Global Temperature Prediction based on Time Series and Global Climate

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Abstract. Global warming is one of the topics of the highest public concern in recent years. This paper mainly analyzes and forecasts the global temperature. This paper have established three models to describe the past and predict the future global temperature level. The first model is the integrated model of ARIMA and BP neural network, which can flexibly mine the linear and nonlinear relationships behind the data. The second model is the Full Convolution Network (FCN) model, which can predict end-to-end time series. The third model is the SVR-QM model based on climate indicators. The three models are established at different angles, and all have good fitting effects.

Keywords: Global Temperature, ARIMA-BP Model, FCN Model, SVR-QM Model.

1. Introduction

Global warming is one of the topics of the highest public concern in recent years.

The whole earth will be directly or indirectly affected by global warming. Humans can clearly feel the harm brought by global warming, such as high temperature death, poor grain harvest, water shortage and ecosystem damage.

From 1981 to 1990, the global average temperature increased by 0.48 ℃ compared with 100 years ago. The 1990s was the warmest decade since temperature recording began in the mid-19th century. In 2019, global climate system warming accelerated, leading to earlier phenological period, glacier melting and sea level rise[1].

This year, a large number of amazing temperature reports were presented to us. There is no doubt that the earth is burning. There is only one earth for mankind. Climate change, a global non-traditional security issue, has posed a serious challenge to the international order and human survival.

Many scholars have used various methods to study the characteristics of global temperature changes. According to the characteristics of time series analysis and global climate change, this paper uses three methods to predict global future temperature from different perspectives[2-3].

2. Prediction Model of Global Temperature Level

In this paper, three models are established to describe the past and future global temperature levels, and the above temperature ranking model is used to describe relevant information in the analysis.

2.1. Model 1: ARIMA and BP Neural Network Integration Model

The month-temperature is a time series that is very obvious to meet the cyclic characteristics. The global temperature level can be well predicted by using the time series analysis method. Single integer autoregressive moving average model (ARMIA) is one of the most widely used time series prediction models at present because of its simplicity, feasibility and flexibility. However, this problem is not a simple linear relationship, and ARMIA model is difficult to mine the complex nonlinear relationship

behind its data. Therefore, this paper integrates BP neural network model in ARMIA model, so that the model can analyze both linear time series and nonlinear components [4-5].

The mathematical description of ARIMA model is as follows:

$$\Delta^d y_t = \theta_0 + \sum_{i=1}^{p} \phi_i \Delta^d y_{t-1} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \tag{1}$$

Where, $\Delta^d y_t$ is the sequence of y_t after d differential transformation, ε_t is the random error at time t, and p and q are the orders of the model.

The mathematical description of BP neural network model is as follows:

$$y_t = w_0 + \sum_{j=1}^{Q} w_j g(w_{0j} + \sum_{i=1}^{P} w_{ij} y_{t-i}) + \varepsilon_t \tag{2}$$

Where, w_j and w_{ij} are the relevant parameters of the hidden layer in the network, P is the number of input layer nodes, Q is the number of hidden layer nodes, and $g(\cdot)$ is the logistics function $g(x) = \frac{1}{1+e^{-x}}$.

In this paper, a time series process is considered to consist of two parts, a linear structure and a nonlinear structure, and time series y_t is considered to be composed of two parts, linear autocorrelation subject L_t and nonlinear residual N_t, as shown in the following equation:

$$y_t = L_t + N_t \tag{3}$$

The ARIMA model is used to model the linear part, and the residual error between the prediction result and the original sequence is set as e_t, then:

$$e_t = y_t - \hat{L}_t \tag{4}$$

The sequence e_t implies the nonlinear relationship in the original sequence, substitute the BP neural network model for fitting, modify the residual sequence relationship, and obtain:

$$e_t = f(e_{t-1}, e_{t-2}, \cdots, e_{t-n}) + \varepsilon_t \tag{5}$$

Where, $f(\cdot)$ is a nonlinear function determined by the BP neural network model, and ε_t is random error.

The predicted value of the BP neural network model can be calculated through e_t, and the calculation formula of the prediction result of the integrated model is shown in the following formula:

$$\hat{y}_t = \hat{L}_t + \hat{N}_t \tag{6}$$

2.2. Model 2: Full Convolutional Network Model

In this paper, machine learning is added to the ARIMA and BP neural network integration model to improve the traditional time series model, but there are still shortcomings.

This paper decides to use a powerful and simple model —— Full Convolution Network (FCN) for prediction. The model uses depth neural network to predict end-to-end time series, without any processing in feature engineering and data preprocessing[6].

In this paper, FCN is executed as a feature extractor. Its final output comes from the softmax layer. The basic block is a roll up layer, followed by a batch normalization layer and a ReLU activation layer. The convolution operation is completed by three 1-D cores with the size of {8,5,3}, without stepping. The basic convolution blocks are as follows:

$$y = W \otimes x + b \tag{7}$$

$$s = BN(y) \tag{8}$$

$$h = \mathrm{Re}LU(s) \tag{9}$$

Where, $\otimes$ is the convolution operator.

In this paper, the final network is constructed by stacking three convolutional blocks with a filter size of {128,256,128} (Figure 1). The method of batch normalization is used to accelerate the convergence speed and improve the generalization ability.

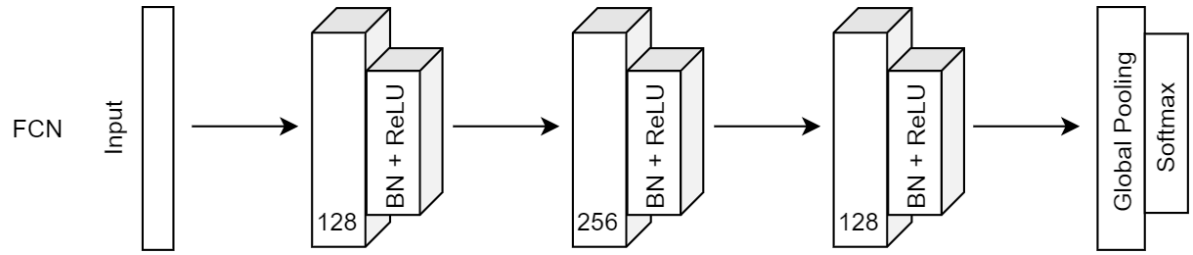


Figure 1. FCN Network Model Structure

After the convolution block, the features are input into the global average pooling layer instead of the full connection layer, which greatly reduces the weight. One of the advantages of FCN is the invariance of the number of parameters in 4 layers (5) of time series with different lengths. This invariance allows the use of transfer learning methods, so that the data set used in this paper on the global temperature level can train the model, and then fine tune it on the target data set[7-9].

2.3. Model 3: SVR-QM Set Simulation and Deviation Correction Model

In the above two models, this paper uses univariate time series data. However, the two models only use time as the analysis factor, ignoring the influence of other factors. Therefore, this paper considers the use of various characteristics of temperature changes to simulate and predict global temperature levels. Coupled Model Intercomparison Project (CMIP) has entered the sixth stage (CMIP6), providing extremely rich global climate model data. Based on climate indicators and scenario data, this paper establishes SVR-QM ensemble simulation and deviation correction model to analyze the future global temperature level (Figure 2).

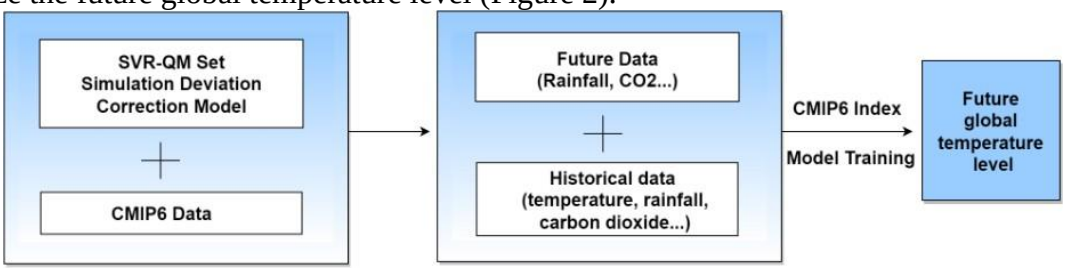


Figure 2. SVR-QM Model Specific Method

The data used in this study are from the daily grid dataset of global historical climate. The data set consists of daily observation data from more than 100000 stations in more than 180 countries and regions, including daily precipitation, daily snowfall, snow depth and other variables, all of which are under strict quality control. The quantile mapping technique (QM) is used to align the cumulative distribution function (CDF) of two data series. This distribution based method is considered to be the most effective deviation correction method [10]. In this paper, the output of the SVR set simulation model and the measured data are taken as the input of the QM method, and the quantile relationship is finally obtained. A comprehensive method of SVR-QM set simulation and deviation correction is established. The comprehensive method is as follows:

$$P_q = f_{sta}^{-1}(f_m(p_m)) \tag{10}$$

Where, P_q is the correction quantity after quantile mapping, f_{sta}^{-1} is the inverse CDF corresponding to the observation data, f_m is the CDF of the set simulation data generated by SVR, and p_m is the SVR simulation data.

The QM method used in this paper is based on quantile-quantile (Q-Q) graph. The diagram represents the Q-Q relationship between the modeling sequence and the observation sequence.

3. Results

3.1. Model 1 Solution and Result Analysis

It can be seen from Figure 3 that the predicted curve is well matched with the actual curve.

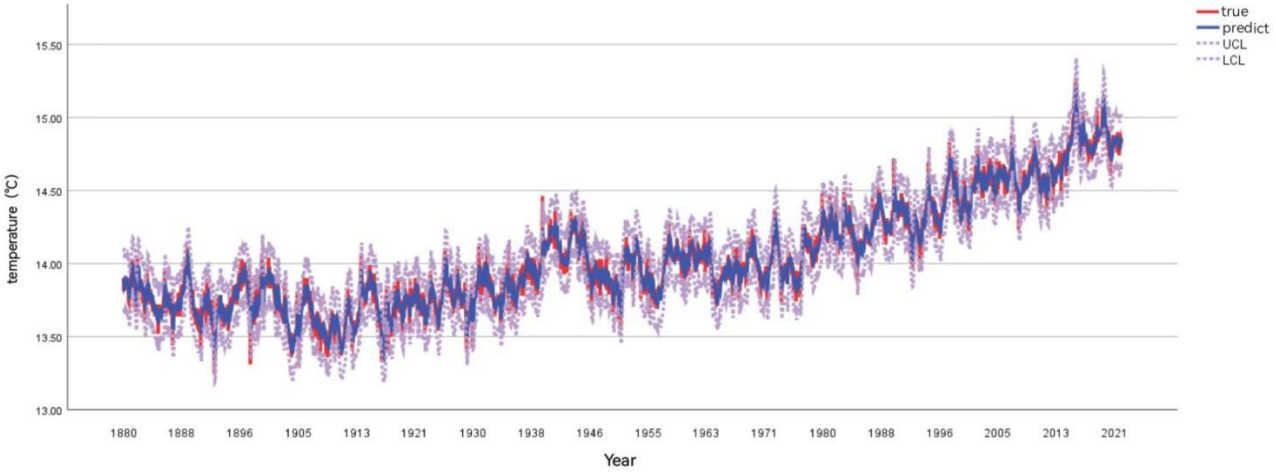


Figure 3. Prediction Results for Model 1

According to the prediction, the average temperature in 2022 is 14.83 ℃, the average temperature in 2023 is 14.89 ℃, and the average temperature in 2024 is 14.94 ℃. The average annual temperature rise is 0.337%.

3.2. Model 2 Solution and Result Analysis

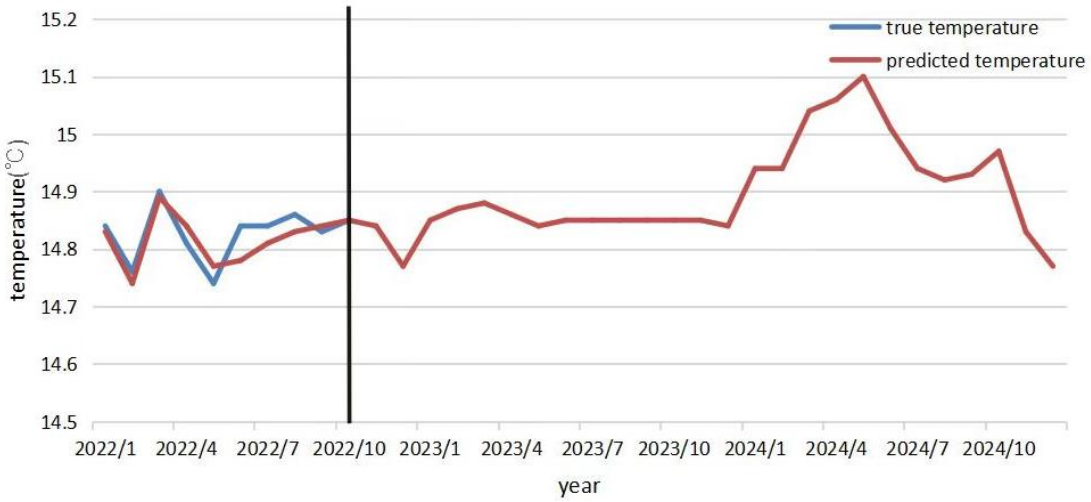


Figure 4. Prediction Results for Model 2

It can be seen from Figure 4 that the average temperature in 2022 is 14.81 ℃, the average temperature in 2023 is 14.85 ℃, and the average temperature in 2024 is 14.96 ℃. The average annual temperature rise is 0.382%.

For the degree of data fitting, this paper uses the evaluation index square root error $RMSE$ and goodness of fit R^2 to evaluate.

The more the $RMSE$ value is, the better the fitting effect is. The calculation formula is:

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - f(x_i))^2} \tag{11}$$

The value range of R^2 is [0,1]. The larger the value, the higher the degree of interpretation of the independent variable to the dependent variable. The calculation formula is:

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} = \frac{SS_{reg}}{SS_{tot}} \tag{12}$$

Where, SS_{reg} is explainable variance, SS_{res} is sum of squares of residuals, and SS_{tot} is sum of squares of the dataset itself.

It can be seen from Table 1 that the model fits well and is persuasive.

Table.1. Evaluation Index Results for Model 2

$RMSE$	R^2
0.256	0.911

3.3. Model 3 Solution and Result Analysis

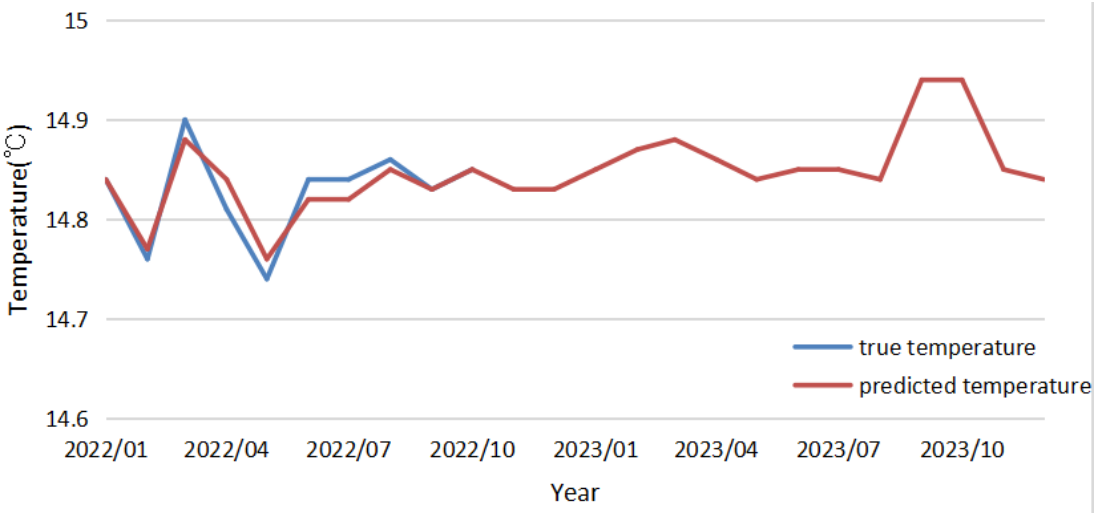


Figure 5 Prediction Results for Model 3

It can be seen from Figure 5 that the average temperature in 2022 is 14.83 ℃, and the average temperature in 2023 is 14.87 ℃. The average annual temperature rise is 0.269%.

For the degree of data fitting, this paper uses the evaluation index $RMSE$ and $Rbias$ to evaluate. It can be seen from Table 2 that the model fits well and is persuasive.

Table.2. Evaluation Index Results for Model 2

$RMSE$	$Rbias$
0.249	1.170

3.4. Model Comparison

The three models have their own advantages and characteristics in predicting global temperature, but the results are different. In particular, when predicting the global average temperature levels in 2050 and 2100, the SVR-QM model predicted a warming rate 48% higher than the other two models.

The SVR-QM model uses different data and calculation methods from the other two models. SVR-QM model uses global climate characteristics and greenhouse gas content for calculation, while ARIMA-BP model and FCN model are univariate time series analysis, and the calculation is relatively

simple. In addition, the three models use different evaluation indicators, so the accuracy of the three models cannot be judged from the results.

This paper unifies the indicators of each model to compare the three models. Finally, this paper selects the evaluation indicators $RMSE$ and R^2 to evaluate the degree of fitting of the model.

Table 3 shows that the FCN model has the best fitting effect. As mentioned earlier, although the FCN model is simple to use, its performance is very powerful. ARIMA-BP model and SVR-QM model are both effective in $RMSE$ and R^2, indicating that these two models are suitable for solving the problem of global temperature prediction.

Table.3. Forecast Results of Global Average Temperature in 2050 and 2100

Model	$RMSE$	R^2
ARIMA-BP	0.376	0.825
FCN	0.256	0.911
SVR-QM	0.249	0.723

4. Conclusions

Massive global climate data provides the basis for global temperature analysis and prediction. This paper uses three different methods to build a global temperature prediction model. Experimental results show that the three models have good predictability and robustness, and have certain practical application value.

Global warming is a worldwide problem, and by predicting temperature data, credible predictions can be made about future environmental development, providing a basis for macro decision-making on global environmental issues. In order to adapt to, slow down or even change global warming, human beings must understand global warming more accurately and take corresponding measures.

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