A Study on the Applicability of ARIMA and ANN Models for Drought Prediction Postprint

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Date: 2018-10-23T00:00:00+00:00

Abstract

Drought prediction constitutes a prerequisite foundation for effectively responding to drought risks. Based on daily precipitation and temperature data from seven stations in the Sanjiang Plain during 1960–2016, this study employs ARIMA and ANN models to analyze, model, and predict Standardized Precipitation Evapotranspiration Index (SPEI) series at different time scales. Model effectiveness was evaluated using correlation coefficient R, Nash–Sutcliffe Efficiency coefficient NSE, Kendall rank correlation coefficient, Mean Squared Error MSE, and Kolmogorov–Smirnov (K–S) test. Subsequently, 12-step ahead predictions were conducted using both ARIMA and ANN models, and the predicted values were compared with actual observations. The results indicate that: (1) the predictive capability of both ARIMA and ANN models for SPEI gradually improves with increasing time scale; (2) the prediction accuracy of both models for 3- and 6-month scale SPEI is relatively low, while that for 9-, 12-, and 24-month SPEI exceeds 70%; (3) for the three time scales of SPEI-9, SPEI-12, and SPEI-24, the prediction accuracy of the ANN model surpasses that of the ARIMA model.

Full Text

Abstract

Drought is one of the major natural disasters, whose occurrence is linked to a sustained lack of precipitation. Drought forecasting provides vital evidence and support for preventing losses from drought disasters, and therefore it is of great significance. In this study, a series of the Standardized Precipitation Evapotranspiration Index (SPEI) at different time scales were calculated based on daily precipitation and temperature data from seven meteorological stations in Sanjiang Plain, northeast China from 1960 to 2016 and were used to forecast drought using ARIMA and ANN models. In the stage of training and testing, the fitting degrees of the models were evaluated and validated, and the optimal ARIMA and ANN models were chosen with the help of six fitting evaluation methods: the correlation coefficient (R), Nash-Sutcliffe efficiency coefficient (NSE), Kendall rank correlation coefficient, mean square error (MSE), and Kolmogorov-Smirnov (K-S) test. Then, 12 values for the 12 months in 2016 were predicted by the optimal models and were compared with the corresponding observations. The results are shown as follows: (1) The prediction ability of ARIMA and ANN models based on SPEI was both increased with the increase of time scale in Sanjiang Plain. (2) The two models had poor prediction accuracy for SPEI-3 and SPEI-6. For the SPEI value of 9, 12, and 24 months, all models worked well with accuracy more than 70%. (3) For the SPEI value of 9, 12, and 24 months, the prediction accuracy of the ANN model is better than that of the ARIMA model. In particular, the prediction accuracy for one-month forecast of SPEI-12 and 24 at all stations was more than 80%. All these showed that the prediction model of ANN has strong maneuverability and can effectively predict drought at a large time scale in Sanjiang Plain. The drought prediction at small time scale (3 and 6 months) needs to be improved in future studies.

Keywords: drought; ARIMA model; ANN model; SPEI; Sanjiang Plain

1. Introduction

Drought is a major natural disaster that causes significant losses to agricultural production and socioeconomic systems. Accurate drought forecasting provides crucial support for disaster prevention and mitigation efforts. The Standardized Precipitation Evapotranspiration Index (SPEI) combines the sensitivity of the Palmer Drought Severity Index to temperature with the multi-scale characteristics of the Standardized Precipitation Index (SPI), making it widely applicable for drought monitoring and forecasting.

2. Methodology

2.1 Study Area and Data

The study area is the Sanjiang Plain in northeast China. Daily precipitation and temperature data from seven meteorological stations spanning 1960–2016 were used to calculate SPEI values at multiple time scales (3, 6, 9, 12, and 24 months). The data were divided into a training period (1960-2005) and a testing period (2006-2015) for model development, with 2016 data reserved for validation.

2.2 ARIMA Model

The Autoregressive Integrated Moving Average (ARIMA) model is a stochastic time series forecasting method. The general ARIMA(p,d,q) model can be expressed as:

$$\phi_p(B)\nabla^d Y_t = \theta_q(B)e_t$$

where $\phi_p(B)$ and $\theta_q(B)$ are the autoregressive and moving average operators respectively, ∇^d represents differencing of order d, and e_t is white noise. Model parameters were selected using the Akaike Information Criterion (AIC), and stationarity was achieved through appropriate differencing.

2.3 Artificial Neural Network Model

A Nonlinear Autoregressive (NAR) neural network was employed, which has proven effective for time series forecasting. The NAR model structure is given by:

$$y(t) = f(y(t-1), y(t-2), \dots, y(t-d))$$

where d represents the delay order and $f(\cdot)$ is a nonlinear function approximated by the network. The Levenberg-Marquardt algorithm was used for training:

$$X_{k+1} = X_k - (J^T J + uI)^{-1} J^T e$$

where J is the Jacobian matrix, I is the identity matrix, and u is a learning parameter.

2.4 Evaluation Metrics

Six statistical measures were employed to evaluate model performance:

1. **Correlation Coefficient (R)**: Measures linear correlation between observed and predicted values
2. **Nash-Sutcliffe Efficiency (NSE)**: Evaluates model predictive power
3. **Kendall’ s Tau ( )**: A non-parametric rank correlation coefficient
4. **Mean Square Error (MSE)**: Quantifies prediction error magnitude
5. **Kolmogorov-Smirnov Test (K-S)**: Assesses distributional similarity

3. Results and Discussion

3.1 Model Training and Testing

Both ARIMA and ANN models showed improved predictive capability with increasing SPEI time scales. For short time scales (SPEI-3 and SPEI-6), prediction accuracy was relatively poor. However, for SPEI-9, SPEI-12, and SPEI-24, all models achieved accuracy exceeding 70%. The ANN model consistently outperformed the ARIMA model, particularly for longer time scales.

The average evaluation metrics across all seven stations demonstrated that the ANN model achieved superior performance with R values above 0.92, NSE above

0.85, and MSE below 0.15 for SPEI-12 and SPEI-24. The K-S test results confirmed that the ANN model better captured the statistical distribution of drought indices.

3.2 Drought Forecasting

One-month ahead forecasts for 2016 showed that the ANN model provided robust predictions for SPEI-12 and SPEI-24, with accuracy exceeding 80% at all stations. The model' s superior performance at larger time scales can be attributed to the stronger temporal persistence and more stable patterns in accumulated precipitation and evapotranspiration data. In contrast, short-term drought forecasting (3-6 months) remains challenging due to higher variability and noise in the data.

4. Conclusions

The study demonstrates that both ARIMA and ANN models are capable of drought forecasting using SPEI data in the Sanjiang Plain, with prediction accuracy improving at longer time scales. The ANN model exhibits stronger predictive performance, particularly for SPEI-12 and SPEI-24, achieving over 80% accuracy for one-month forecasts. However, forecasting accuracy for short time scales (3-6 months) requires further improvement. Future research should focus on integrating additional climate variables and exploring hybrid modeling approaches to enhance short-term drought prediction capabilities.

References

[1] WANG Lina, SU Jing, ZHENG Xiaodong, et al. Research progress of agricultural drought risk in China[J]. Water Sciences and Engineering Technology, 2011, (2): 3-7.

[2] ZHANG Yuhu, LIU Kaili, CHEN Qiuhua, et al. Bivariate probability distribution of meteorological drought characteristics in the Aksu Basin using Copula[J]. Scientia Geographica Sinica, 2014, 34(12): 1480-1487.

[3] XIE Pei, GU Yanling, ZHANG Yuhu, et al. Precipitation and drought characteristics in Xinjiang during 1961-2015[J]. Arid Land Geography, 2017, 40(2): 332-339.

[4] ZHANG Yuhu, XIANG Liu, SUN Qing, et al. Construction and application of hydrological drought prediction model for Copula in Bayesian framework[J]. Scientia Geographica Sinica, 2016, 36(9): 1437-1444.

[5] WU Jing, LUO Yi, LI Jia, et al. The evaluation of CMIP5 model for simulation of precipitation and drought characteristics in China' s northwest arid region[J]. Arid Land Geography, 2014, 37(3): 499-508.

[6] LI Weiguang, HOU Meiting, CHEN Huilin, et al. Study on drought trend in south China based on standardized precipitation evapotranspiration index[J].

Journal of Natural Disasters, 2012, 21(4): 84-90.

[7] ZHANG Y, LI W, CHEN Q, et al. Multi-models for SPI drought forecasting in the north of Haihe River Basin, China[J]. Stochastic Environmental Research & Risk Assessment, 2017, 31(10): 2471-2481.

[8] LIU Haiping. The fractal analysis of major indexes and BP neural network prediction in China[D]. Dalian: Dalian University of Technology, 2013.

[9] XIN RB, JIANG ZF, LIN, et al. An air quality predictive model of Liangang of Qingdao City based on BP neural network[J]. Advanced Materials Research, 2013, 756-759: 3366-3371.

[10] ZHAO Hao. Based on MATLAB dynamic neural network time series forecast research on state price[J]. China Economist, 2015, (9): 284-286.

[11] DJERBOUAIS, SOUAG-GAMANE D. Drought forecasting using neural networks, wavelet neural networks and stochastic models: A case of the Algerois Basin in north Algeria[J]. Water Resources Management, 2016, 30(7): 2445-2464.

[12] BARUA S, PERERA BJC, NGAW M, et al. Drought forecasting using an aggregated drought index and artificial neural network[J]. Journal of Water & Climate Change, 2010, 1(3): 193.

[13] BELAYNEH A, ADAMOWSKI J, KHALIL B, et al. Long-term SPI drought forecasting in the Awash River Basin in Ethiopia using wavelet neural network and wavelet support vector regression models[J]. Journal of Hydrology, 2014, 508(2): 418-429.

[14] LUO Minmei. Study on soil water inversion in Huai River basin based on AMSR-E and ANN artificial neural network[D]. Chengdu: Sichuan Agricultural University, 2013.

[15] SHEN Guoqiang, ZHENG Haifeng, LEI Zhenfeng. Applicability analysis of SPEI for drought research in northeast China[J]. Acta Ecologica Sinica, 2017, 37(11): 3787-3795.

[16] WANG Yuanyuan, ZHANG Bo. The spatial and temporal characteristics of drought and waterlogging in Longdong area based on standardized precipitation index in recent 40 years[J]. Journal of Natural Resources, 2012, 27(12): 2135-2144.

[17] ZHANG Yuejun, HAO Zhiwen, WANG Yan, et al. Multiscale characteristics of drought based on SPEI and SPI in association with climate index in Taiyuan[J]. Ecology and Environmental Sciences, 2014, 23(9): 1418-1424.

[18] HAN Ping, WANG Pengxin, WANG Yanji, et al. Drought forecasting based on the standardized precipitation index at different temporal scales using ARIMA models[J]. Agricultural Research in the Arid Areas, 2008, 26(2): 212-218.

[19] WANG Lin, CHEN Wen. The multi-temporal scale evolution characteristics of drought in southwest China in the past 100 years[J]. Advances in Meteorological Science and Technology, 2012, 2(4): 21-26.

[20] ADAMOWSKI IJ, CHAN HF, PRASHER SO, et al. Comparison of multiple linear and nonlinear regression, autoregressive integrated moving average, artificial neural network and wavelet artificial neural network methods for urban water demand forecasting in Montreal, Canada[J]. Water Resources Research, 2012, 48(1): 273.

[21] YUE Xinzheng, LI Leimin, SUN Fei. Parametric modeling and prediction of quartz flexible accelerometer based on NAR dynamic neural network[J]. Journal of Wuhan University, 2016, 31(1): 88-92.

[22] DENG Xingsheng, WANG Yan. Application of dynamic neural network in deformation prediction[J]. Journal of Wuhan University, 2008, 33(1): 93-96.

[23] VICENTE-SERRANO SM, BEGUERIA S, LOPEZ-MORENO JI. A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index[J]. Journal of Climate, 2010, 23(7): 1696-1718.

[24] LIU Ke, JIANG Dabang. Analysis of dryness/wetness over China using standardized precipitation evapotranspiration index based on two evapotranspiration algorithms[J]. Chinese Journal of Atmospheric Sciences, 2015, 39(1): 23-36.

[25] GB/T 20481—2006, Classification of meteorological drought[S]. Beijing: Standards Press of China, 2006.

[26] PEARSON ES, HARTLEY HO. Biometrika tables for statisticians[M]. London: Cambridge University Press, 1956.

[27] LI Baolin, ZHOU Cheng. Climate variation and desertification in west sandy land of Northeast China Plain[J]. Journal of Natural Resources, 2001, 16(3): 234-239.

[28] WANG Chunyi, CAI Jingjing, ZHANG Jiquan. Risk assessment of drought and chilling injury of maize in northeast China[J]. Transactions of the Chinese Society of Agricultural Engineering, 2015, 31(6): 238-245.

[29] HU Xinxin, ZHANG Yuhu, XIANG Liu. Study on the characteristics of meteorological drought in Aksu region of Xinjiang[J]. Journal of Anhui Agricultural Sciences, 2015, 43(35): 96-100+104.

[30] MISHRA AK, DESAI VR. Drought forecasting using stochastic models[J]. Stochastic Environmental Research and Risk Assessment, 2005, 19(5): 326-339.

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