations, projections suggested that Abali station would experience the least warming of about 1-2 ^{0}C, and Doshan Tappeh station would experience the largest warming of about 3-4 ^{0}C among all scenarios at the end of the 21st century. Moreover, the projected changes in temperature were greater for stations located in Tehran megacity than stations in its neighboring areas, like Karaj and Abali stations. This may be because the ANN approach is capable of incorporating the effect of the urban environment into the projections. Therefore, the coarse resolution GCM outputs for the study region are corrected for the Tehran Urban environment by establishing a relationship between baseline simulations and observations. Furthermore, as Stott and Kettleborough (2002) showed, the contribution of scenario uncertainty to projections would increase for lead times of more than 30 years. As the multi-model projections indicate, differences among scenarios became more pronounced in the second part of the 21st century, which is compatible with similar results such as those of Stott and Kettleborough (2002) and Hawkins and Sutton (2009). The scenarios departed from each other in projections after the first period (2020–2039), and the divergence grew among the scenarios up to the end of the 21st century. A2 was the scenario with the greatest increase, and B1 was the scenario with the smallest increase at the end of the century in all stations.

Figure 3 illustrates the future changes in precipitation for every station. The ANN approach projected a decrease in precipitation in all stations and for all scenarios. Comparing the three scenarios (A2, A1, B, and B1) showed that the projected patterns were similar in all stations and differed mainly in their amplitude. Among the stations, ANN projections indicated that the Karaj station would experience the least reduction of about 1.5-2 mm among all scenarios at the end of the 21st century. Similar to temperature, the Doshan Tappeh station experienced the largest changes. The ANN projected the greatest reduction of about 7–9.5 mm at the end of the 21st century. Climate models represented general patterns of temperature fairly better than precipitation. Among stations, projections were more uncertain in Abali station. Projections had greater amplitude in Abali than in other stations. In the long-term, B1 did not indicate any reductions in this station and diverged from the other two scenarios since the first period. However, A1B and A2 projected a decrease in precipitation similar to other stations. Similar to temperature projection, scenarios departed from each other in projections after the first period, and the uncertainty grew among the scenarios in the second part of the 21st century. Moreover, A2 projected the largest decrease, and B1 projected the smallest decrease in precipitation at the end of the 21st century in all stations.

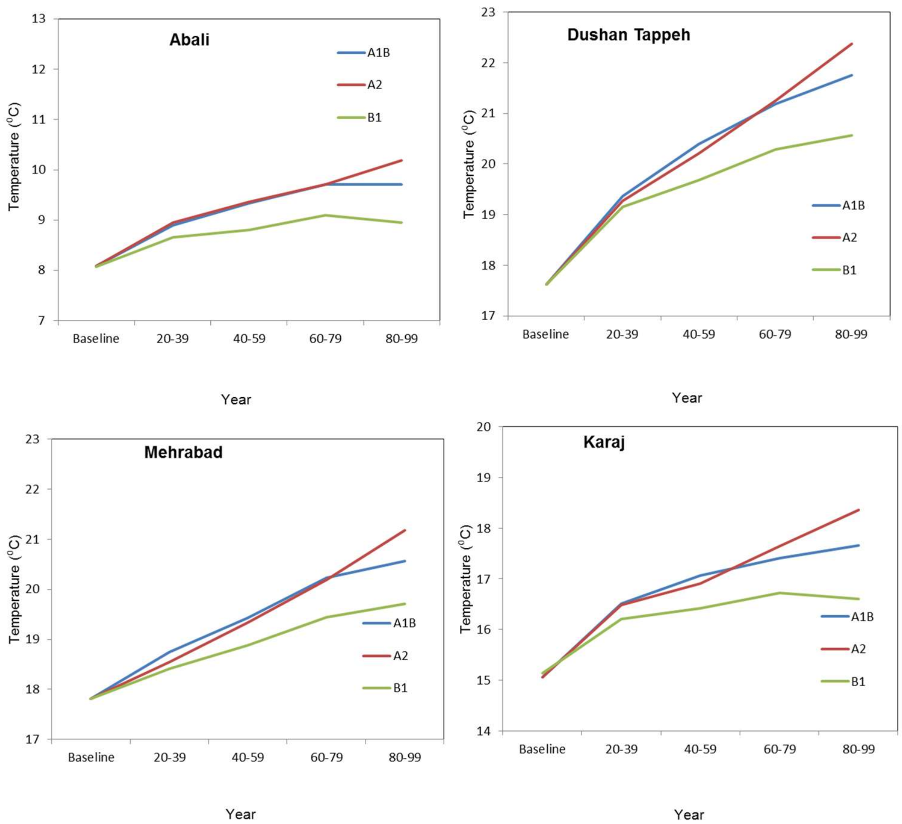

Figure 2. Multi-model projection of temperature by the ANN combination approach.

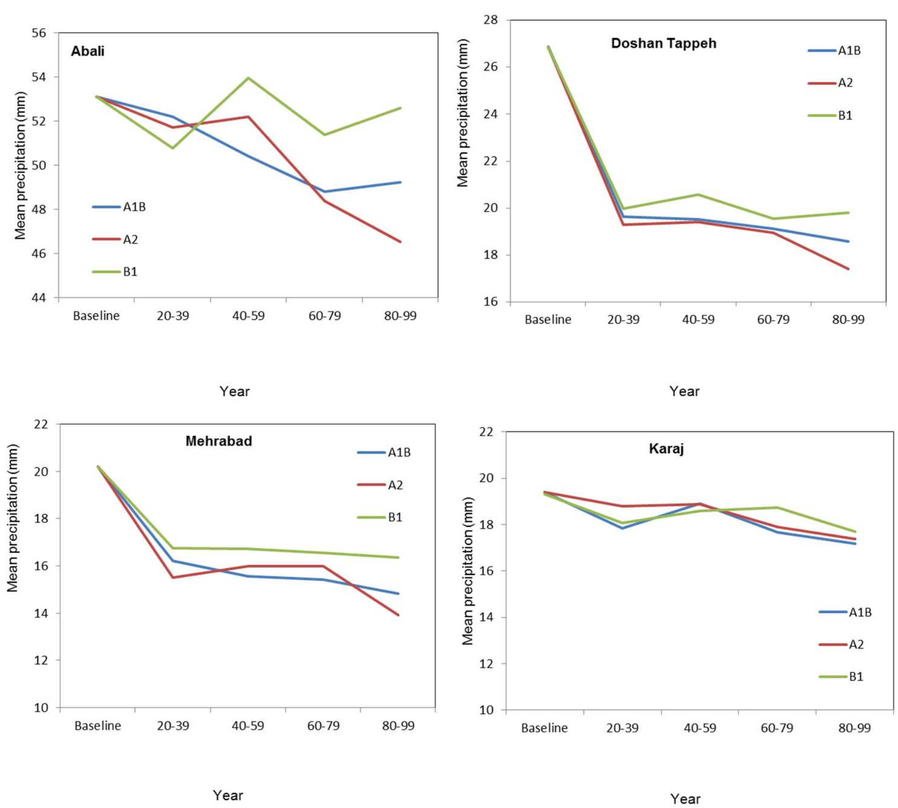

Figure 3. Multi-model projection of precipitation by the ANN combination approach.

4 Conclusion

The goal of this study was to investigate whether combining model projections by ANN combination approach could improve multi-model projections and therefore reduce the uncertainty in climate projections. To establish a reference for the ANN combination approach, the equal weighting of the models (the mean model) and single climate models (the best single model) was also considered in the study.

Simulations of climate variables of the historical period showed that the ANN combination approach was successful in combining the outputs of several climate models and in reducing the uncertainty in simulations of historical climate variables. Based on the calculated performance indices for the three approaches, we can conclude that projections based on single model simulation might not yield reliable results because single model simulations showed that the identity of models and their ranking based on their skill changed between the two variables and also among stations. The mean model was also not skillful enough to give a reliable projection of the historical climate. However, calculated performance indices indicated that combining model projections by the ANN approach significantly improved the simulations of historical temperature and precipitation than the single model and the mean model approaches. Based on the historical skill of each approach, we can conclude that the ANN approach could give the best estimate of future trends of temperature and precipitation for a local environment. Therefore, the ANN approach was used to estimate projections of future temperature and precipitation for the study region.

The ANN approach can benefit the climate change projections due to the fact that it derives an optimal combination of several climate models by correlating the GCM simulations at the grid-scale to observations of climate variables at the local scale. Therefore, this procedure reduces the subjectivity and uncertainty aspects in constructing and combining metrics used for weighting the models and delivers a multi-model projection that has been corrected for a specific local environment, especially for urban environments. However, the ANN approach is subject to some limitations which exist in similar skill-based performance studies of models. The optimal combination of models is derived based on the skill of the models in the simulation of the historical climate. The underlying assumption governing this approach is the stationary relation between observed and simulated trends. This relation is formed in the training period of the ANN-based on the twentieth-century climate and is applied to future simulations. A debate that exists here is that the skills of climate models are evaluated based on their performance in historical climate conditions, and, likely, the present optimal combination of models may not be the optimal combination in the future climate. This issue is due to some limitations that exist among present models. For instance, some characteristics of the climate models, such as model parameterizations or impacts of some physical processes, such as carbon cycle feedbacks, may change under future climate forcing (Frame et al., 2007; Knutti et al., 2010). However, the only guidance that we have to evaluate the performance of current models is to evaluate their skills by comparing their simulations against observations of different historical climate aspects. We might not be able to judge whether the closest projection to a multi-model average of future projections would be the best estimate of future climate due to the mentioned limitations, but for the historical climate, we can decide that if a methodology gives better simulations of different aspects of historical climate compared to observations, it would be a more skillful methodology and might give more reliable results for present climate. Consequently, using the skills of models based on their historical performance may be a good measure for constructing a multi-model combination of models. The difficulty remains in how to integrate the historical skills of models into their future projections. In this research study, we tried to address this issue by associating multiple climate models' projections with climate observations at a local station. Still, the methodology is subject to some limitations. Therefore, as many studies such as Knutti et al. (2010) have suggested, future research would benefit from developing methodologies to select and weight models and developing new approaches to combine multi-model projections to assess and reduce uncertainty in future climate projections.

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