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Prediction of Meteorological Drought with Different Methods in Dongsheng of Inner Mongolia, China

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Abstract:

Drought is one common natural disaster throughout the world. Meteorological drought is a moisture deficiency status caused by the unbalance between precipitation and evaporation. The intensity of drought is usually reflected by the degree of rainfall deficiency. Dongsheng District of Ordos, Inner Mongolia, China belongs to the continental climate of the temperate zone and is prone to climate changes. Thus, studying the effects of regional climate changes on ecological restoration and agricultural production is of high significance. In this study, meteorological data from 1988 to 2018 in this region were collected, and then the major influence factors and occurring rules of meteorological drought in these 31 years were analyzed. Two drought indices suitable for this region were selected. Afterwards, drought prediction models were constructed and used to forecast the occurrence of drought in the future 5 years. (1) Correlation analysis of meteorological factors showed 4 of 8 factors were highly correlated, including relative humidity, precipitation temperature and evaporation, and the correlation coefficients were 0.751, 0.747 and 0.651. Air temperature and ground temperature were positively correlated and gradually rose year by year. The sunshine duration varied largely year by year and was correlated negatively with precipitation and positively with evaporation. The precipitation was negatively correlated with evaporation, but the precipitation did not largely vary from year to year. (2) Prediction models combining back-propagation neural networks and PA were of high precision in prediction. It was predicted the PAs of 2020 and 2022 were as low as -19.069 and -18.951 respectively, and thus gentle drought will occur in these two years.

***Keywords**: Meteorological drought, Drought index, Correlation analysis, Back-propagation neural network.*

I. INTRODUCTION

Drought is one of the most common natural disasters that extensively occur in the world and refers to a water shortage status caused by the imbalance between water input and output due to long-term rainfall

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deficiency [1-3]. Drought disasters occur gradually regularly and are featured by higher occurrence rates, stronger intensity, wider extent [4-6], and especially higher destructiveness [7]. Because of the severe influence degrees, drought disasters are threatening social progress and economic development. Under the background of global warming, the drying trend has become one of the hot spots of researchers globally [8-9]. Statistics show 70% of natural disasters are meteorological disasters, and drought disasters account for about 50% of meteorological disasters and have caused the severest economic losses [10-12].

Back-propagation (BP) neural networks are widely used in modeling, evaluation and prediction and involve medicine, agriculture, architecture and other fields [13-15]. BP neural networks have also been successfully applied into hazard predication and evaluation of the ecoenvironment. For instance, BP neural networks precisely predicted sandstorms in Xilingol [16] and offered novel methods and technical means for agricultural production and environmental protection. In this study, regression and BP neural networks were combined and used to predict the occurrence of drought. Also the reliability and practical values of BP neural networks in disaster prevention were further validated.

Dongsheng District of Ordos, Inner Mongolia, China, belongs to the continental climate in the temperate zone and is prone to climate changes. Severe soil erosion has considerably inhibited the growth of plants in this region. Thus, based on meteorological data, relevant drought indices, varying process and rules of meteorological drought, and occurrence rates and intensity of drought were analyzed. Drought prediction models were built by combining regression analysis and BP neural networks. To effectively predict and respond to drought and to weaken the effects of drought, we analyzed the effects of climate changes on ecological restoration and agricultural production in this region [17].

II. THE STUDY AREA AND METHODS

2.1 The Study Area

Dongsheng District (E 109°08′04″-110°23′11″, N 39°10′07″-39°58′51″) is located at the east middle part of Ordos Plateau, Inner Mongolia, and covers an area of 2512.3 km^2. Dongsheng belongs to the continental climate of the temperate zone and is featured by low assurance rate and high annual variation of precipitation. This district belongs to the semiarid continental monsoon climate of the typical moderate temperature zone and enjoys evident seasons, intense solar radiation, long sunshine time and an average sunshine duration of 2900-3100 h. The annual average precipitation is about 400 mm, annual evaporation is 2093 mm, annual mean temperature is 6.2-8.7 ℃, and yearly total radiation of 143.4 kCal/m^2. Wind is strong and persistent in spring, and the annual wind speed is 3.2 m/s with the mean of 32 m/s, and the days of strong wind are 10-30 d.

The surface matters in this region mainly originated from feldspathic sandstone, loess and red soil, from which various soils have developed. Dongsheng displays the warm grassland vegetation form with an evident vegetation transition from grasslands to desert steppes, and inherits the species of North China flora and Mongolia flora. Due to the reinforcement of soil erosion and human economic activities in recent

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years, natural woody plants can hardly grow there and the existing vegetation types are basically dominated by artificial plants. The major afforestation species include *Hippophae rhamnoides* Linn., *Pinus tableulaeformis*, *Caragana korshinskii* Kom., and *Prunus sibirica*.

2.2 Methods

2.2.1 Study design

Firstly, the daily meteorological data in recent 31 years were collected from Dongsheng, and the correlations of 8 meteorological factors (e.g. precipitation, evaporation, relative humidity, temperature) with meteorological drought were analyzed. Then correlation analysis, regression analysis and plotting of meteorological data were conducted on Excel and SPSS 20.0. Then BP neural networks were built on Matlab and used to predict drought in 2019-2023.

2.2.2 Selection of meteorological indices

(1) Percentage of anomaly (PA)

The PA of precipitation is the percentage of "difference between the amount of precipitation and perennial average precipitation within a certain period" to "perennial average precipitation in the same period". PA with definite meaning and simple computation is largely dependent on average values. TABLE I listed the *Meteorological Drought Intensity Standard of China* [18].

$$PA = \frac{precipitation\ of\ a\ period - perennial\ precipitation\ of\ the\ same\ period}{perennial\ precipitation\ of\ the\ same\ period} \times 100\% \tag{1}$$

TABLE I. Drought Intensity division standard with corresponding PA

Grade	Type	Precipitation anomaly percentage (%)		
		Monthly scale	Seasonal scale	Annual scale
1	Drought-free	-40<PA	-25<PA	-15<PA
2	Mild drought	-60<PA≤-40	-50<PA≤-25	-30<PA≤-15
3	Middle drought	-80<PA≤-60	-70<PA≤-50	-40<PA≤-30
4	Heavy drought	-95<PA≤-80	-80<PA≤-70	-45<PA≤-40
5	Special drought	PA≤-95	PA≤-80	PA≤-45

(2) Standardized precipitation evaporation index (SPEI)

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SPEI is the normalized cumulative probability of a series of difference between precipitation and potential evaporation. SPEI has become an ideal tool for drought process monitoring and for evaluation of effects of temperature rise on drought [19-20]. Specifically, drought is characterized by how the difference of precipitation and potential evaporation deviates from the average status. This index considers the effects of drought on evaporation and the space conformity of the standardized precipitation index. It considers multiple time scales and can be computed easily. Among many drought indices, SPEI clearly reflects the fine variation in the drought process [21]. Firstly, the monthly potential evaporation and precipitation were computed, and the difference series between precipitation and evaporation was normalized. Then the probability distribution F(x) of monthly accumulated water deficit series was standardized. The computational procedures were listed below [22-23].

The series of difference between precipitation and evaporation was normalized. Due to the possible presence of negative data in the original data, the log-logistic distributions of the 3 parameters were used in the fitting, and the data of SPEI corresponding to each difference was computed.

The accumulation function of Log-logistic probability distribution was:

$$F(x) = \left[1 + \left(\frac{\alpha}{\chi-\gamma}\right)^{\beta}\right]^{-1} \tag{2}$$

$$\alpha = \frac{(w_0-2w_1)\beta}{\Gamma(1+1/\beta)\Gamma(1-1/\beta)} \tag{3}$$

$$\beta = \frac{2w_1-w_0}{6w_1-w_0-6w_2} \tag{4}$$

$$\gamma = w_0 - \alpha\Gamma(1+1/\beta) \times \Gamma(1-1/\beta) \tag{5}$$

Where Γ is the factorial function; w_0, w_1, w_2 are the probability weighted matrices of the original data series differences. It is computed as follows:

$$w_s = \frac{1}{N}\sum_i^N (1-F_i)^s D_i \tag{6}$$

$$F_i = \frac{i-0.35}{N} \tag{7}$$

The probability distribution F(x) of monthly accumulated water deficit series was standardized; when the accumulation $P \leq 0.5$, $w = -2\ln(P)$. It was deduced that:

$$SPEI = W - \frac{c_0+c_1w+c_2w^2}{1+d_1w+d_2w^2+d_3w^3} \tag{8}$$

where W is the cumulative probability function deduced from evaporation and precipitation; $c_0 =$

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$2.5156,\ c_1 = 0.8029,\ c_2 = 0.0103,\ d_1 = 1.4328,\ d_2 = 0.1893$ and $d_3 = 0.0013$.

At P>0.5, we expressed 1-P as P, and changed the sign of SPEI.

The normal standardization eliminated the space-time distribution, so SPEI can reflect the drought or flooding at different time scales and in different regions. The drought intensities at different SPEIs were listed in TABLE II.

TABLE II. Drought intensity division standard with corresponding SPEI

Grade	Type	SPEI range
1	Normal	-0.5＜SPEI
2	Mild drought	-1.0＜SPEI≤-0.5
3	Moderate drought	-1.5＜SPEI≤-1.0
4	Severe drought	-2.0＜SPEI≤-1.5
5	Extreme drought	SPEI≤-2.0

2.2.3 Data analysis

(1) BP neural networks

A typical BP neural network consists of an input layer, a hidden layer and an output layer. Its rationale is that: it connects the input layer with weights and delivers to the hidden layer; after the neurons of the hidden layer are summarized, a certain responded output is generated from a transfer function and transferred via the next layer of connecting weights to the output layer. The output layer summarizes the neurons and generates a new response output. Then the output is compared with the expected output. If the two are consistent or share a minor difference, this network can be considered as being capable of handling this problem. If the difference is large or unsatisfactory, the difference between the network output and the expected output is returned. The training and learning are repeated by adjusting the linking weights, until the output is close to reality [24]. As reported, a 3-layer BP network can approach any rational function [25-28]. The increment of one layer can further decrease errors, but complicates the network. So far, the existing BP networks mostly contain 3 layers.

The samples in this study were meteorological data from 1988 to 2014 and the time node was 10 years. For instance, in the 10 years from 1988 to 1997, the meteorological data in 1988 were predicted, so the meteorological data in each year from 1988 to 2014 were predicted and then compared with the real data, which ensured the maximization of modeling samples. The simulation effect was tested before modeling based on smaller samples, which ensured the real significance of modeling. The meteorological data of 4 years from 2015 to 2018 were predicted and compared with real data, which validated the reliability of the model.

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(2) Multiollinear regression models

The multiollinear regression model was expressed as follows:

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p + \varepsilon \tag{9}$$

where the dependent variable *y* is a randomly observed value; β_0 is a constant term; β_1, $\cdots$, β_p are partial regression coefficients; β_i (i=1,2, ⋯, p) means the average variation of y caused by the per unit change of x_i when other independent variables are unchanged.

Let the number of independent variables be p and express it in a vector (x_1, x_2, ⋯, x_p). Let the number of observed objects be n; the observed value of group i (i=1, 2, ⋯, n) be (y_i, x_{i1}, x_{i2}, ⋯, x_{ip}). The dependent variable y and the independent variables x_1, x_2, ⋯, x_p obeyed the following linear relationship:

$$y_i = Y_i + \varepsilon_i = b_0 + b_1 x_{i1} + \cdots + b_p x_{ip} + \varepsilon_i \tag{10}$$

where $\varepsilon_i$is the residual error and is the difference between the measured value and the estimated value of y_i. The residual errors were not decided by independent variables and obeyed a distribution of N(0, δ^2). It helped to judge whether the new model held and whether other variables should be introduced to the model [29].

The meteorological factors with strong correlations were selected as independent variables, and models were built with PA and SPEI as dependent variables. Based on contrastive analysis of measured data in recent 6 years, the above meteorological data that passed the BP neural networks were substituted into this model.

III. RESULTS AND DISCUSSION

3.1 Correlation Analysis of Meteorological Factors

In practical correlation analysis, much data of factors were collected, and some factors were superposed. Thus, the heterogeneity and similarity of different factors should be considered and thereby further analysis be conducted. Here the distance analysis from correlation analysis was adopted to differentiate the similarity of different factors. To ensure the completeness and reliability of data, we based all drought indices on annual changes, which excluded the large errors caused by data deficiency or seasonal effects.

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TABLE III. Correlations among different meteorological factors

	Evaporation capacity	Relative humidity	Hours of sunshine	Pressure	Air temperature	Precipitation	Wind speed	Ground temperature
Evaporation capacity	1.000							
Relative humidity	0.651*	1.000						
Hours of sunshine	0.384	-0.581*	1.000					
Pressure	0.450	0.239	0.001	1.000				
Air temperature	-0.067	-0.222	0.034	-0.027	1.000			
Precipitation	-0.141	0.715*	-0.443	-0.152	0.102	1.000		
Wind speed	0.747*	0.376	0.218	0.178	-0.311	-0.010	1.000	
Ground temperature	-0.243	-0.654*	0.291	-0.412	0.289	-0.639*	-0.752*	1.000

Note: * p<0.05

Eight indices including mean annual evaporation, relative humidity, sunshine duration, pressure, temperature, precipitation, wind speed and ground temperature from 1988 to 2018 were analyzed (TABLE III). Evaporation was positively correlated with relative humidity and wind speed; relative humidity was correlated positively with precipitation and negatively with sunshine duration and ground temperature. Ground temperature was negatively correlated with both wind speed and precipitation. However, the variation of wind speed was very complex and cannot be easily judged.

3.2 Risk Analysis of Meteorological Drought by Using Two Indices - SPEI Drought Threshold

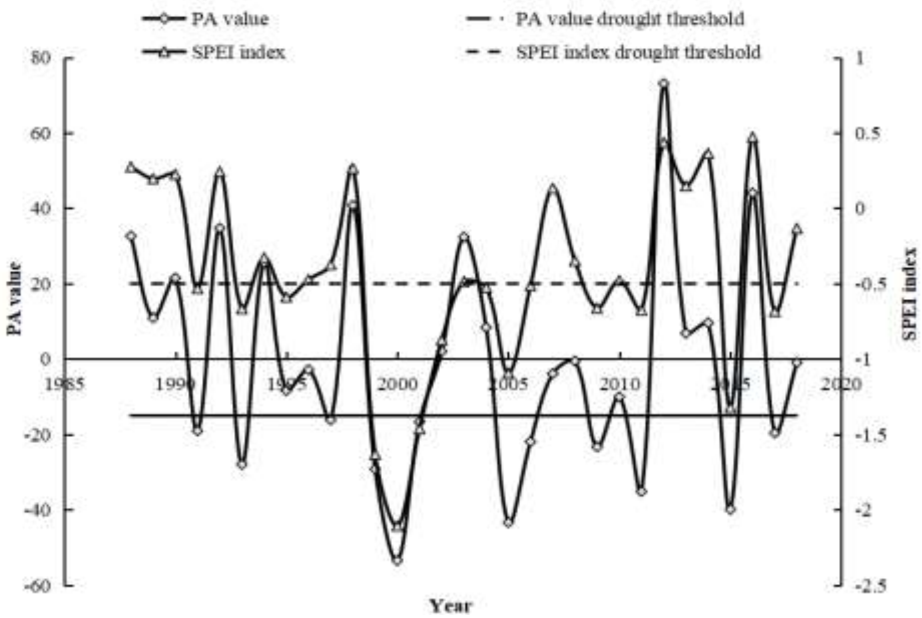

Fig 1: Prediction of drought based on SPEI and PA in Dongsheng in recent 31 years

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Analysis of SPEI from 1988 to 2018 in Dongsheng showed SPEI reached the drought threshold by 16 times in the recent 31 years, accounting for 51.6% of tested years (Fig 1). The intensity classification showed SPEI in 2000 exceeded -2.0, indicating extreme drought in this year. Also severe drought occurred in 1999 and 2001. Modest drought happened in 2005, and slight drought occurred in 1991, 1993, 1995, 1996, 2002, 2003, 2004, 2006, 2009, 2010, 2015 and 2017. Among the years without reaching the drought threshold, SPEI maximized in 2012, indicating no drought occurred in this year.

Analysis of PA from 1988 to 2018 in Dongsheng showed drought occurred 12 times in the recent 31 years, accounting for 38.7% of tested years (Fig 1). Grade analysis showed extreme drought occurred in 2000, as PA was up to -53.46%; severe drought happened in 2005 and 2015; modest drought attacked Dongsheng in 2011; gentle drought happened in 1991, 1993, 1997, 1999, 2001, 2006, 2009 and 2017. Among the tested years without reaching the drought threshold, PA maximized in 2012.

Based on the above two drought indices, the situations of drought in recent 31 years were analyzed. The frequency of drought measured by each drought index was summarized. Results showed the times of droughts determined from PA and SPEI were slightly different, but the yearly variations of drought were consistent. Severe drought occurred in 1999, 2000 and 2001, and the most severe drought happened in 2000. Gentle drought occurred in 2005, and no drought happened in 2012. The meteorological data showed the drought predictions in Dongsheng by these two indices were consistent with the history of typical dry years, indicating these two indices can well reflect the changes of drought in this region as described by records.

3.3 Prediction of Meteorological Drought in Dongsheng

Correlation analysis showed precipitation, evaporation, relative humidity and temperature were all highly correlated and were the major influence factors on drought and can well reflect meteorological drought. Thus, these 4 factors were selected as independent variables, and PA and SPEI were used as dependent variables in the prediction models.

2.3.1 Meteorological drought prediction models

TABLE IV listed the relevant indices of PA fitting models. Results showed the coefficient of multiple correlation was R=0.998, coefficient of determination was R^2=0.995, and the adjusted R^2 was =0.994, suggesting this model made large regressive contribution and the fitness of the regression model was high. TABLE V listed the analysis of variance (ANOVA) results of fitted PA. Results showed the fitted model of meteorological drought was very significant (P<0.01).

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TABLE IV. Adjustment of coefficient of determination of PA fitting model

Summary of meteorological drought models								
					Changed statistics			
R	**R^2**	**Adjust R^2**	**Error of standard estimation**	**R^2 changes**	**F value change**	**df1**	**df2**	**P value change**
0.998	0.995	0.994	2.162	0.995	1350.735	4	26	0.000

TABLE V. ANOVA of the PA model

model	quadratic sum	df	mean square	F value	P value
recurrence	25254.294	4	6313.573	1350.735	0.000
residual	121.529	26	4.674		
total	25375.822	30			

In all, with the PA of drought as the dependent variable, and evaporation (X_1), relative humidity (X_2), temperature (X_3) and precipitation (X_4) as the independent variables, the regression equation was as follows:

$$Y_{(PA)} = -111.438 + 0.001X_1 + 0.268X_2 - 0.375X_3 + 0.251X_4 \quad (11)$$

TABLE VI listed the relevant indices of the SPEI fitting model. Results showed the coefficient of multiple correlation was R= 0.891, coefficient of determination was R^2= 0.671, and adjusted R^2 was = 0.643, suggesting this model made large regressive contribution, and the fitness of the regression model was high. TABLE VII listed the ANOVA results of the SPEI model. Results showed the fitted model of meteorological drought was very significant (P<0.01).

TABLE VI. Adjustment of coefficient of determination of the SPEI model

Summary of meteorological drought models								
					Changed statistics			
R	**R^2**	**Adjust R^2**	**Error of standard estimation**	**R^2 changes**	**F value change**	**df1**	**df2**	**P value change**
0.891	0.671	0.643	0.394	0.671	13.262	4	26	0.000

TABLE VII. ANOVA of the SPEI model

model	quadratic sum	df	mean square	F value	P value
recurrence	8.219	4	2.055	13.262	0.000
residual	4.028	26	0.155		
total	12.247	30			

In all, with the SPEI of drought as the dependent variable, and evaporation (X_1), relative humidity (X_2),

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temperature (X_3) and precipitation (X_4) as the independent variables, the regression equation was as follows:

$$Y_{(SPEI)} = -1.465 + 0.003X_1 - 0.054X_2 + 0.023X_3 - 0.006X_4 \tag{12}$$

The two models showed the PA model was more precise than the SPEI model. Thus, the PA model was selected in the prediction. The measured meteorological data from 2013 to 2018 were substituted to the PA model to compare the model-predicted data and the measured data and to test the reliability of the models.

The measured and predicted data of PA based on yearly changes showed the PA in 2015 exceeded -30%, modest drought occurred, and PA exceeded the drought threshold in 2017, and gentle drought occurred (Fig 2). Comparison of measured data and predicted data showed the absolute error of PA maximized to -11.18% in 2016, and minimized to 1.263% in 2017, and the total average error was 3.633%. Thus, the PA in Dongsheng was described as $Y = -111.438 + 0.001X_1 + 0.268X_2 - 0.375X_3 + 0.251X_4$ and used to predict the drought in this region.

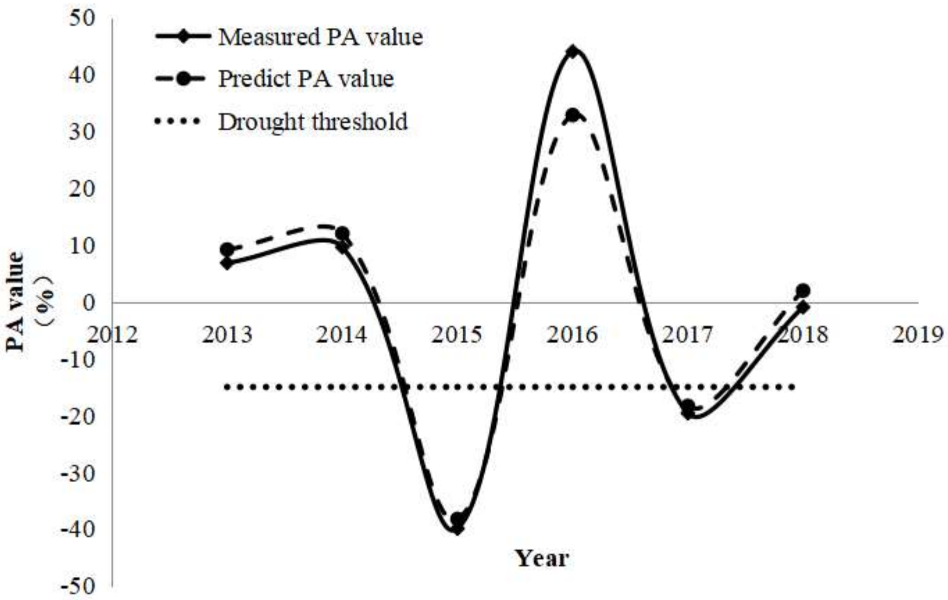

Fig 2: Variations of measured PA and predicted PA from 2013 to 2018

2.3.2 Meteorological data predicted by BP neural networks

Fig 3 showed the data predicted by neural networks and the real data based on 4 meteorological factors from 1988 to 2014. Clearly, the measured data of evaporation, precipitation, relative humidity and temperature were well consistent with the data predicted by neural networks in the 27 years. The measured data were close to the predicted data, suggesting the models based on BP neural networks were reliable and

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can be used into further analysis.

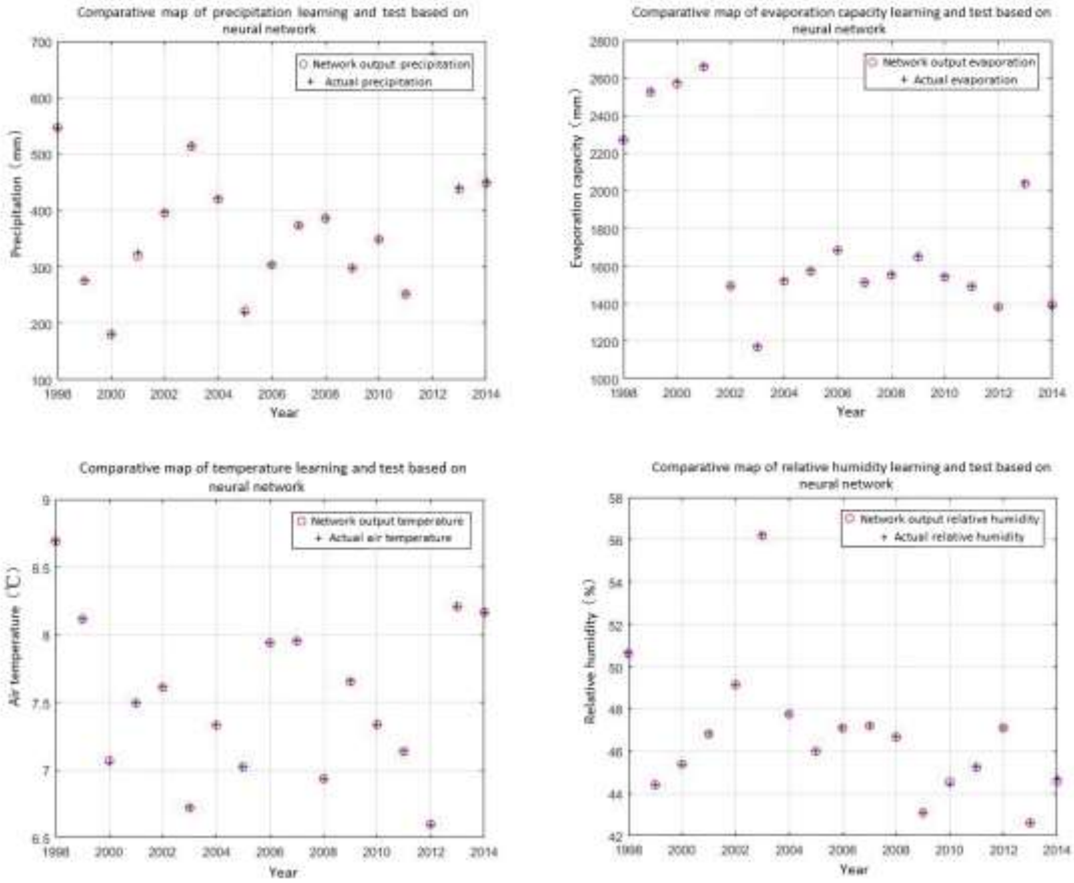

Fig 3: Comparison between neural network-predicted data and real data

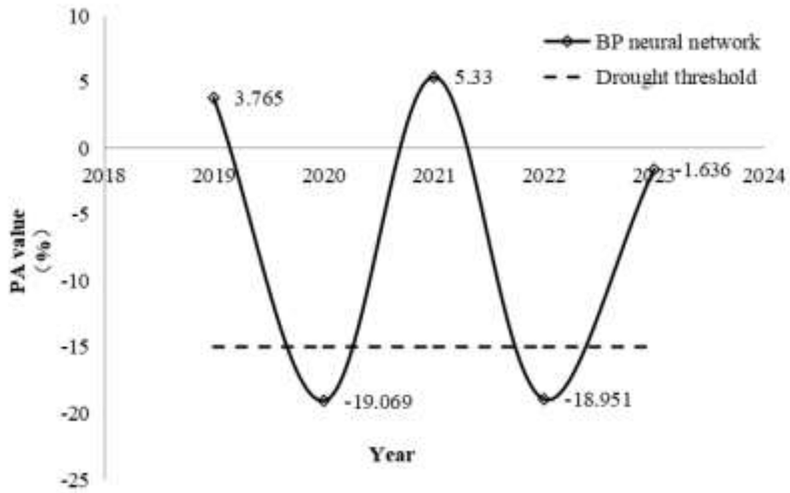

Fig 4: Changes of PA predicted by BP neural networks from 2019 to 2023

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The changing trends of PA predicted by BP neural networks from 2019 to 2023 were illustrated in Fig 4. Clearly, drought will occur in 2020 and 2022, and the PA will reach -19.07% and 18.91% respectively, which both belong to gentle drought. No drought will occur in 2019, 2021 or 2023.

IV. DISCUSSION

Analysis of drought indices showed since the causes of drought were complex and multiple, it was hard to find a universal drought index [30-32]. The monitored results at the same region differed among drought indices or at the same index differed among regions. Thus, any drought index is significantly specific in regional characteristics or time scales. Prior to regional drought monitoring, it should be ensured the drought index was accurate. The monitoring effect of the same region should be tested by using multiple appropriate drought indices, which ensured the reliability and rationality of drought monitoring. Then the optimal index was identified for fine analysis, which further improved the accuracy of drought monitoring [33-35]. Among the causes of drought, precipitation was the major influencing factor, and the PA of precipitation only took into account the single factor, and the drought monitoring was unaffected by time scales. SPEI reflected the occurrence of drought on basis of precipitation and potential evaporation [36-38].

As for the establishment of prediction models, among the models with PA and SPEI as dependent variables during meteorological drought prediction, the PA model was more effective, indicating PA can well reflect the changing trend of drought, while SPEI well uncover the process of drought variation. Furthermore, the data of SPEI should be standardized and thus were modestly different from the measured meteorological data. Thus, the coefficient of determination R^2 in the drought prediction model based on measured values of SPEI was very low, but this model was yet significant. The PA model was very practical for prediction of drought trend. The PA model was applicable to the situations when the meteorological factors fluctuated severely, and was effective and precise to some extent in simulating the drought changing trend. Comparative analysis of measured data and predicted data of PA demonstrated that the absolute errors of PA variation were large in 2016. Comparison of the 4 major meteorological factors showed the differences between the measured and predicted data of precipitation were large, and precipitation was a major influence factor on PA. Despite the evident errors in PA in 2016, the precision of data was high and significant.

So far, artificial neural networks still suffer from some limitations, such as the numbers of layers and nodes in the hidden layer, which are yet determined according to tentative calculation and experience. In this study, repeated debugging and comparison showed the predictive results were closest to the measured data when the hidden layer contained 2 layers and 5 nodes. Moreover, the parameters of the neural network models were of no concrete physical meaning and thus cannot reflect the relationships among different factors. Thus, the models and the network training method should be improved. In addition to the above 4 major influence factors, other factors and indirect factors of meteorological drought should also be tested so as to further uncover the formation process of drought.

V. CONCLUSIONS

(1) Correlation analysis of meteorological factors showed 4 of 8 factors were highly correlated, including relative humidity, precipitation temperature and evaporation, and the correlation coefficients were 0.751, 0.747 and 0.651. Air temperature and ground temperature were positively correlated and gradually rose year by year. The sunshine duration varied largely year by year and was correlated negatively with precipitation and positively with evaporation. The precipitation was negatively correlated with evaporation, but the precipitation did not largely vary from year to year.

(2) PA and SPEI were used separately to predict drought in recent 27 years in Dongsheng. Prediction models combining back-propagation neural networks and PA were of higher precision. It was predicted the PAs of 2020 and 2022 were as low as -19.069 and -18.951 respectively, and thus gentle drought will occur in these two years.

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