Establishment of Wheat Yield Prediction Model in Dry Farming Area Based on Neural Network

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ABSTRACT

The accurate prediction of wheat yield based on the wheat yield data of the previous years can help to balance the relationship between market supply and demand and formulate appropriate purchase price and make allocation plans, which has important practical significance for the study of national economic industrial structure. This study proposes an artificial neural network model for wheat yield prediction by simulating the information processing mode of brain neural network and combining the characteristics of wheat yield data in dry farming areas, uses IOWA operator to establish a prediction model combining BP, RBF, and GRNN neural network models, and conducts an empirical study on the models. The results show that the average error rate of BP, RBF, GRNN and IOWA-based combined neural network model is less than 10%, and the error rate of the combined prediction model is the smallest, suggesting that these four kinds of neural network models have a satisfactory effect on wheat yield prediction and the combined neural network prediction model has a better accuracy and effect for wheat yield prediction in the dry farming areas, providing an important theoretical basis for the accurate prediction of wheat yield in dry farming areas in the future.

Key Words: BP Neural Network, RBF Neural Network, GRNN Neural Network, Wheat Yield, Combined Prediction Model

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Introduction

As the reform and opening-up proceeds, the government's investment in rural science and technology innovation is increasing, and the preferential policies for agriculture are continuously released, laying a foundation for the increase of wheat yield and income in rural areas. The dry farming area is the major region for wheat production in China, wherein a series of agricultural policies have been introduced, such as increasing capital and technological inputs, adjusting minimum grain purchase prices, adoption of new mechanized equipment and quality, and the use of green production technologies. The introduction of these appropriate policies is based on the wheat yield data of the previous years and future wheat yield prediction data. Therefore, research on wheat yield prediction has certain practical significance.

China is facing a structural contradiction between the increase in population and the reduction in the area of cultivated land. Wheat yield is not only an agricultural issue, but it is also closely related to the economic development of the country and the living standard of the residents. Thus, whether the yield of wheat can meet the daily needs of the people is an important issue that the government is concerned about. However, since wheat yield is greatly affected by the environmental climate, it is impossible to determine (Jacobs, 1988; Clark and Mccracken, 2009; Kapetaniosa *et al.*, 2008). To make more accurate predictions on wheat yield with purpose to balancing the relationship between supply and

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demand in the market is the basic guarantee for formulation of purchase price, allocation plan and storage and transportation. In the studies on the grain yield prediction, time series model and regression model are more commonly used, in addition to remote sensing technology model, climate production model, input-output model, and gray theoretical model, (Zou *et al*., 2007; Aßmann *et al*., 2009; Shukla and Jharkharia, 2013) which predict the output of grain from different angles respectively. With certain non-linear and non-local characteristics, the neural network simulates the way the brain operates and can well deal with the problems of uncertainty, unknown ambiguity, and multiple condition factors (Mainland, 2010; Yang, 2015; Chen, 2014). For example, the threshold setting is used to simulate the cell's inhibition and excitation state, and the neural network structure composed of basic building blocks is used to simulate the connection and hierarchical structure of cells. Therefore, it is widely used in grain yield prediction. Liu Xiaobin's nonlinear multi-layer feedforward neural network combined model improves prediction accuracy (Hongzhi *et al*., 1997). Zou combines the AMIMA model and the neural network model, and uses the combined model to predict the price of wheat in China, which proves that the combined model has better prediction effect (Zou *et al*., 2007).

Therefore, as for the wheat yield prediction in dry farming area, this study selects the data of wheat yield in dry farming area of China as the samples, constructs wheat yield prediction models using BP, RBF and GRNN neural networks, and carries out yield prediction and analysis respectively in combination with the actual situation. In addition, three kinds of neural network models are combined based on IOWA operator, and the prediction results of the combined model are compared with those of these single neural networks, thus to select the neural network models suitable for wheat yield prediction.

Neural Network System

Neural networks have been developed to deal with complex problems such as non-linearity through the learning of external data knowledge, and its development begins with the neuron model proposed by Mc Culloch and Pitts with biological cell inhibition and excitatory response. In addition, Grossberg's adaptive resonance theory proposed based on the law of information processing in psychology and biology has a far-reaching impact on the development of neural networks (Igathinathane and Chattopadhyay, 1997). The characteristics of neural network make it to become a kind of intelligent information processing system simulating the work of human brain, and a tool for human to study the mystery of brain.

Neural model

Biological cells are the material basis of neural networks. The neurons simulate the basic operating rules of human biological nerve cells, and the tiny neurons constitute a huge neural network structure system through different connection and combination methods. The system has nonlinear and adaptive information processing capability, as shown in Figure 1.

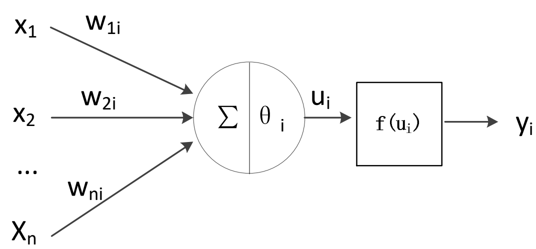

Figure1. A schematic diagram of the neuron model

Where, x represents the source of information, the input of neurons; w represents the transfer efficiency between neurons, which is the weight coefficient, θ represents the threshold of the neuron, f represents the mathematical model function of the neuron delivery efficiency, and y represents the output of the neurons.

The transfer function is the core part of neuron, which mainly includes step transfer function (discrete output model), linear transfer function (linear continuous model) and S transfer function (nonlinear continuous model). Assuming $u = \sum_{i=1}^{n} w_{ji} x_j - \theta_i$, then the three transfer function formulas are:

step transfer function (discrete output model):

$$f(u_i)=\begin{cases}1, & u_i\geq 0\\ 0, & u_i<0\end{cases} \quad (1)$$

linear transfer function (linear continuous model):

$$f(u_i)=ku_i \quad (2)$$

S transfer function (nonlinear continuous model):

$$f(u_i)=\frac{1}{1+e^{-u_i}} \tag{3}$$

Structure of neural network

The neural network structure is composed of neurons connected by such different topological structures, as single-layer forward network, forward network with feedback, forward network combined with each other in the layer, and interconnected network.

(1) Single-layer forward network: it consists of the input layer that only receives from the previous layer, with no feedback signal, as shown in Figure 2.

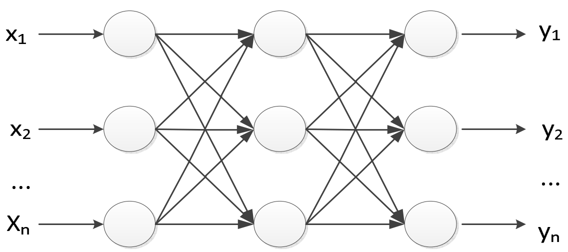

Figure 2. Single-layer forward network

(2) Forward network with feedback

Forward network with feedback: It consists of an input layer, a hidden layer, and an output layer, which has a forward information feedback mechanism, as shown in Figure 3.

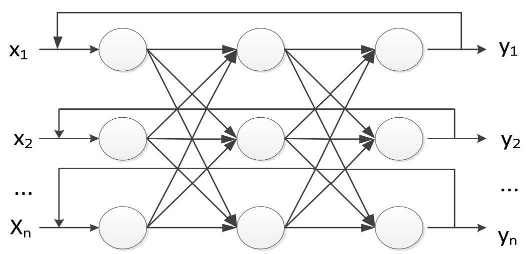

Figure 3. Feedforward network with feedback

(3) Forward network combined with each other in the layer: It adopts horizontal connections and can suppress or excite reactions at the same time, as shown in Figure 4.

(4) Interconnected network: Neurons are connected in two ways: local connection and global connection, as shown in Figure 5.

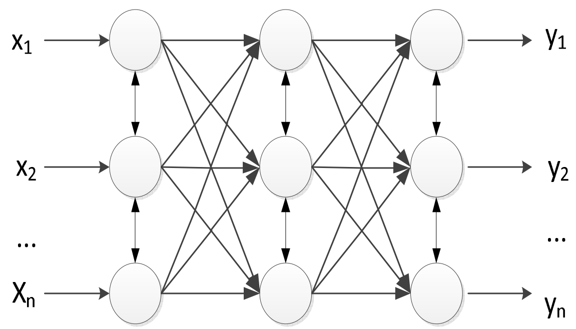

Figure 4. Forward network combined with each other in the layer

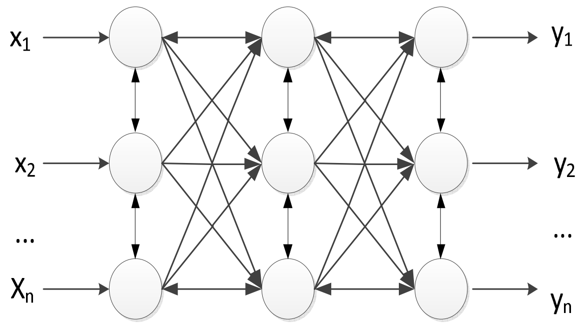

Figure 5. Interconnected network

Prediction modeling and data preparation

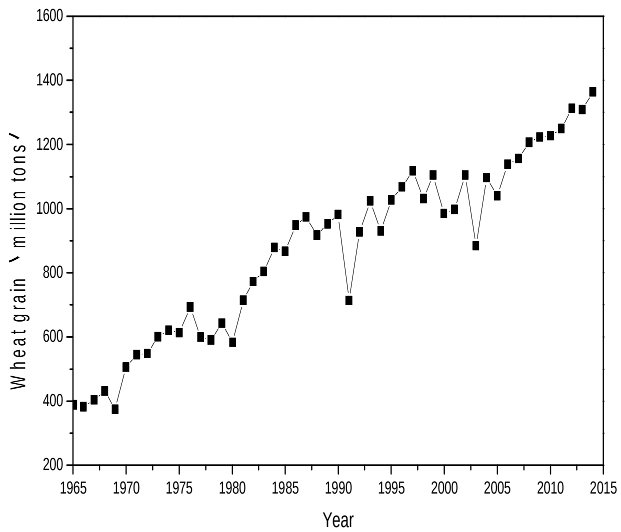

Figure 6. Wheat yield from 1965 to 2014 year in dry farming areas

Since wheat yield has a nonlinear variation and long-term memory characteristics, it can be predicted (Lv, 2013; Choyakh, 2008; Weir, 1991). In this study, BP, RBF and GRNN neural networks are used to train and predict wheat yield in dry farming areas, and these models are compared with each other by error. The wheat yield in the drying farming area during 1965-2014 is selected for model prediction, wherein the data of 1965-2007 is used as the network training sample, and the data of 2008-2014 is used as a forecast sample, as shown in Figure 6.

Prediction of Wheat Yield Based on Neural Network

BP neural network

BP neural network utilizes the principle of error back propagation to back-propagate the difference between input and output to the entire network, and obtains optimal results through repeated learning. The specific training flow is as shown in Figure 7.

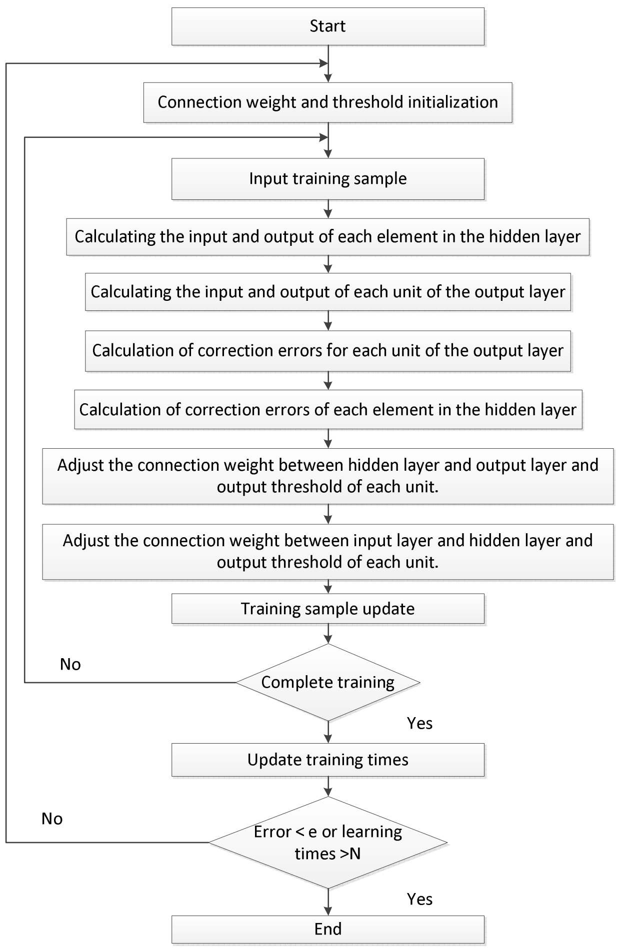

Figure 7. BP network training flow chart

(1) Design of input and output quantities

Assuming that the autocorrelation coefficient R (k) of the time series delayed by k steps of wheat yield in dry farming areas is:

$$R(k)=\frac{\sum_{i=k+1}^{n}\left[x^{*}(i)-h_x\right]\left[x^{*}(i-k)-h_x\right]}{\sum_{i=1}^{n}\left[x^{*}(i)-h_x\right]^2} \tag{4}$$

$$h=\frac{\sum_{i=1}^{n}x^{*}(i)}{n} \tag{5}$$

Based on the autocorrelation analysis of wheat yield data in the dry farming areas, the number of delayed steps is selected as 3, and the input and output matrix of the BP neural network are constructed.

(2) Design of the hidden layer

The determination of the hidden layer node is to determine the initial range first based on the reference formula, and then to use the trial and error method to change the hidden layer nodes continuously until the optimal number of nodes is determined.

$$l<n-1 \tag{6}$$

$$l<\sqrt{m+n}+a \tag{7}$$

$$l=\log_2^n \tag{8}$$

$$l=2n+1 \tag{9}$$

Since the number of input layers and output layers in the neural network structure is 1, it can be determined that the initial number of hidden layers is 3-10 according to the above Formulas (6) to (9), and the trial and error results are shown in Table 1.

As can be seen from Table 1, when the number of hidden layer nodes is 10, the error of the BP neural network model after training for 10,000 times is the smallest, which is 0.0025, and the neural network has the best generalization ability.

Table 1. Hidden layer nodes try to make up the results

Number of neurons	3	4	5	6	7	8	9	10
Network error	0.0073	0.0061	0.0053	0.0050	0.0048	0.0044	0.0026	0.0025

(3) Prediction of BP neural network

From the above, it can be seen that the BP neural network model established in this study is a single-layer hidden layer, whose number of both input and output nodes is 1 and number of hidden layer nodes is 10. A frequency of 10,000, a rate of 0.5, and a target of 0.001 are selected for the training of wheat yield data from 1965 to 2007, and the results are shown in Figure 8. The wheat yield from 2008 to 2014 is predicted by using the trained BP neural network model, and the results are as shown in Figure 9.

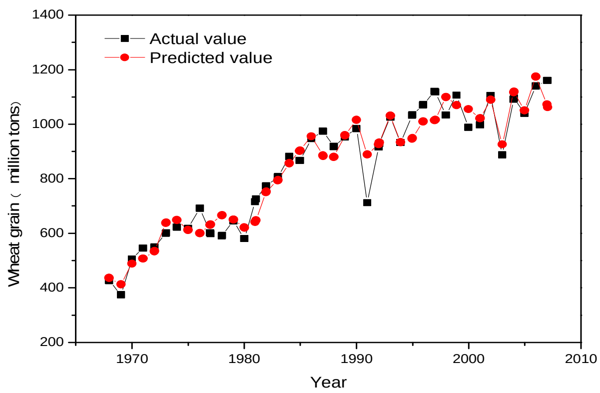

Figure 8. BP neural network training sample results

As can be seen from Figures 8 and 9, the predicted values in both the training sample and the test sample are in good agreement with the actual values except for some individual values that are slightly inconsistent, showing that BP neural network wheat yield prediction model has a good prediction effect. The error analysis between the predicted values and the actual values is shown in Table 2, from where it can be seen that the average error of prediction is 6.8%, less than 10%, suggesting that it is feasible to use BP neural network model to predict wheat yield.

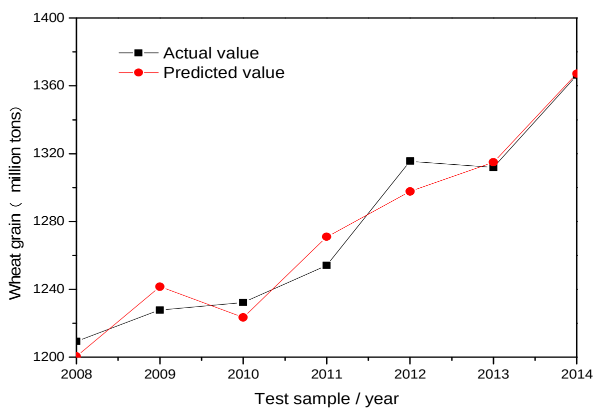

Figure 9. Test sample results of BP neural network

Table 2. Prediction error of BP neural network

Year	Actual value	Predicted value	Absolute error	Relative error
2008	1209.3	1200.5	-0.220	-0.729
2009	1227.9	1241.6	0.340	1.109
2010	1232.2	1223.5	-0.218	-0.706
2011	1254.2	1271.0	0.420	1.339
2012	1315.6	1297.8	-0.445	-1.354
2013	1311.8	1314.9	0.077	0.236
2014	1366.3	1367.2	0.023	0.066

Prediction of RBF neural network

RBF neural network is a kind of radial basis neural network after introducing radial basis function by simulating the local response characteristics of biological neuron cells.

By adjusting the parameters through nonlinear processing, and setting the SPREAD of the neural network as 0.3 and the number of nodes in the hidden layer as 40, the wheat output data from 1965 to 2007 are trained. The results are shown in Figure 10. After 30 times of training, the mean square error is 0.0024, which means the model is feasible at this time. Then the wheat yield from 2008 to 2014 is predicted by using the trained RBF neural network model, and the results are shown in Figure 11.

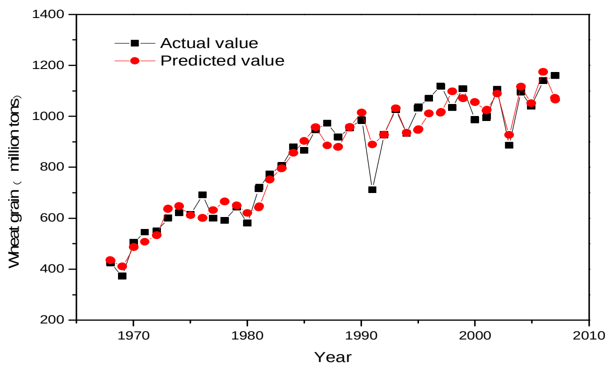

Figure 10. RBF neural network training sample results

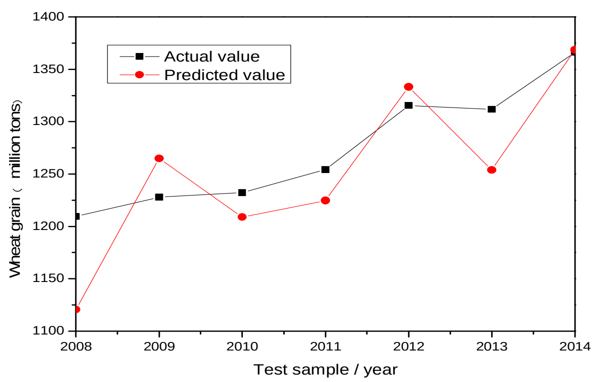

Figure 11. Test sample results of RBF neural network

Table 3. Prediction error of RBF neural network

Year	Actual value	Predicted value	Absolute error	Relative error
2008	1209.3	1120.5	-0.523	-1.833
2009	1227.9	1264.8	0.105	0.363
2010	1232.2	1208.8	-0.015	-0.050
2011	1254.2	1224.7	-0.086	-0.279
2012	1315.6	1333.3	0.040	0.129
2013	1311.8	1253.8	-0.016	-0.052
2014	1366.3	1368.7	0.001	0.004

As can be seen from Figures 10 and 11, the predicted values in both the training sample and the test sample are in good agreement with the actual values except for some individual values that are slightly inconsistent. The error analysis between the predicted value and the actual value is shown in Table 3, from where it can be seen that the average error of prediction results is 5.25%, which is less than 10%, indicating that RBF neural network has a good prediction effect.

GRNN neural network

GRNN neural network belongs to RBF neural network, which is produced by combining radial basis neurons and linear neurons and has strong non-linear mapping ability, certain fault tolerance and robustness. It can better deal with nonlinear problems and unstable data.

Through the design and verification of GRNN neural network parameters, the SPREAD of neural network is selected to be 0.1 for the training of the wheat yield data from 1965 to 2007. The results are shown in Figure 12. The trained GRNN neural network model is used to predict the wheat yield from 2008 to 2014, and the results are shown in Figure 13.

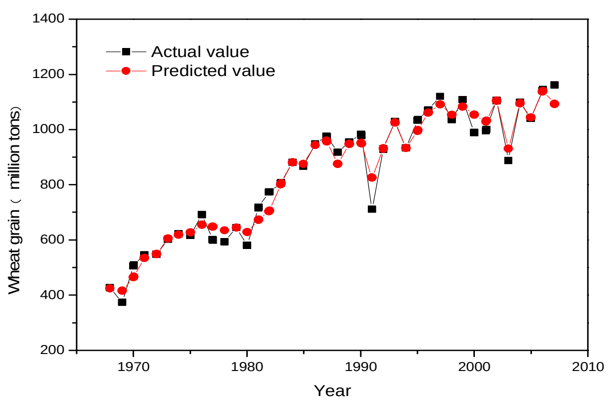

Figure 12. GRNN neural network training sample results

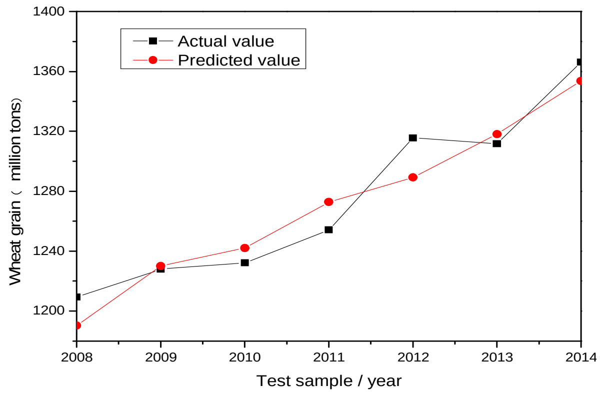

Figure 13. Test sample results of GRNN neural network

As can be seen from Figures 12 and 13, the predicted values in both the training sample and the test sample are in good agreement with the actual values, which means the prediction performance is favorable. The error analysis between the predicted values and the actual values is shown in Table 4, from where it can be seen that the average error of the prediction results is less than 6%, indicating that it is feasible to use the prediction model based on GRNN neural network model to predict wheat yield.

Table 4. Prediction error of GRNN neural network

Year	Actual value	Predicted value	Absolute error	Relative error
2008	1209.3	1190.3	-0.475	-0.016
2009	1227.9	1230.0	0.050	0.002
2010	1232.2	1242.0	0.246	0.008
2011	1254.2	1272.8	0.465	0.015
2012	1315.6	1289.3	-0.658	-0.020
2013	1311.8	1318.1	0.156	0.005
2014	1366.3	1353.7	-0.315	-0.009

Combined Prediction of Grain Yield Based on IOWA Operator

Due to the complexity of the prediction environment, a single model often leads to incompleteness of predicted information. Therefore, a combined prediction model is established by weighting and combining the above single prediction models, which can retain the independence of the individual prediction models, ensure the integrity of the predicted information, and improve the reliability of the prediction performance.

Combined model and its prediction

IOWA operator combined prediction is to use the weighted average method of total error to determine the weighted average coefficient, so as to obtain a satisfactory prediction effect. The

Table 5. Prediction accuracy of neural network prediction models at different time points

Number	1	2	3	4	5	6	7
a_{1t}	0.778	0.658	0.781	0.578	0.553	0.921	0.975
a_{2t}	0.475	0.893	0.983	0.912	0.958	0.982	0.997
a_{3t}	0.523	0.948	0.752	0.533	0.840	0.842	0.683

Table 6. Predicted value of four neural network prediction models (unit： million tons)

Year	Actual value	Predicted value of BP neural network	Predicted value of RBF neural network	Predicted value of GRNN neural network	Predictive value of IOWA operator combined model
2005	1042.1	925.7	1052.2	1042.6	1059.2
2006	1141.5	962.6	1175.4	1139.1	1159.7
2007	1160.6	1042.0	1073.4	1092.8	1104.8
2008	1209.3	1200.5	1120.5	1190.3	1199.3
2009	1227.9	1241.6	1264.8	1230.0	1237.9
2010	1232.2	1223.5	1208.8	1242.0	1251.1
2011	1254.2	1271.0	1224.7	1272.8	1280.8
2012	1315.6	1297.8	1333.3	1289.3	1296.4
2013	1311.8	1314.9	1253.8	1318.1	1329.0
2014	1366.3	1259.2	1368.7	1353.7	1357.0

formula of wheat yield model in dry farming area can be expressed as:

$$\hat{Y}_{T+N}=IOWA\left(\begin{matrix}<\bar{a}_1(T),y_{2\,T+N}>,\\<\bar{a}_2(T),y_{3\,T+N}>,<\bar{a}_3(T),y_{3\,T+N}>\end{matrix}\right) \quad (10)$$

Substitute the prediction accuracy of each neural network (Table 5) into Formula (10), the model formula is obtained as follows:

$$\min S(w_1,w_2,w_3)=523.47w_1^2+13.65w_1w_2+213.47w_2^2+89.22w_1w_3+179.25w_3^2+42.32w_2w_3 \quad (11)$$

$$s.t.\begin{cases}w_1+w_2+w_3=1\\w_i\geq 1,\ \ i=1,2,3\end{cases} \quad (12)$$

It can be seen that the optimal weight coefficients are 0.1586, 0.2041, and 0.637, which are substituted into the IOWA operator combined prediction formula to obtain the predicted values at different time points, as shown in Table 6.

Model evaluation

(1) The comparison of the predicted and actual values of the four neural network prediction models is as shown in Figure14. It can be seen from the Figure that the BP neural network model has the lowest proximity and the IOWA combined prediction model has the highest proximity, which is superior to that of the single prediction models, indicating that the prediction result of the combined model is more reliable.

(2) Error comparison

In order to further evaluate the advantages and disadvantages of the combined model, the errors of the four neural network prediction models are calculated and compared respectively, and the results are shown in Table 7.

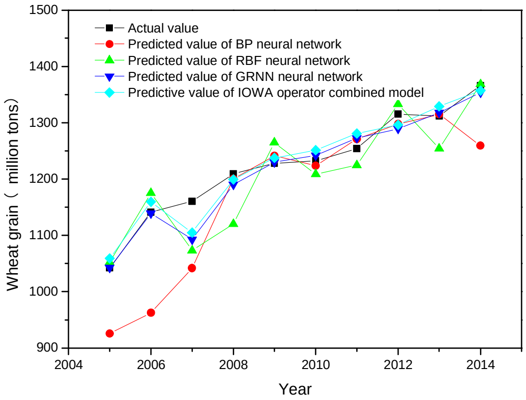

Figure 14. Predicted values of four neural network prediction models

Table 7. Model error comparison

Model	MAE	RMSE	MSPE	MAPE
BP	87.212	122.34	0.041	4.2%
RBF	74.058	117.99	0.009	3.5%
GRNN	56.058	81.44	0.004	2.7%
IOWA	33.198	62.72	0.002	1.5%

It can be seen from Table 7 that the MAE, RMSE, MSPE and MAPE of the IOWA operator combined prediction model are smaller than those of the single neural network prediction models, suggesting that the IOWA combined neural network model has the best effect and a higher accuracy in predicting the wheat yield in the dry farming areas, thus it is a superior combined prediction model. In addition, the mean absolute percentage error (MAPE) of all the models is less than 10%, which indicates that the application of neural network model in wheat yield prediction is feasible.

Conclusions

China faces the structural contradiction between the increase of population and the decrease of cultivated land area, which will restrict the development of economy and the improvement of people's living standard. The accurate prediction of wheat yield based on the wheat yield data of the previous years can help to balance the relationship between market supply and demand, formulate appropriate purchase price and make allocation plans, which has important practical significance for the study of national economic industrial structure. Through the analysis of the functions of biological neural networks, simulation of the working methods of brain neural networks, and combination with the data characteristics of wheat yield in dry farming areas, the present study first establishes the artificial wheat yield prediction model based on neural networks, and then uses IOWA operator to establish a prediction model combining BP, RBF, GRNN neural network models, and conducts an empirical research on the prediction model.

(1) The prediction models based on BP, RBF, and GRNN neural networks are established, with the wheat yield data from 1965 to 2007 used for training, and the wheat yield data from 2008 to 2014 used to analyze the prediction of the models. The results show that the average errors of BP, RBF and GRNN neural network models are all less than 10%, indicating that the three neural network models have a satisfactory prediction effect on wheat yield.

(2) Among BP, RBF and GRNN neural network models, BP neural network model has slow convergence and random weight, threshold and network structure. The determination of the optimal hidden layer of the RBF neural network model cannot be guaranteed, and it takes a lot of time to determine the number of hidden layer nodes. It is easy for the convergence result of local minimum to occur to the GRNN neural network model.

(3) The three neural network models BP, RBF and GRNN are weighted by the IOWA operator to obtain the combined neural network wheat yield prediction model based on the IOWA operator. Through the comparison of the four models, it is found that the MAE, RMSE, MSPE, and MAPE of the combined prediction model are smaller than those of the single neural network prediction models, suggesting that the IOWA combined neural network model has the best effect and a higher accuracy in predicting the wheat yield in the dry farming areas, thus it is a superior combined prediction model.

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