# Application of PSO_BP Neural Network Model based on Influence Factor Correlation for Phreatic Water Depth Prediction

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Abstract: The lack of groundwater level data will lead to untimely water resources management and control. Using groundwater phreatic depth influencing factors to predict the water level can provide a basis for the rational use of water resources. This paper took Xianyang city as the study area, used correlation analysis to identify the correlation between population, gross regional product, meteorological factors and phreatic water depth, established PSO_BP neural network model to predict the phreatic water depth in Xianyang city according to the correlation, and analyzed the prediction results and evaluates the applicability of the model. The results show that the relative error of the PSO_BP neural network prediction model does not exceed 2.5%, the minimum error is 1.65%, and has the same changing trend as the measured value, which indicates that the prediction model has high accuracy and good feasibility. The model can provide an effective prediction method for phreatic water depth of burial research and has good application prospects.

## 1 INTRODUCTION

With the rapid development of national economy, water resources extraction is increasing. In the arid northwest of China, surface water resources can hardly meet people's daily water demand, and groundwater extraction has become the main way of water resources utilization. The change of groundwater level is a very complex natural process, which is a comprehensive effect of the groundwater system stimulated by a variety of inputs (Chi et al., 2008). There are many influencing factors and complex structure of the groundwater system, topography and geomorphology, meteorology, human activities, etc. can cause the change of subsurface phreatic water depth (Li et al., 2018). In some places where no or little information is available, it is difficult to obtain direct data on phreatic water depth, and the lack of information not only restricts the reasonable control of groundwater resources, but also indirectly limits the economic development of cities by blindly exploiting groundwater beyond the carrying capacity of regional water resources. Therefore, exploring the factors influencing the phreatic water depth and establishing a phreatic water depth prediction model to predict the phreatic water depth can provide a scientific basis for the development and utilization of groundwater resources, which is of great significance to the rational control and sustainable utilization of water resources.

Groundwater systems are complex and the process of water level change is difficult to predict. From the early deterministic methods such as analytical methods and physical simulation (Ping et al., 2006) to the current uncertain methods by building stochastic models (Wang et al., 2015), there are more and more methods for water level prediction with higher and higher accuracy. A BP artificial neural network model with a mapping relationship between the groundwater level and its influencing factors was established and used for the dynamic prediction of the groundwater level (Zhao et al., 2002). In recent years, BP artificial neural network method has been widely used and promoted in groundwater dynamic prediction because of its powerful ability to deal with nonlinear dynamical systems, but it also has its own limitations, it has problems such as long training time when predicting groundwater level, falling into local minimum when solving and slow speed when converging (Chi et al., 2008). A combination term of learning rate adaption and increasing momentum was used to improve the



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BP neural network and a simulation prediction model of groundwater depth in western Jilin was established, the model simulation and prediction accuracy were high (Lu et al., 2007). Then genetic algorithm was used to optimized the BP neural network, a short-term prediction of groundwater level was made in the study area, results showed that the improved neural network model is a more ideal prediction model for predicting short-term groundwater level (Chi et al., 2008). Next wavelet analysis function was introduced to improve the node calculation of the traditional neural network model, the improved BP neural network model was applied in groundwater prediction in Xinjiang region, the prediction results were higher than the prediction accuracy of the traditional BP neural network model (Xie, 2016). Afterwards, an improved particle swarm algorithm was proposed to optimize the thresholds and weights of BP networks, a tailings dam groundwater level prediction model was established, the results showed that the model improved the prediction accuracy (Zhen et al., 2019). However, most of these groundwater prediction methods establish groundwater level prediction models considering only groundwater level autocorrelation or perform groundwater level prediction at a single monitoring station, which makes it difficult to obtain data directly affecting groundwater level changes when prediction is performed in a larger area and causes difficulties in prediction work. In order to solve the above problems, this paper proposes a BP neural network model based on particle swarm optimization to address the problems of slow convergence of BP neural network, easy to fall into local minimum and low prediction accuracy. The global search ability of the particle swarm algorithm is used to optimize the topology, connection weights and thresholds of the neural network, and the good global search ability of the particle swarm algorithm is combined with the good local search ability of the BP algorithm to improve the generalization ability and learning performance of the neural network, thus improve the overall search efficiency of the neural network.

In this paper, taking Xianyang city of Shaanxi province as an example, collecting meteorological data, socio-economic data and measured phreatic water depth data, then calculating the correlation between the three types of data, while establishing BP neural network based on PSO improvement .And the influencing factor with good correlation is selected as the input of groundwater phreatic water depth prediction, the groundwater depth of the current month is taken as the output to establish a phreatic water depth prediction model, and use this model to realize the prediction of phreatic water depth in Xianyang city.

## 2 OVERVIEW OF THE STUDY AREA

Xianyang City is located at the middle of the Guanzhong Basin, between 107°38′ and 109°10′ E longitude and 34°11′ and 35°32′ N latitude, and is a medium industrial city in Shaanxi Province with textile, electronic, and mechanical industries, which not only has a long history and culture, but also has a leading economic position in the province. Figure 1 is the geographic location map of the study area. The groundwater level in Xianyang City is in constant change, and it is most affected by human factors mainly extraction (Zhen, 2012). The water used for industrial and agricultural production, lives of urban and rural residents in Xianyang mainly comes from exploration of groundwater (He et al., 2012), and the groundwater has always accounted for more than 80% of the total water supply in the city, which is the most important source of water supply in Xianyang City (He et al., 2015). The long-term massive exploitation of groundwater has led to a continuous decline in the groundwater level, ground subsidence, ground fractures and other environmental geological problems, which have seriously affected city's industrial and agricultural production, even affect the lives of the people. Before the mid-1980s, the amount of groundwater mining in Fengdong general over-mining area of Qindu District was about $2500\times10^4 m^3/a$. Since the water source in the northwest suburbs of Qindu District was put into construction in 1989, the amount of groundwater mining in the area reached $3000\times10^4 m^3/a$, resulting in a sharp decline in the groundwater level. From 1987 to 1999, the water level of local lots had dropped from 8.10 m to 27.00 m, reaching the lowest water level in history. Ground subsidence in the urban area of Xianyang, the central part of the accumulated subsidence 13.4 ~ 25.7 mm, has formed 0.3 ~ 0.8 mm ground cracks in the north- east or nearly east-west direction, causing cracks in more than 20 buildings with width of the cracks 1.0 ~ 10.0 cm (Zhai, 2020). If the management of groundwater exploitation is not strengthened, the ground settlement, ground cracks, and building cracks will further deteriorate.

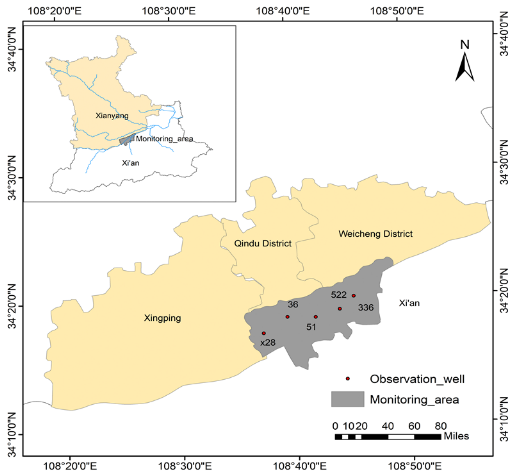


Figure 1: Location map of the study area.

## 3 MATERIALS AND METHODS

From the results of previous studies, it can be seen that the depth of phreatic water in the study area is mainly influenced by three major factors: meteorological factors, hydrological factors and human factors (Zhen, 2012), with hydrological factors as direct influencing factors, meteorological factors and human factors as indirect influencing factors. The direct influence factors of phreatic water depth were used to predict the phreatic water depth with high accuracy, but in some special cases, the actual condition to predict phreatic water depth will not ideal, there may be a lack of some runoff information, or the amount of groundwater extraction is difficult to obtain, increasing the difficulty of phreatic water depth prediction to some extent. In this paper, the correlation between non-direct influence factors and phreatic water depth is considered, established stochastic model by using uncertainty method according to correlation coefficient. The data materials used in this paper are socio-economic data, meteorological data and phreatic water depth data of Xianyang city (Tao et al., 2013). The socio-economic data include gross regional product and population data was obtained from the National Economic and Social Development Statistical Bulletin of Xianyang City from 2000-2015. The meteorological data include daily precipitation, sunshine hours, average air pressure, average temperature and average relative humidity of Xianyang City meteorological station (Qindu 57048) from 2000-2015 was selected from the national meteorological network (http://data.cma.cn/). The phreatic water depth data of Xianyang city was obtained from Shaanxi Province Groundwater Level Almanac. First used correlation analysis to identify the correlation between population, gross regional product, meteorological factors and phreatic water depth, then established PSO_BP neural network model, the influencing factor with good correlation is selected as the input of groundwater phreatic water depth prediction, the groundwater depth of the current month is taken as the output. The model is continuously trained, and the model parameters are saved when the output error reaches the set value. The model is the final predictive model and use this model to predict depth of phreatic water.

Due to the long-time span of the collected data, there are a number of missing data problems, and in addition, some of the collected data scales are not consistent with the required data scales. Therefore, scale conversion and interpolation of the collected data are needed to ensure data integrity and consistency. The gross production value is converted from annual to monthly scales using a simple arithmetic average method; the population data are interpolated according to the change trend, and the interpolation formula is:

$$Po_i = Po_{12} - \frac{1}{12}(12 - i)(Po_{12} - LPo_{12}) \qquad (1)$$

In the formula, $Po_i$ is the population in month $i$ of the year, $LPo_{12}$ is the population of the previous month of December. Unlike socioeconomic data, meteorological data are daily data, which are converted from small to large scales. The conversion of meteorological data from daily to monthly scales can be achieved with a simple statistical aggregation. Among the 5 elements of meteorological data, precipitation and sunshine hours can be converted by simply summing the daily values of each month; the remaining 3 elements need to be averaged over the months. The transformed and interpolated data are used as training data for the prediction model.

The dynamic groundwater monitoring in Xianyang City has been started since 1985, and the monitoring area is bounded by a line from Yanwang Village to Changxing Village East in the east, Xi'an City in the south, Xingping City in the west, and the Gao Gan Canal in the north, covering an area of about 160 km$^2$. 44 groundwater resource level monitoring points are available in the city, including 20 diving monitoring points, and the monitoring wells that meet the requirements are selected. x28, 36, 336, 51, and 522. 36, 336, 51, and 522 have complete observation data from 2000-2015, and the time interval of observation can also meet the requirements, so the phreatic water depth data of these five groundwater level observation wells are used for model validation.

# 4 CORRELATION ANALYSIS

In this paper, the prediction model is established using the uncertainty method, and the correlation between the depth of phreatic water and other factors is analyzed using the Spearman correlation analysis based on the advantages of current big data and considering the influence of other indirect factors on the depth of phreatic water. Table 1 is the analysis result of the correlation The correlation between the depth of phreatic water and other factors in Xianyang city varies, with the correlation coefficients of the five observation wells being larger than those of gross regional product (-0.838), population (0.742), precipitation (0.205), mean air pressure (-0.268), and mean air temperature (0.268). The correlation with precipitation (correlation coefficient of 0.205), mean air pressure (correlation coefficient of -0.268) and mean air temperature (correlation coefficient of 0.228) is small, and the correlation with mean relative humidity (correlation coefficient of 0.049) is very small and close to none. In general, the correlation between phreatic water depth and population and gross regional product is large, and the correlation with average relative humidity is small. The results of the correlation analysis are consistent with the actual situation of Xianyang City.

Table 1: Analysis result of the correlation.

| phreatic water depth | well36 | well51 | well336 | wellx28 | well522 |
|---|---|---|---|---|---|
| Population (ten thousand) | -0.498** | -0.068 | 0.742** | -0.433** | .532** |
| Gross regional product ( 100 million yuan) | -0.838** | -0.536** | 0.417** | -0.374** | 0.188** |
| Precipitation (mm) | 0.106 | 0.123 | 0.198** | 0.205** | 0.194** |
| Sunshine hours (hours) | 0.018 | 0.019 | 0.032 | 0.145* | 0.074 |
| Mean air pressure (hPa) | -0.082 | -0.176* | -0.190** | -0.234** | -0.268** |
| Average temperature (℃) | 0.077 | .0145* | 0.179* | 0.261** | 0.228** |
| Average relative humidity (%) | 0.049 | 0.001 | -0.009 | -0.011 | 0.003 |
| *. At the 0.05 level (two-tailed), the correlation is significant. | | | | | |
| **. At 0.01 level (two-tailed), the correlation is significant. | | | | | |

# 5 MODEL ESTABLISHMENT

## 5.1 BP Neural Network based on PSO Improvement

It has been mathematically demonstrated that BP neural networks have a strong nonlinear mapping capability, do not require an exact mathematical model, and are easy to utilize for implementation and computation. Let the input pattern of the network be $x = (x_1, x_2, .., x_n)^T$, the implicit layer has $q$ cells, The output of the implicit layer is $z = (z_1, z_2, .., z_q)^T$, the output layer has $m$ cells, their output is $y = (y_1, y_2, .., y_m)^T$, the target output is $t = (t_1, t_2, .., t_m)^T$, the transfer function from the implicit layer to the output layer is $f$, the transfer function of the output layer is $g$ (Zhou & Tao, 2015), This leads to the formula :

$$z_j = f\left(\sum_{i=1}^{n} w_{ij}x_i - \theta\right) = f\left(\sum_{i=0}^{n} w_{ij}x_i\right) \quad (2)$$

In the formula, $z_j$ denotes the output of the $j$-th neuron of the hidden layer, $w_{0j} = 0$, $x_0$=-1.

$$y_k = g\left(\sum_{j=0}^{q} w_{jk}\, z_j\right) \quad (3)$$

In the formula, $y_k$ denotes the output of the $k$-th neuron of the output layer. The error between the network output and the target output at this point is:

$$\varepsilon = \frac{1}{2}\sum_{k=1}^{m}(t_k - y_k) \quad (4)$$

Particle swarm algorithm can converge to the global optimal solution with higher probability, with faster computation speed and better global search capability (Gao & Li, 2012). Suppose there are N particles forming a cluster in a D-dimensional target search space, where the $i$-th particle is represented as a D-dimensional vector:

$$X_i = (x_{i1}, x_{i2}, \dots, x_{in}), \mathrm{i} = 1,2, \dots \mathrm{N} \tag{5}$$

The "flight" velocity of the$i$-th particle is also a D-dimensional vector, denoted as:

$$V_i = (v_{i1}, v_{i2}, \dots, v_{in}), i = 1,2, \dots N \tag{6}$$

The optimal position searched by the $i$-th particle so far is called the individual extreme value, denoted as:

$$P_{best} = (P_{i1}, P_{i2}, \dots, P_{iD}), i = 1,2, \dots, N \tag{7}$$

The optimal position searched by the whole particle swarm so far is the global extremum, denoted as:

$$G_{best} = (p_1, p_2, \dots, p_D) \tag{8}$$

$c_1, c_2$ is the learning factor, also known as acceleration constant; $v_{ij}$is the velocity of particle $i$, $v_{ij} \in [v_{imin}, v_{imax}]$; $x_{ij}$ is the position of particle $i$, $x_{ij} \in [v_{imin}, v_{imax}]$.

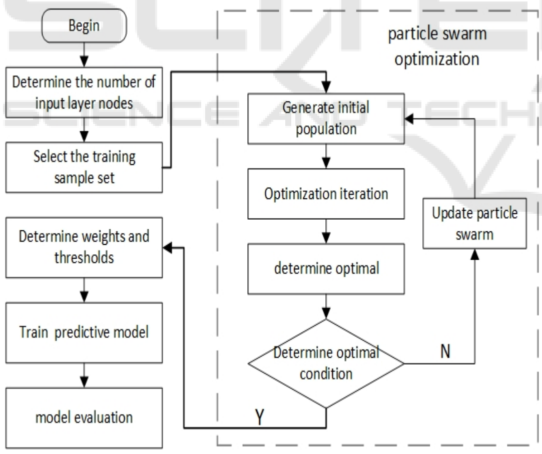


Figure 2: Flowchart of PSO optimized BP neural network algorithm.

The principle of PS0 to improve BP neural network is to use the global search ability of PSO to get the optimal individual to assign the initial weights and thresholds to the BP neural network. The output error of the training sample set through the neural network is passed to PSO to establish the adaptation function, and the adaptation function is used to calculate the adaptation values of the population and individuals, and when the adaptation value reaches the optimal adaptation value, the search is stopped and the optimal value is input to the BP neural network part, and finally the neural network prediction is performed by the optimal initial threshold and weights.

The neural network construction is divided into 3 parts, which are network structure determination, particle swarm algorithm optimization, and neural network prediction. The flow chart is as follows (Figure 2).

## 5.2 Model Building

As previous experience, bp neural network generally chooses one input layer and one output layer. According to the results of the correlation analysis in section 4, six elements with greater correlation, namely, regional gross product, population, precipitation, average air pressure, sunshine hours and average temperature data were selected as the input of the model, i.e., one layer of network input, the number of nodes was 6, and the output result is the phreatic water depth data. The collected data is divided into 2 groups, these data of each month from 2000 to 2013 were used to train the model called training sample sets, and the 2014-2015 data for each month were used to test the model called the test sample set. And the final PSO-BP neural network model was constructed through repeated training sample set data. Here are the data of 5 observation wells, so there are 5 sample sets ,the training sample set of five observation wells was repeatedly trained, and the training was stopped when the predicted phreatic water depth variation process of the model was consistent with the measured value and the relative percentage error was less than 5%, and the population size of the PSO algorithm was finally determined to be 20, the number of evolution was 100, and the convergence factor was selected as the empirical value $c_1 = c_2 = 1.49445$ The number of hidden layer nodes for BP network training is 10, the number of iterations is set to 40, and the learning rate is 0.1.

# 6 MODEL PREDICTION RESULTS AND DISCUSSION

The trained PSO-BP neural network model will simulate the variation of the burial depth of the 5 observation wells and the changes between the elements, and then obtain the predicted data of each observation well and output the results, in order to visually display the prediction results of the 5 observation wells, the prediction result data is displayed in the form of a line graph, and for the convenience of comparison, the measured data is also displayed together. The comparison results between the predicted and measured values are shown in Figure 3(a-e).

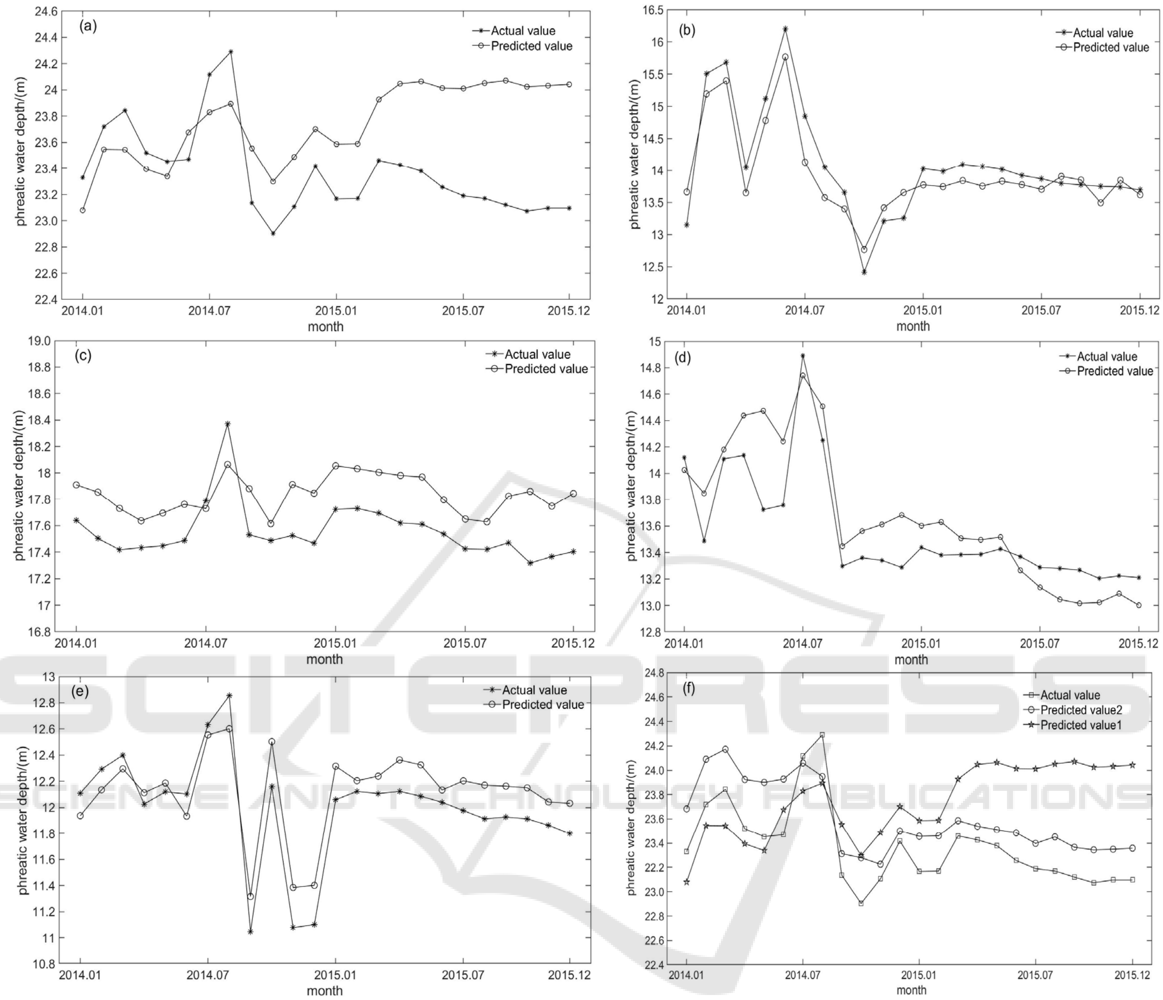


Figure 3: Comparison of measured and simulated values from observation wells.



In order to quantify the accuracy of the model in groundwater diving burial simulation, three evaluation metrics were used in this study, namely root mean square error RMSE, mean absolute error MAE mean absolute percentage error MAPE. RMSE reflects the deviation between the predicted value and the measured value. MAE is the average of the absolute error, which can reflect the actual situation of the prediction value error. MAPE is the mean absolute percentage error. The specific calculation formula is as follows:

$$RMSE = [\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2]^{1/2} \tag{9}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \tag{10}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{11}$$

In the formula, $n$ is the total number of samples, $y_i$ is the actual value of the $i$-th sample, and $\hat{y}_i$ is the predicted value of the $i$-th sample. The results are shown in Table 2.

The model was used to predict the phreatic water depth of five observation wells in Xianyang City, and it can be seen from Figure 3(a-e) that the model can output complete prediction data of phreatic water depth, and the prediction results are generally consistent with the trend of the measured values of phreatic water depth of five observation wells. On the whole, although the model has some relative errors, it can predict the trend of phreatic water depth more accurately. The relative percentage error between the prediction results and the measured values was no more than 2.5%, and the largest error was in observation well 36(Figure 3a), with a relative percentage error of 2.18%. The best prediction results were obtained for observation well x28(Figure 3d) and observation well 522(Figure 3f), with relative percentage errors of 1.69% and 1.65%, respectively, which is consistent with the correlation analysis of the six factors with the phreatic water depths of observation wells x28(Figure 3d) and 522(Figure 3f). Observation well 36(Figure 3a) and observation well 51(Figure 3b) showed poorer predictions than the other observation wells, which may be due to the poor correlation between the selected input factors and the subsurface phreatic water depths.

Table 2: Simulation evaluation results.

| | RMSE | MAE | MAPE |
|---|---|---|---|
| well36 | 0.58007 | 0.50764 | 2.18% |
| well51 | 0.32285 | 0.28605 | 2.02% |
| well336 | 0.32120 | 0.30588 | 1.74% |
| wellx28 | 0.27284 | 0.22866 | 1.69% |
| well522 | 0.21226 | 0.19682 | 1.65% |

The main influencing factors of phreatic water depth of each observation well are different, and the prediction with too many unrelated factors as training models does not get better prediction results. Since observation well 36 is only significantly correlated with population and gross regional product, for observation well 36, the model is adjusted to select population, gross regional product, precipitation, and mean air pressure as model inputs, and the model training parameters are adjusted to predict the variation pattern of observation well 36, as shown in Figure 3(f), and the RMSE of the model is 0.35297 and the MAE is 0.33711, with an average absolute error of 1.45%. This is 0.73% less than the average absolute error of using the previous six factors as model inputs, and the trend of phreatic water depth variation is more accurately portrayed. The five monitoring wells are all in the same hydrogeological unit, and the distance between all the wells is not large, if only based on the hydrogeological conditions, the input variables of the PSO_BP model for the five monitoring wells are the same, but the significant factors selected by correlation analysis are input to the model, and a better prediction effect is achieved. Therefore, the model should be combined with quantitative methods to achieve better prediction results.

# 7 CONCLUSION

This paper studied the prediction of phreatic water depth in the absence of subsurface phreatic water depth information, takes Xianyang City as the study area, analyzed the correlation between phreatic water depth and other factors, selects factors with significant correlation such as population, gross regional product and precipitation to build a phreatic water depth prediction model, and uses PSO-BP neural network for prediction, the main conclusions are as follows:

- The correlation between phreatic water depth, socio-economic factors and meteorological factors was analyzed by Spearman's correlation analysis, and the results showed that the correlation between phreatic water depth and population and gross regional product in Xianyang City was the most significant, and the correlation with average temperature and precipitation was small, and the correlation with average relative humidity was extremely small.
- The groundwater burial depth prediction model based on correlation combined with PSO_BP neural network was established to predict the test samples, and the prediction results have the same trend with the actual measured data, and the model has high accuracy and good stability.
- In the prediction of phreatic water depth, the accuracy of the predicted results is higher for the influence factors with high correlation input, and it is extremely important to consider different influence factors on the prediction of phreatic water depth.

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