Ann. For. Res. 65(1): 10590-10600, 2022
ISSN: 18448135, 20652445

ANNALS OF FOREST RESEARCH
https://www.e-afr.org/

PREDICTION OF ATMOSPHERIC TEMPERATURE IN BEIJING BASED ON ARTIFICIAL NEURAL NETWORK

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Abstract: Climate change affects the growth and development of plants and has an important impact on forests. We use artificial neural network (ANN) to predict the change of monthly atmospheric temperature in Beijing City. We divide the atmospheric temperature data from 1951 to 2021 into training data sets (1951-2007) and prediction data sets (2008-2021), and use the 20 month data as model input to predict the atmospheric temperature in the next month. Thirteen various training functions were trained and compared. The ANN model was tested by correlation coefficient (R), root mean square error (RMSE), and mean absolute error (MAE) and good results were obtained. Bayesian Regularization (trainbr) is the best performing algorithms compared to other algorithms with R value of 0.9977 and the lowest error values for RMSE (0.7557), MAE (0.6173). This method has good generalization ability and can be used to forecast atmospheric temperature in other regions.

Keywords: atmospheric temperature, artificial neural network, prediction, training algorithm, forest.

Abbreviations: *SLA: Specific Leaf Area, LAI: Leaf Area Index, ANN: Artificial Neural Networks, AI: Artificial Intelligence, CG: Conjugate Gradient, GD: Gradient Descent, QN: Quasi-Newton, LM: Levenberg-Marquardt, BR: Bayesian Regularization, RMSE: Root Mean Square Error, MAE: Mean Absolute Error*

1. Introduction

The atmospheric temperature affects air quality, terrestrial biodiversity, tree species, forest fires, forest pests, structure and function of forest ecosystem, and human health (Ducci F 2021; Long, Zang et al. 2011; Öztürk, Bolat et al. 2015; Guo, Wang et al. 2021; Aalto, Tyystjärvi et al. 2022).

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Tropical forests evolved under relatively narrow temperature conditions, so these forests may be more vulnerable to temperature changes than forests in high latitudes. The crown of the lowland tropical forest may have exceeded the maximum temperature for photosynthesis. The leaf temperature in the middle canopy and lower canopy under shade is equal to the atmospheric temperature, while the leaf temperature in the uppermost canopy is higher than the atmospheric temperature. In addition, the top layer of the canopy is the only layer that exceeds the optimal value of the average photosynthetic temperature. Therefore, continuous warming may weaken the carbon sink capacity of tropical regions (Miller, Carter et al. 2021). Compared with forests at lower elevations, tropical cloud forests are characterized by lower temperatures. The mean height of plants, mean specific leaf area (SLA) and its plasticity are significantly correlated with atmospheric temperature (Long, Zang et al. 2011). The correlation between air temperature, bryophyte cover and lichen cover in tropical cloud forests is also positive in Cusuco National Park, Honduras (Batke, Murphy et al. 2015). The atmospheric temperature affects the seasonal leaf development of deciduous trees. The leaf area index (LAI) as an indicator of leaf development is significantly affected by the current year's atmospheric temperature (Öztürk, Bolat et al. 2015). The monthly total temperature change of northern forest is closely related to wetland, water body and canopy cover, while in tundra, the change is related to terrain solar radiation, altitude and snow cover. The research results will help to predict the local impacts of climate change on forests and tundra ecosystems in northern Europe (Aalto, Tyystjärvi et al. 2022). The climate in Slovenia has warmed in recent decades, with an increase of about 0.4°C per decade. Climate change will strongly influence temperate forests such as mesic Slovenian forests (Kutnar L et al. 2021). Accurate prediction of atmospheric temperature is of great significance for forest growth and development.

Global atmospheric temperature was 1.09 °C higher in 2011-2020 than 1850-1900 (IPCC AR6). A series of climate models were often used to predict climate change in the past few years (Tewari, Mishra et al. 2022; Zhou, Yu et al. 2022). Owing to the difference of climate feedback process of different models, there is great uncertainty in climate sensitivity, which affects the credibility of climate forecast (Guo, He et al. 2022). Artificial Neural Networks (ANN) explored artificial intelligence (AI) techniques in computing the rendition and superiority utilizing appropriate and admissible input parameters (Hirigoyen A et al. 2021). ANN has been widely used in forest ecology and atmospheric science (Astsatryan, Grigoryan et al. 2021; Guo, He et al. 2020; Guo and He 2021; He, Guo et al. 2022; Shrivastava et al. 2022). ANN has the ability to deal with nonlinear problems (Awolusi, Oke et al. 2019; Pakalapati, Tariq et al. 2019; Perera, Azamathulla et al. 2020 ; Nasrudin, Jewaratnam et al. 2020). Compared with the two PPM models, the ANN model decreased the RRMSE by about 3% and 4% in predicting diameter distribution, respectively. The ANN performed well for the prediction of the diameter distribution with high practicality (Long S et al. 2021). Therefore, we use different training algorithms to predict atmospheric temperature in Beijing City.

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2. Materials and Methods

2.1 Monthly average atmospheric temperature

The monthly average atmospheric temperature time series in Beijing City were divided into two data sets, one subset for calculating the parameters of models and for training the artificial neural network (1951-2007); the other for model prediction (2008-2021).

2.2 Artificial neural network

Artificial neural network (ANN) has a comparatively simple implementation, can approximate highly complex functions, and can summarize examples that have not been formulated, seen or practiced before. Artificial neural network can completely realize nonlinear modeling without knowing the relationship between input and output parameters in advance (Braik, Sheta et al. 2020). As shown in Figure 1, the artificial neural network has three layers. Artificial neural networks (ANNs) are composed of interconnected computing elements, which are called neurons with inputs and outputs. The output of each neuron is obtained by subsequently applying the transfer function to the sum of weighted inputs and offsets (biases) (Shah and Mishra 2020). Six training algorithms with thirteen different training functions were used in the research. The training functions of Conjugate Gradient (CG) are traincgb, traincgp, traincgf and trainscg. While, The training functions of Gradient Descent (GD) are traingd, traingdm, traingda and traingdx. The training functions of Quasi-Newton (QN) are trainbfg and trainoss. The training functions of Bayesian Regularization (BR), Levenberg-Marquardt (LM), and Resilient Backpropagation (Rprop) are trainbr, trainlm and trainrp, respectively (Nasrudin, Jewaratnam et al. 2020).

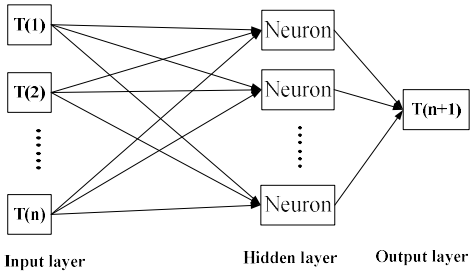

Figure 1. The schematic diagram of the artificial neural network for predicting atmospheric temperature

2.3. Criteria of evaluation

Statistical tools such as root mean square error (RMSE), the mean absolute error (MAE), and correlation coefficient (R) are exploited in order to assess the effectiveness of ANN model developed in this study and its ability to make precise predictions. The RMSE, MAE, and R are calculated by the following equations:

$$RMSE = \sqrt{\frac{\sum (A_l - B_l)^2}{D}} \quad (1)$$

$$R = \frac{\sum (A_l - \bar{A})(B_l - \bar{B})}{\sqrt{\sum (A_l - A)^2 (B_l - \bar{B})^2}} \quad (2)$$

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$$MAE = \frac{1}{D}\sum\left|A_l - B_l\right| \quad (3)$$

A_l denotes the measured atmospheric temperature, B_l denotes the predicted atmospheric temperature, $\bar{A}$ is the mean of the measured atmospheric temperature, and $\bar{B}$ is the mean of the predicted atmospheric temperature.

3. Results

3.1 Change of annual average atmospheric temperature in Beijing City from 1951 to 2021

As shown in Figure 2, the average atmospheric temperature in Beijing City in 2021 is 2.5 ℃ higher than that in 1951. The long-term trend of annual average temperature from 1951 to 2021 is 0.412℃/10 years, with an average increase of 0.412 ℃ every 10 years. In 2021, the global average temperature is 1.11 ℃ higher than the pre-industrialization level, which is one of the seven warmest years since there are complete meteorological observation records. From 1951 to 2021, China's annual average surface atmospheric temperature showed a significant upward trend, with a warming rate of 0.26 ℃/10 years. The atmospheric temperature in Beijing City is rising faster than that in the world and China.

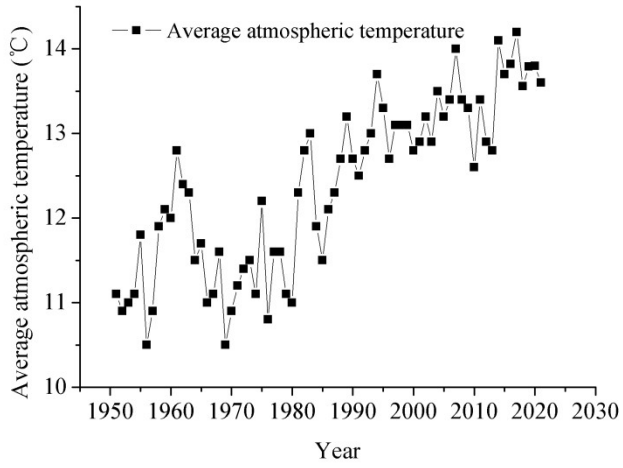

Figure 2. Change of annual average atmospheric temperature in Beijing City from 1951 to 2021

3.2 Performance of different neurons in input and hidden layers for predicting of monthly average atmospheric temperature

The amounts of neurons in input and hidden layers are practiced by trial and error. The statistical indicators (R, RMSE, and MAE) of different numbers of nodes in the input layer (Table 1) and hidden layer (Table 2) is listed. Table 1 implies the various input neurons and Table 2 implies different neurons in the hidden layer. Tables 1 and Tables 2 show simulation of monthly average atmospheric temperature during the training and predicting phases. Twenty variables are selected for the prediction model input. We use the most recent 168 months from January 2008 to December 2021 during the prediction phases. Additionally, the number of neurons in the hidden layer is nineteen. Eventually, network topologies of the ANN (20-19-1) are the best one.

Table 1. Performance comparison between different input neurons for ANN

Neurons	R		RMSE (℃)		MAE (℃)	
	training	predicting	training	predicting	training	predicting
1	0.8472	0.8418	5.7342	5.8913	5.0546	5.2456
2	0.9874	0.9881	1.7099	1.702	1.3437	1.305
3	0.9907	0.9922	1.4726	1.4332	1.1681	1.1859
4	0.9914	0.9926	1.4233	1.4751	1.1222	1.2094
5	0.9904	0.9917	1.495	1.6292	1.1721	1.3625
6	0.9914	0.9924	1.4172	1.4868	1.1021	1.213
7	0.992	0.9925	1.3637	1.4365	1.0691	1.1654
8	0.9928	0.9934	1.2963	1.3078	1.0311	1.0709
9	0.993	0.9929	1.2725	1.3286	0.9956	1.0901
10	0.9932	0.994	1.2535	1.2165	0.9839	0.9879
11	0.9937	0.9944	1.2119	1.1707	0.9574	0.9363
12	0.9938	0.9947	1.1996	1.1282	0.9434	0.8785
13	0.9941	0.994	1.1679	1.2015	0.9324	0.9677
14	0.9942	0.994	1.1573	1.1986	0.9214	0.9463
15	0.9947	0.9947	1.1059	1.1274	0.8658	0.8984
16	0.9946	0.9946	1.1207	1.1361	0.8789	0.9165
17	0.9943	0.9947	1.1457	1.1368	0.9048	0.9239
18	0.9945	0.9946	1.1308	1.1366	0.8947	0.915
19	0.9948	0.9947	1.0927	1.1402	0.8682	0.9399
20	0.9974	0.9977	0.7735	0.7557	0.6065	0.6173
21	0.9927	0.9936	1.3089	1.3723	1.0405	1.126

Table 2. Performance comparison between various neurons in hidden layer.

Nodes	R		RMSE (℃)		MAE (℃)	
	training	predicting	training	predicting	training	predicting
1	0.9925	0.9933	1.3158	1.2695	1.054	1.0036
2	0.9932	0.9938	1.2586	1.2115	0.9961	0.9572
3	0.9935	0.994	1.2318	1.1949	0.97	0.9524
4	0.994	0.9949	1.1796	1.0998	0.9284	0.8956
5	0.9947	0.995	1.1128	1.1055	0.8913	0.8918
6	0.9954	0.9951	1.0379	1.0907	0.8298	0.8789
7	0.9951	0.9952	1.0699	1.0738	0.8464	0.8482
8	0.9955	0.9957	1.0265	1.0196	0.8121	0.8414
9	0.9955	0.9961	1.0251	1.0177	0.8129	0.8377
10	0.9961	0.9965	0.9562	0.9721	0.7634	0.7902
11	0.9964	0.9957	0.9149	1.0428	0.7281	0.8339
12	0.9963	0.9967	0.9333	0.9296	0.7356	0.7748

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13	0.9961	0.9966	0.9479	0.9361	0.7483	0.7374
14	0.9969	0.9974	0.8433	0.8309	0.6711	0.6633
15	0.997	0.997	0.8369	0.8891	0.6592	0.7167
16	0.9973	0.997	0.7992	0.8692	0.6384	0.699
17	0.9974	0.9974	0.7795	0.8075	0.6083	0.636
18	0.997	0.9967	0.8363	0.9045	0.6667	0.7181
19	0.9974	0.9977	0.7735	0.7557	0.6065	0.6173
20	0.9971	0.9976	0.8235	0.7941	0.6554	0.6351
21	0.9966	0.9968	0.8923	0.8998	0.71	0.7313

3.3 Performance of various training algorithms for ANN

Training algorithms of the ANN for predicting monthly average atmospheric temperature are also practiced by trial and error. Table 3 demonstrates the performances of training algorithms for predicting monthly average atmospheric temperature in Beijing City. Trainbr is the algorithm that best predicted monthly average atmospheric temperature, followed by trainlm. It showed the best performance in simulating monthly average atmospheric temperature in Beijing City during the training stage and the prediction stage. The simulated monthly average atmospheric temperature is extraordinarily close to the actually atmospheric temperature.

Table 3. Comparative performance of various training algorithms in Beijing City.

Training	**R**		**RMSE (℃)**		**MAE (℃)**	
Functions	training	predicting	training	predicting	training	predicting
trainbr	0.9974	0.9977	0.7735	0.7557	0.6065	0.6173
trainlm	0.9951	0.9951	1.0682	1.0689	0.8189	0.8654
traingdx	0.9326	0.9272	4.1754	4.3532	3.4049	3.4366
traingd	0.8763	0.8797	5.5828	5.6588	4.7125	4.9874
traingdm	0.8165	0.8032	6.3137	6.5993	5.3389	5.6279
traingda	0.8165	0.8032	6.2281	6.5311	5.0585	5.3887
trainrp	0.9924	0.9933	1.3452	1.4615	1.0799	1.2317
traincgp	0.9927	0.9941	1.3187	1.4032	1.0569	1.1633
traincgf	0.9859	0.9875	1.8498	1.925	1.4286	1.6182
traincgb	0.9926	0.9933	1.3179	1.4447	1.0597	1.1849
trainscg	0.9931	0.9945	1.2676	1.3723	1.0106	1.1547
trainbfg	0.8611	0.8553	5.486	5.7054	4.4645	4.6784
trainoss	0.9051	0.9024	4.5906	4.787	3.9087	4.1078

The RMSE values for the ANN utilizing trainbr and trainlm for the training stage are 0.7735 ℃, and 1.0682 ℃, respectively. The R values for the ANN utilizing trainbr and trainlm during the training stages are 0.9974 and 0.9951, respectively. The MAE for the ANN utilizing trainbr and trainlm are 0.6065 ℃and 0.8189℃, respectively.

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3.4 Prediction of monthly average atmospheric temperature in Beijing City

In the predicting period, average atmospheric temperature in the next month is predicted utilizing the previous months' atmospheric temperature. Table 3 demonstrates the predicting performance utilizing trainbr and trainlm for the optimized ANN model. For monthly average atmospheric temperature in Beijing City during the predicting stage, the R, RMSE, and MAE for trainbr are 0.9977, 0.7557 ℃, 0.6173 ℃, respectively; the R, RMSE, and MAE for trainlm are 0.9951, 1.0689 ℃, 0.8654 ℃, respectively.

Figure 3 displays predicted monthly average atmospheric temperature in Beijing City from 2008 to 2021 using trainbr. In the predicting phase, the predicted values and the measured values are very close, especially in the simulated maximum and minimum values.

Figure 4 displays predicted monthly average atmospheric temperature using trainlm. In the predicting phase, the forecasting average atmospheric temperature is similar to the predicted average atmospheric temperature, especially in the simulated maximum and minimum values. These results show that tranbr and trainlm have similar prediction effects.

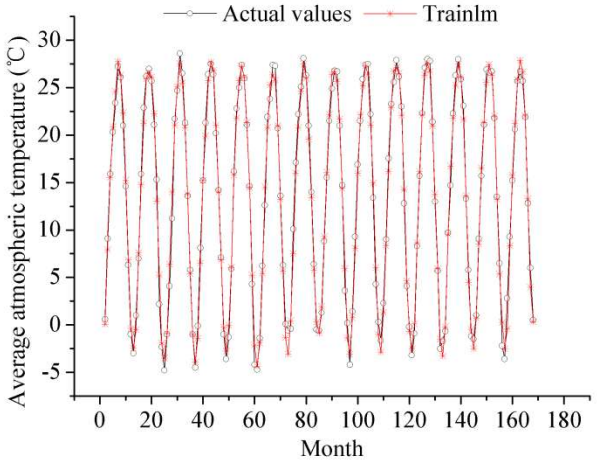

Figure 3. Prediction of monthly average atmospheric temperature in Beijing City from 2008 to 2021 using trainbr

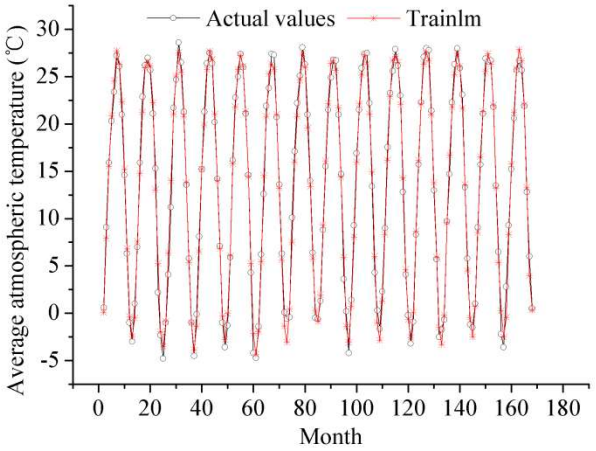

Figure 4. Training and prediction of monthly average atmospheric temperature in Beijing City from 2008 to 2021 using trainlm

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4. Discussion

Various neural networks have been used to simulate and predict the atmospheric temperature. The comparison of measured and predicted outdoor atmospheric temperature ($R^2 > 0.9$, RMSE <2 °C) determines the accurate training of the ANN for the prediction of outdoor air temperature for four European cities (Chania, Granada, Ancona and Mollet) (Papantoniou and Kolokotsa 2016). The ANN model has about 75.6% accuracy to predict the temperature for the next 24 hours in the Ararat valley (Armenia) (Astsatryan, Grigoryan et al. 2021). The deep neural network (DNN) model (DNNM-3) for temperature prediction in New Delhi outperformed the other models with an accuracy rate of about 96.4% (Shrivastava, Shrivastava et al. 2022). the RMSE, R^2 and MAE of ST-Net changed about 69%, 15.3% and 69.4% respectively compared to CNN. At the first hour of the future in China, the RMSE, R^2 and MAE of ST-Net (deep spatial and temporal networks) reached 0.63, 0.98, and 0.45, respectively (Wu, Fu et al. 2022). The ANN system was trained by 90% of the monthly land surface air temperatures from ERA5 (1950–2019) and verifying with the remaining 10%. Validations display obvious improvements of ANN over the original empirical orthogonal teleconnection method: the global spatial correlation coefficient rises from 65% to 80%, and the global root-mean-square difference declines from 0.99° to 0.57°C over 1850-2020 (Huang, Yin et al. 2022). The U-net neural network of forecasting surface air temperature over Xinjiang displays the best correction performance with the highest R and the lowest MAE (Zhu, Zhi et al. 2022). ANN is utilized to forecast the surface atmospheric temperature anomalies in Japan in the winter months. The results are validated utilizing anomaly correlation coefficient (ACC) skill scores with the observation. The ANN forecasts have higher ACC skill scores compared to the North American Multimodel Ensemble (NMME) model skill scores (Ratnam, Nonaka et al. 2021). The ANN model is a promising tool for forecasting the winter air temperature. Furthermore, It is feasible to predict atmospheric temperature using ANNs.

5. Conclusions

The average atmospheric temperature in Beijing City in 2021 is 2.5 ℃ higher than that in 1951. The long-term trend of annual average temperature from 1951 to 2021 is 0.412℃/10 years, with an average increase of 0.412 ℃ every 10 years. The atmospheric temperature in Beijing City is rising faster than that in the world and China.

In this study, monthly average atmospheric temperature in Beijing from 1951 to 2021 was simulated and predicted. Through a comparative analysis, trainbr has the best prediction ability, and trainlm is the second; twenty and nineteen neurons are used as input parameters and hidden parameters of the artificial neural network, separately. The main drawback is that we did not consider the influence factors of temperature. In the future, we will use DNN, RNN, LSTM, CNN, CNN-LSTM to predict atmospheric temperature. we will also consider other factors as the input of neural network and conduct research in other regions, such as solar radiation, carbon dioxide, aerosol, etc.

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6. Acknowledgments

This research was funded by the National Natural Science Foundation of China (41572150), Shandong Province Higher Educational Humanities and Social Science Fund (J18RA196), and State Key Laboratory of Loess and Quaternary Geology Found (SKLLQG1907).

7. Compliance with Ethical Standards

Conflict of interest

The authors declare that they have no conflict of interest.

Data archiving statement

Extra data is available by emailing to guoqingchun@lcu.edu.cn in on reasonable request.

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