Precipitation forecasting by large-scale climate indices and machine learning techniques Postprint

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Abstract

Global warming is one of the most complicated challenges of our time causing considerable tension on our societies and on the environment. The impacts of global warming are felt unprecedentedly in a wide variety of ways from shifting weather patterns that threatens food production, to rising sea levels that deteriorates the risk of catastrophic flooding. Among all aspects related to global warming, there is a growing concern on water resource management. This field is targeted at preventing future water crisis threatening human beings. The very first stage in such management is to recognize the prospective climate parameters influencing the future water resource conditions. Numerous prediction models, methods and tools, in this case, have been developed and applied so far. In line with trend, the current study intends to compare three optimization algorithms on the platform of a multilayer perceptron (MLP) network to explore any meaningful connection between large-scale climate indices (LSCIs) and precipitation in the capital of Iran, a country which is located in an arid and semi-arid region and suffers from severe water scarcity caused by mismanagement over years and intensified by global warming. This situation has propelled a great deal of population to immigrate towards more developed cities within the country especially towards Tehran. Therefore, the current and future environmental conditions of this city especially its water supply conditions are of great importance. To tackle this complication an outlook for the future precipitation should be provided and appropriate forecasting trajectories compatible with this region' s characteristics should be developed. To this end, the present study investigates three training methods namely backpropagation (BP), genetic algorithms (GAs), and particle swarm optimization (PSO) algorithms on a MLP platform. Two frameworks distinguished by their input compositions are denoted in this study: Concurrent Model Framework (CMF) and Integrated Model Framework (IMF). Through these two frameworks, 13 cases are generated: 12 cases within CMF,

each of which contains all selected LSCIs in the same lead-times, and one case within IMF that is constituted from the combination of the most correlated LSCIs with Tehran precipitation in each lead-time. Following the evaluation of all model performances through related statistical tests, Taylor diagram is implemented to make comparison among the final selected models in all three optimization algorithms, the best of which is found to be MLP-PSO in IMF.

Full Text

Preamble

Precipitation forecasting using large-scale climate indices and machine learning techniques

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Abstract: Global warming represents one of the most complex challenges of our time, placing considerable strain on societies and the environment. Its impacts are being felt unprecedentedly across a wide spectrum, from shifting weather patterns that threaten food production to rising sea levels that increase the risk of catastrophic flooding. Among these impacts, water resource management has emerged as a growing concern, aimed at preventing future water crises that threaten human wellbeing. The first stage in such management is identifying prospective climate parameters that influence future water resource conditions. Numerous prediction models, methods, and tools have been developed and applied for this purpose. Building on this trend, the current study compares three optimization algorithms on a multilayer perceptron (MLP) network platform to explore meaningful connections between large-scale climate indices (LSCIs) and precipitation in Iran' s capital. Iran is located in an arid and semi-arid region and suffers from severe water scarcity caused by years of mismanagement, a situation intensified by global warming. This has propelled a significant portion of the population to migrate toward more developed cities within the country, particularly Tehran. Consequently, the current and future environmental conditions of this city—especially its water supply—are of great importance. To address this challenge, a future precipitation outlook must be provided and appropriate forecasting trajectories compatible with the region' s characteristics must be developed. To this end, the present study investigates three training methods—backpropagation (BP), genetic algorithms (GAs), and particle swarm optimization (PSO)—on an MLP platform. Two frameworks distinguished by their input compositions are employed: Concurrent Model Framework (CMF) and Integrated Model Framework (IMF). Through these frameworks, 13 cases are generated: 12 cases within CMF, each containing all selected LSCIs at the same lead-times, and one case within IMF constituted from the combination of the most correlated LSCIs with Tehran precipitation in each lead-time. Following evaluation of all model performances through statistical tests, the Taylor diagram is implemented to compare the final selected models across all three optimization algorithms. The best performing model is found to be MLP-PSO in IMF.

Keywords: backpropagation; genetic algorithms; machine learning; multilayer perceptron; optimization; particle swarm; Taylor diagram

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1 Introduction

There is growing emphasis on sustainable development in water resource management, a field targeted at preventing future water crises that threaten human populations. The first stage in such management is recognizing prospective climate parameters that influence future water resource conditions. Numerous prediction models, methods, and tools have been developed and applied for this purpose. Indeed, it is well established within climate science literature that teleconnection—a valuable concept in climatology—has considerable ability to explain and project climate parameters [?].

Teleconnection examines distant phenomena to study regional climate conditions. Because these large-scale climate phenomena are repetitive, they are categorized as patterns [?], which can be effective both locally and globally, creating substantial variability in climate parameters. Furthermore, they can result in drought and wet periods worldwide by altering precipitation trends [?, ?, ?, ?, ?, ?, ?]. Many definitions have been suggested for these patterns, with the primary one identifying teleconnection as a large-scale atmospheric-oceanic pattern that is constant, repetitive, and large-scale oscillated in certain parameters such as pressure [?]. For instance, El Niño—a large-scale oceanic warming in the tropical Pacific Ocean—occurs repetitively every few years [?]. Its accompanying atmospheric component, the Southern Oscillation, represents the principal mode of pressure variability in the tropics and affects the climate of many regions worldwide [?]. Connections between these patterns and climate parameters across different regions have been observed in numerous studies [?, ?, ?, ?, ?, ?]. A well-known pattern is the North Atlantic Oscillation (NAO), whose station-based index in winter represents a major climate variability mode in the North Atlantic Ocean, defined as the difference in normalized mean winter (December to March of the next year) sea level pressure (SLP) anomalies between Iceland and Portugal [?]. Most modern NAO indices, however, are based on the simple difference in surface pressure anomalies between various northern and southern locations, such as Gibraltar and Reykjavik [?, ?]. This pattern has been shown to strongly impact winter precipitation in Hungary [?], Turkey [?], and Mediterranean precipitation trends [?]. The Indian Ocean Dipole (IOD), a coupled ocean-atmosphere phenomenon, is another remarkable pattern defined in 1999 as a dipole pattern of sea surface temperature (SST) variability in the tropical Indian Ocean [?]. This pattern is normally characterized by anomalous cooling of SST in the southeastern equatorial Indian Ocean and anomalous warming of SST in the western equatorial Indian Ocean [?]. In the Mediterranean region, the Eastern Mediterranean Pattern (EMP), related to the 500 hPa geopotential height between its east and west sides, is quite dominant [?].

The connections between these and many other patterns with climate parameters have been examined in numerous studies, particularly those employing machine learning approaches. The main difference between machine learning and statistical trajectories lies in their focus: statistical methods concentrate more on testing hypotheses, whereas machine learning approaches focus on formulating the process of generalization as a search through possible hypotheses [?]. Furthermore, machine learning emphasizes prediction based on known features learned from exposure to datasets during training [?]. In Iran, few studies have emphasized using such approaches for large-scale climate indices (LSCIs) [?, ?].

Iran, located in an arid and semi-arid region, suffers from severe water scarcity caused by years of mismanagement and intensified by climate change [?], which has consequently propelled a large portion of the population to migrate toward more developed cities, especially Tehran province. Sharp population growth in this province over recent years provides clear evidence of this rapid immigration. According to the Statistical Center of Iran (2018), over the last 10 years, Tehran province's population increased from less than one million to over 15 million. This means the province, covering just 2% of Iran' s total area, hosts 20% of the country' s population, with 86.5% residing in urban areas—particularly Tehran metropolitan, with about 8 million inhabitants. Providing water supplies is among the most critical environmental issues in this metropolitan area. To address this challenge, a future precipitation outlook must be provided and appropriate forecasting trajectories compatible with the region' s characteristics must be developed. To this end, this paper aims to compare the prediction capability of LSCIs by examining over 39 patterns and emphasizing the application of three optimization algorithms in the multilayer perceptron network.

2 Datasets

Tehran metropolitan, facing the Alborz mountain range on one side and Iran' s central desert on the other, varies significantly in elevation from north to south (averaging 900 m a.s.l.). This substantial difference causes a pronounced influence on precipitation variability across the city. Overall, Tehran is a semi-arid city with a mean annual precipitation of 230 mm. Among numerous synoptic stations across the city, the oldest is Meharabad (35.69°N, 51.31°E; 1191 m a.s.l.), which maintains the longest climate records since 1951. Monthly precipitation data from this station for a 62-year period (1951–2012) were obtained from the Iran Meteorological Organization (IMO).

Teleconnection patterns with the most qualified datasets that have been suggested in previous studies for the case-study region [?, ?, ?, ?, ?, ?, ?] were obtained from the National Oceanic and Atmospheric Administration (2015) for the period 1951–2012 .

3 Methodology

The schematic diagram of the entire study trajectory is shown in Figure 1 [Figure 1: see original paper]. As illustrated, this study consisted of four main steps. The first involved data collection and selection of the most appropriate LSCIs, followed by defining the two main frameworks (Concurrent Model Framework (CMF) and Integrated Model Framework (IMF)). Pearson correlation was then used to identify the most correlated LSCIs in each time lag before establishing the IMF. The third step involved generating three modeling methods: BP-based (backpropagation-based) MLP (multilayer perceptron), GA-based (genetic algorithm-based) MLP, and PSO-based (particle swarm optimization-based) MLP. Finally, the most appropriate case was identified using the Taylor diagram.

3.1 Principal component analysis (PCA)

The concept of PCA is to reduce dimensions in datasets containing a large number of interrelated variables [?]. PCA is a useful tool for investigating correlations among numerous parameters simultaneously, finding data subsets, and identifying outliers. Linear combinations of principal components can reproduce parameters characterizing objects in the dataset [?]. In this study, 36 LSCIs were entered into the PCA process for reduction. As a first step, the correlation matrix was preferred over the covariance matrix since its application is more common [?]. The most critical aspect of PCA is determining the optimized number of principal components (PCs) to prevent serious information loss. Among various criteria and algorithms for selecting PC numbers, the commonly used Kaiser' s rule [?], which suggests retaining only those principal components with variances exceeding 1, was applied. After implementing varimax rotation on the loading matrix [?] (Eq. 1), LSCIs with high rotated loadings were retained. Consequently, 9 LSCIs were selected from the original 36: Southern Oscillation Index, Multivariate ENSO Index, East Central Tropical Pacific SST, Central Tropical Pacific SST, Bivariate ENSO Time series, Oceanic NINO Index, Atlantic Meridional Mode, North Tropical Atlantic SST Index, and Tropical Northern Atlantic.

$$\text{Loading matrix} = VL^{1/2}, \quad (1)$$

where V is the eigenvectors matrix and $L^{1/2}$ is the diagonal matrix of respective eigenvalues.

3.2 Multilayer perceptron (MLP)

The study of artificial neural networks is motivated by their similarity to biological systems consisting of numerous simple nerve cells (neurons) working massively in parallel and linked in a weighted manner [?]. Equation 2 formulates the neural neuron operation:

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right), \quad (2)$$

where y is the scalar output [?]; f is the neuron activation or transfer function; and w_i, x_i, and b are the weight, input, and bias of the ith member, respectively. MLP is the most frequently used neural network [?], belonging to the feed-forward artificial neural network class and consisting of at least three layers: input, hidden, and output [?]. Figure 2 [Figure 2: see original paper] demonstrates the schematic MLP topology used in this study. A three-layer MLP with one hidden layer was implemented. In the input layer, one neuron was considered for each input; the number of hidden layer neurons in each model was selected based on trial and error and is reported in the relevant section. The number of neurons in the output layer, as shown, represents the modeled precipitation measure for each month.

3.3 Optimization methods

The training methods employed in this study were BP, GAs, and PSO. BP is an approach for calculating the gradient of the loss function of an MLP network with respect to its weights [?]. Although computationally expensive, the academic community has demonstrated how simply the weights of its hidden layer can be optimized. This method applies the gradient descent algorithm to minimize network error. Typically, gradient descent adapts weights based on a comparison between desired and actual network responses [?]; however, it can become trapped in local minima when navigating a rugged error surface. Consequently, many alternatives have been proposed, such as GAs and PSO. In this study, the Levenberg-Marquardt function was selected to train the BP-based MLP network, as it yielded better accuracy than other training approaches. The activation functions applied in hidden and output layer neurons were sigmoid and linear functions, respectively. Additionally, the number of hidden layer neurons was experimentally selected for each model to achieve the lowest error value.

Genetic algorithm (GA) is an evolutionary algorithm in which a population of individuals evolves based on bio-inspired theories such as selection, mutation, and crossover [?] to generate high-quality solutions for optimization problems [?]. These algorithms encode potential solutions to specific issues on simple chromosome-like data structures [?], competing to achieve increasingly better results [?]. Regarding the gradient descent algorithm' s limitations, implementing

GA as a complete substitute might lead the model to more precise conclusions.

Particle swarm optimization (PSO) draws inspiration from the social and collective behavior of biological organisms, specifically the movement of population members based on both group experience and individual experience. This seeking behavior was associated with optimization searches for solutions to nonlinear equations in real-valued search spaces [**?**]. The population is considered a cumulus of particles i where each has a position $x_i \in \mathbb{R}^D$ (for $i = 1, \dots, M$) in a multidimensional space. These particles are evaluated at a particular position using an optimization function to recognize their fitness value and save the best solution. All particles change their positions in the search space according to a velocity function v_i that considers the best position of a particle in the population P_g (social component) as well as their own best position P_i (cognitive component) [**?**]. The particles repetitively move to different positions until they find an optimum [**?**].

For all optimization methods, datasets must be divided into three sets: training, validation, and test. In this study, the first 70%, the next 15%, and the last 15% of the entire dataset were dedicated to training, validation, and test sets, respectively. Since the MLP was implemented for time series, random data splitting was inappropriate; therefore, a solid chronological division of datasets was applied.

3.4 Frameworks

This study employed two different model frameworks varying in input composition: CMF and IMF. In CMF, all contemporary LSCIs were entered into 12 individual models for each lead-time from 0 to 11 months in advance (Eq. 3), whereas in IMF, the best LSCIs in each time lag—based on Pearson correlation —were entered into a single model (Eq. 4).

$$P_n = f(\mathrm{Nino3.4}_n, \mathrm{Nino4}_n, \mathrm{AMM}_n, \mathrm{MEI}_n, \mathrm{SOI}_n, \mathrm{TNA}_n, \mathrm{NTA}_n, \mathrm{ONI}_n, \mathrm{BEST}_n), \quad (3)$$

where P_n is the amount of monthly precipitation in month n. In Equation 3, all LSCIs share the same time lags, resulting in 12 models from P_n to P_{n-11}. In contrast, Equation 4 associates precipitation in month n with a combination of the most correlated LSCIs across time lags covering n to $n-12$:

$$P_n = f(\mathrm{LSCI}_n, \mathrm{LSCI}_{n-1}, \mathrm{LSCI}_{n-2}, \dots, \mathrm{LSCI}_{n-12}), \quad (4)$$

3.5 Model performance evaluation

Root mean square error (RMSE) and mean absolute error (MAE) were employed in the model evaluation stage, both standard statistical metrics for measuring model performance across various fields including meteorology, air quality, and climate research. These metrics were applied to select the most appropriate model in each optimization method based on the lowest error value. Additionally, Z-test was investigated to indicate model accuracy in terms of similarity between the means of desired and actual model responses. In Z-test, as long as the Z value (Eq. 5) remains below the critical value, the null hypothesis ($H_0 : \mu_1 = \mu_2$, where μ_1 and μ_2 are the means of the two comparing populations) is fulfilled and the model maintains the dataset mean approximately constant [?]. The Z value formula is:

$$Z = \frac{\bar{x}_1 - \bar{x}_2}{\sigma_{\bar{x}1-\bar{x}_2}}, \quad (5)$$

where μ is the mean of each population; $\bar{x}$ is the mean of the sample drawn from each population; σ is the standard deviation; n is the sample size drawn from each population [?]; and subscripts 1 and 2 represent observed and predicted values, respectively. The standard error is calculated as:

$$\sigma_{\bar{x}1-\bar{x}_2} = \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}, \quad (6)$$

Applying Z-test to the final three models made the results more reliable through re-evaluation.

3.6 Taylor diagram

Taylor diagram was applied to compare the performance of final selected models. This diagram is particularly useful for assessing the relative merits of competing models and monitoring overall performance as a model evolves [?]. Its structure is shown in Figure 3 [Figure 3: see original paper], where the correlation coefficient between simulated and observed datasets is given by the azimuthal angle, and the standard deviation of the simulated set is proportionally related to the radial distance from the origin [?].

4 Results and discussion

For all 13 cases (12 generated in CMF and 1 in IMF), BP-based MLP, GA-based MLP, and PSO-based MLP were developed. Among the 9 selected LSCIs, SOI, Nino3.4, and Nino4 were highly correlated with Tehran monthly precipitation; therefore, the IMF input for all three optimization methods was the combination of these three indices across lead-times (Eq. 7):

$$P_n = f(\mathrm{SOI}_n, \mathrm{Nino3.4}_n, \mathrm{Nino3.4}_{n-1}, \mathrm{Nino3.4}_{n-2}, \mathrm{Nino3.4}_{n-3}, \mathrm{Nino3.4}_{n-4}, \mathrm{Nino3.4}_{n-5}, \mathrm{Nino3.4}_{n-6}, \mathrm{Nino4}_{n-7}, \mathrm{Ni}$$

RMSE, MAE, Z-test, and Taylor diagram were used to identify the most appropriate model among all 36 outcomes. The results for all three optimization methods through CMF and IMF are presented in Figure 5 [Figure 5: see original paper], enabling visual comparison across all lead-times. The x-axis shows the cases used in this study (12 cases from simultaneous to 11-month lead-time in CMF and 1 case in IMF).

According to Figure 5a, the best monthly model in BP-based MLP based on error values was the 3-month lead-time in CMF, with RMSE and MAE of 19.37 mm and 12.38 mm, respectively—both lower than other cases. Its hidden layer contained 8 neurons, selected through trial and error. Except for this case, IMF outperformed all CMF cases, demonstrating its superior prediction ability.

Figure 5b presents corresponding information for the GA-based MLP model. This algorithm was applied as a complete substitute in the MLP training stage. Its performance is highly dependent on gamma and mutation rate (0.2 and 0.1, respectively). The 8-month lead-time case appeared quite satisfactory, with RMSE of 17.4 mm and MAE of 13.6 mm. Notably, for GA-based MLP, IMF did not show remarkable superiority over CMF cases, unlike BP-based MLP.

Figure 5c indicates PSO-based MLP results. As noted, cognitive and social components are key parameters in PSO performance, which were set to 1 and 2, respectively, based on trial and error. According to Figure 5c, IMF (RMSE: 18.5 mm; MAE: 12.9 mm) remarkably outperformed other cases, while 2-month lead-time appeared more accurate among CMF cases. Z-test results for all selected cases across three methods are presented in Table 2 .

Since the critical Z value at 5% significance level for a two-tailed test is 1.94, which exceeds all calculated Z values (Table 2), the variation between observed and estimated means was not significant. Therefore, these model results can be considered reliable. Comparison of BP-based MLP, GA-based MLP, and PSO-based MLP in 3-month lead-time, 8-month lead-time, and IMF framework are shown in Table 3 , which clearly expresses the difficulty of distinguishing the best model among the three final selected cases based solely on RMSE or MAE. Since judging the most accurate performance might be challenging due to close results, the Taylor diagram provides helpful interpretation. This diagram, considering RMSE, standard deviation of simulated datasets, and correlation coefficient between simulated and observed datasets [?], precisely identifies the best-generated model (Fig. 6 [Figure 6: see original paper]). The reference point on the x-axis, indicating the standard deviation of observations, was 23.54 mm. According to Figure 6, PSO-based MLP was the best case, being closest to the reference point.

5 Conclusions

This study examined three optimization methods—BP, GAs, and PSO—on a multilayer perceptron (MLP) network platform. These methods were applied in the MLP training stage as complete substitutes. Two frameworks, CMF and

IMF, were defined. Through these frameworks, 13 cases were generated: 12 cases within CMF, each containing all selected LSCIs at the same lead-times, and one case within IMF constituted from the combination of the most correlated LSCIs with Tehran precipitation in each lead-time. In each optimization method, the most accurate case was identified based on RMSE and MAE, then assessed using Z-test. Since RMSE and MAE values of selected cases were close, one might conclude all three cases performed with similar accuracy. However, the Taylor diagram revealed that PSO-based MLP in IMF achieved the best performance due to its shortest distance to the reference point. Therefore, Equation 7, as the input combination under PSO-based MLP algorithm, can be reliably applied for precipitation forecasting in Tehran metropolitan. Overall results indicate that IMF produced more precise outcomes and outperformed CMF across all optimization methods.

Previous studies have shown that optimization methods can enhance multilayer perceptron network performance [**?**, **?**, **?**, **?**, **?**]. The results agree with [**?**], suggesting that PSO algorithm can evolve a multilayer perceptron network to generate better results. Although errors in this research appear considerable, the selected model could track future trends more reliably than predict exact precipitation amounts [**?**, **?**, **?**, **?**, **?**, **?**, **?**, **?**]. Despite this, the present study using machine learning achieved an optimum forecast model that explains up to 34% of Tehran' s monthly precipitation. It is recommended that surface parameters coupled with LSCIs be considered to investigate further uncertainty reduction.

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Note: Figure translations are in progress. See original paper for figures.