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Research Article

Prediction of Agricultural Water Consumption in 2 Regions of China Based on Fractional-Order Cumulative Discrete Grey Model

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In this paper, a new forecasting method of agricultural water demand, fractional-order cumulative discrete grey model, is proposed. Firstly, the best fitting of historical data is used to construct the optimization model. MATLAB programming is applied to solve the optimization model and obtain the optimal order. Secondly, the fractional-order cumulative discrete grey model in this paper is compared with GM (1, 1) model to verify the performance of the model. Finally, Handan region of Hebei Province and Jingzhou region of Hubei Province were selected as the study areas to predict their agricultural water consumptions. The results show that the fractional-order cumulative discrete grey model has better prediction performance than the GM (1, 1) model. It can be used as an effective method for forecasting agricultural water consumption.

1. Introduction

Water is an important basic resource and necessity for agricultural production. Affected by regional and natural environment changes, the contradiction between supply and demand of water resources in various regions in China is prominent, which seriously affects the process of economic development in various regions. The key to solve the contradiction between the supply and demand of water resources lies in the accurate prediction of water demand. There are few historical data of agricultural water consumption, and it is affected by many factors, such as economic development level, agricultural structure adjustment, natural climate conditions, and irrigation management level, which shows great randomness and fluctuation between years.

The prediction of agricultural water consumption is an important part of the optimal allocation of regional water resources, and it is the basic work to realize the optimal scheduling of regional water supply. Accurately predicting of regional water consumption is the key to the optimal allocation of water resources in the region. There are many forecasting methods of agricultural water consumption, including principal component analysis method, index analysis method, regression analysis method, grey prediction method, and artificial neural network method.

There are few historical data of agricultural water consumption in general areas. The purpose of this study is to select one forecasting method reasonably and collect the required data for effective forecasting based on the changing law of water consumption. In this paper, based on the existing literature review results and the research focus of the sustainable development of the water resource-environment-economy-society system, a fractional discrete grey model is proposed to predict the agricultural water demand.

The rest of the paper is organized as follows. Literature review is introduced in Section 2. The proposed method, including DGM (1, 1) model and $\mathrm{DGM}^{p/q}(1,1)$ model, is introduced in Section 3. A numerical example is illustrated in Section 4, and conclusions are discussed in Section 5.

2. Literature Review

2.1. Research on Forecasting Methods of Agricultural Water Consumption. Agricultural water consumption is the focus and hotspot in the field of water resources research, but the influencing factors of water consumption are many, and the research methods are endless.

In the research of agricultural water demand forecasting, more scholars are devoted to integrating forecasting methods into concrete practice. Fu et al. [1] applied the back propagation neural network model to predict regional water demand. The quota quantitative method is used to predict and analyze water demand in Zhengzhou region and Aksu region [2, 3]. Lv et al. [4] used principal component analysis to find out the main influencing factors of domestic water, industrial water, and agricultural water in Sichuan Province; they also use regression analysis to model and predict the three aspects of water consumption. Wen et al. [5] used the trend surface analysis method to predict agricultural water demand.

However, the prediction accuracy of each method above is not ideal. The quota method is mainly based on crop characteristics and current irrigation quota, but the preparation of irrigation quota has certain subjectivity and uncertainty. Therefore, it is difficult to achieve accurate prediction by the quota method. The back propagation neural network method requires a large number of data for model training, and there is also the problem of overfitting. Autoregressive and moving average model have high requirements for data stability. Since the actual water consumption series do not fully conform to the exponential relationship, it also limits the application range of the exponential model method. The trend surface analysis requires that the selected trend surface model is not enough, and the fitting accuracy may not reach sufficient accuracy.

2.2. Grey Model Research. Since Professor Deng [6] proposed grey system theory, the grey prediction model has been widely used in industry, agriculture, water conservancy, geology, science and education, military, and many other fields. The grey model is a method to study the "poor information," "small sample," and uncertainty problems, which requires less data and has simple principle. Among them, the GM (1, 1) model is the most widely used model [7]. It is mainly for single-variable systems. The randomness of the weakening sequence is generated by accumulation to find the change law of the system. Based on this, the prediction model of time is established.

After more than 20 years of development, scholars have studied the grey prediction model from different aspects, and these research results have greatly promoted the development of the grey model.

Shu-Hui et al. [8] forecasted agricultural water consumption based on the GM (1, 1) model. Zhang [9] predicted the agricultural water consumption in Korla region based on the GM (1, 1) model. Xiao et al. [10] studied agricultural water use in Shaanxi based on the uncertainty grey model. Zhao et al. [11] predicted agricultural water consumption in Shiyang River Basin based on a combined model. Jiang et al. [12] based on regression analysis and grey model GM (1, 1) method predicted the water demand of Minqin County. Li et al. [13] predicted agricultural water consumption in Tongliao and Baoji by using the fractional-order reverse accumulation grey model.

However, with the expansion of the application scope of the grey prediction model, various new problems emerge one after another, and it is necessary to do more extensive research on the GM (1, 1) model. Since the fractional-order calculus is proposed by Leibniz in 1965, it has shown strong vitality and superiority in control theory, image processing, and other aspects. It is the extension of the integer-order calculus in the usual sense to the fractional-order calculus. Compared with GM (1, 1), the fractional-order grey model improved the prediction accuracy.

To sum up, scholars have carried out different degrees of research on agricultural water consumption in different regions, but a generally accepted viewpoint has not been formed in the research on forecasting methods of water consumption, and there are still shortcomings as follows:

(1) The forecasting methods of agricultural water consumption all have their defects, especially the qualitative research methods are mixed with a few personal subjective factors, so it is necessary to adopt objective methods to reduce the impact of subjective factors and determine the importance of research methods for forecasting.

(2) There are few historical data of agricultural water consumption in general areas, and it is affected by many factors at the same time which is oscillatory. Therefore, it is applicable to use the grey model to predict agricultural water consumption. However, the prediction results show the approximate exponential growth patterns, which is only suitable for short-term prediction. Although researchers have improved and optimized the GM (1, 1) model in many ways, they cannot overcome the inherent error of the grey model from discrete estimation to continuous prediction.

Therefore, based on the idea of the discrete grey model, this paper constructs a kind of direct discrete grey model—fractional accumulated discrete grey model—to overcome the inherent error from discrete estimation to continuous prediction and studies the accumulated generation method of the discrete grey GM (1, 1) model so as to reduce the disturbance bound of the prediction model and improve the accuracy of GM (1, 1) prediction ability and modeling accuracy of the model and expand the theoretical research and application scope of the grey prediction model.

3. Methods

3.1. The Discrete Grey Model (1, 1). Grey prediction is a method to construct a model based on the known information of the sequence and predict the future data with the past data through the model. The model can reflect the development trend of data and make reasonable prediction and judgment according to the model. In the grey prediction model, the accumulation of original data weakens the volatility and randomness of random sequence and enhances the certainty. However, many defects of the GM (1, 1) model have been unable to meet the theoretical basis for our exploration of complex uncertain systems. The discrete grey prediction model proposed by Liu et al. [14] has made us have a deeper understanding of the grey system theory. The proposed discrete grey prediction model theoretically solves the error caused by the jump between the discrete parameter estimation equation and the continuous prediction equation of the original GM (1, 1) model, which has the coincidence of the white exponent, and greatly improves the simulation effect and prediction accuracy of the model.

The theoretical framework is as follows.

Assuming that the nonnegative original sequence is $X^{(0)} = (x^0(1), x^0(2), \ldots, x^0(n))$, first-order summation of the original sequence $X^{(0)}$ by $(1 - \text{AGO})$, the sequence is produced which is $X^{(1)} = (x^1(1), x^1(2), \ldots, x^1(n))$. In this sequence, $x^1(k) = \sum_{i=1}^{(0)} x^{(0)}(i), \quad k = 1, 2, \ldots, n.$

Definition 1. Assuming $x^{(0)}(k)$ and $x^{(1)}(k)$ as already pointed out, the grey equation

$$x^{(1)}(k+1) = \beta_0 + \beta_1 k^{\gamma} + \beta_2 x^{(1)}(k), \tag{1}$$

is called the discrete grey model, where γ is called a power exponent.

Theorem 1. *It is assumed that $X^{(0)}$ is a nonnegative sequence and that $X^{(0)}$ and $X^{(1)}$ are as described in Definition 1. Assume that the power exponent γ of the discrete grey power model is known, and if $\widehat{\beta} = (\beta_0, \beta_1, \beta_2)^T$ is a parameter column, then*

$$\widehat{\beta} = \left(B^T B\right)^{-1} B^T Y, \tag{2}$$

where

$$B = \begin{bmatrix} 1 & 1^{\gamma} & x^{(1)}(1) \\ 1 & 2^{\gamma} & x^{(1)}(2) \\ \vdots & \vdots & \vdots \\ 1 & (n-1)^{\gamma} & x^{(1)}(n-1) \end{bmatrix}, Y = \begin{bmatrix} x^{(1)}(2) \\ x^{(1)}(3) \\ \vdots \\ x^{(1)}(n) \end{bmatrix}. \tag{3}$$

Two corollaries are drawn.

Corollary 1. *When $\gamma = 0$, the discrete grey power model changes to $x^{(1)}(k+1) = \beta_1' + \beta_2 x^{(1)}(k)$; that is, the discrete grey model degenerates to the discrete grey GM (1, 1) model [14].*

Corollary 2. *When $\gamma = 1$, the discrete grey power model is $x^{(1)}(k+1) = \beta_0 + \beta_1 k + \beta_2 x^{(1)}(k)$; that is, the discrete grey power model degenerates into an approximate nonhomogeneous discrete grey GM (1, 1) model [14].*

(3) If $\widehat{\beta} = (\beta_0, \beta_1, \beta_2)^T$ is as stated in Theorem 1 and the initial value condition is $\widehat{x}^1(1) = x^{(0)}(1)$, then the solution of the discrete grey power model is

$$\widehat{x}^{(1)}(k+1) = \begin{cases} k\beta_0 + \beta_1 \sum_{i=1}^{k} i^{\tau} + x^{(0)}(1), \beta_2 = 1, \\ \beta_0 \dfrac{1 - \beta_2^k}{1 - \beta_2} + \beta_1 \sum_{i=1}^{k} i^{\tau} \beta_2^{k-i} + x^{(0)}(1)\beta_2^k, \beta \neq 1. \end{cases} \tag{4}$$

According to the time response formula of the discrete grey power model given in (3), the discrete grey power model retains the power exponential diversity of the power model, which makes the discrete grey power model have better adaptability to data prediction. In addition, according to the parameter estimation method of the discrete grey power model and Corollary 1 and Corollary 2, it avoids the inherent defect of the traditional power model from discrete estimation to continuous prediction; that is, it has the advantage of the discrete grey model from discrete estimation to discrete prediction. Therefore, the newly constructed discrete grey power model has the advantages of both the discrete model and the grey power model, which makes the new model constructed more adaptable to the data.

3.2. Fractional-Order Cumulative Discrete Grey Model. The fractional accumulation makes the original data sequence to satisfy the approximate exponential law. The sequence before the accumulation is called the original sequence, and the sequence after the accumulation is called the generated sequence. Accumulation generation is a method to make the grey process from grey to white, which plays an extremely important role in the grey system theory. The development trend of the grey accumulation process can be seen through the accumulation generation, and the integral characteristics or laws contained in the chaotic original data can be manifested. Accumulation generation is a method to generate a new sequence by successively accumulating the data of each moment in the original data column.

The theoretical framework is as follows:

(1) Assume that the nonnegative sequence $X^{(0)} = |x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)|$,

$$x^{(r)}(k) = \sum_{i=1}^{k} x^{(r-1)}(i), \tag{5}$$

is an r (r is an integer) order summative operator, denoted as

$$X^{(r)} = \left|x^{(r)}(1), x^{(r)}(2), \ldots, x^{(r)}(n)\right|, \tag{6}$$

Then,

$$x^{(r)}(k) = \sum_{i=1}^{k} C_{k-i+r-1}^{k-i} x^{(0)}(i), \tag{7}$$

where $C_{r-1}^0 = 1, C_{k-1}^k = 0, k = 1, 2, \ldots, n.$

(2) Assume that the nonnegative sequence $X^{(0)} = |x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)|$, $x^{(p/q)}(k) = \sum_{i=1}^{k} C_{k-i+(p/q)-1}^{k-i} x^{(0)}(i)$ is an accumulation operator of p/q $(0 < p/q < 1)$ and specify that

$$C_{\frac{p}{q}}^{0} - 1 = 1, C_{k-1}^k = 0, k = 1, 2, \ldots, n \cdot C_{k-i+(p/q)-1}^{k-i} = \frac{(k-i+(p/q)-1)(k-i+(p/q)-2)\cdots(p/q+1)(p/q)}{(k-i)!}, \tag{8}$$

$X^{(p/q)} = |x^{(p/q)}(1), x^{(p/q)}(2), \ldots, x^{(p/q)}(n)|$ is an accumulation sequence of order p/q $(0 < p/q < 1)$.

(3) Assume that the nonnegative sequence $X^{(0)} = |x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)|$ and call $\alpha^{(1)}x^{(1-(p/q))}(k) = x^{(1-(p/q))}(k) - x^{(1-(p/q))}(k-1)$ is the $p/q(0 < p/q < 1)$ order reduction operator.

$$\alpha^{(p/q)}X^{(0)} = \alpha^{(1)}X^{(1-(p/q))} = \left|\alpha^{(1)}x^{(1-(p/q))}(1), \alpha^{(1)}x^{(1-(p/q))}(2), \ldots, \alpha^{(1)}x^{(1-(p/q))}(n)\right|, \tag{9}$$

is a p/q order descending sequence.

(4) Assume that the nonnegative sequence $X^{(0)} = |x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)|$, p/q $(0 < p/q < 1)$ order cumulative sequence is $X^{(p/q)} = |x^{(p/q)}(1), x^{(p/q)}(2), \ldots, x^{(p/q)}(n)|$, and

$$x^{(p/q)}(k+1) = \beta_1 x^{(p/q)}(k) + \beta_2, \quad k = 1, 2, \ldots, n-1, \tag{10}$$

is the order p/q cumulative discrete grey model (it is denoted as $\text{DGM}^{p/q}(1,1)$).

3.3. Modeling Steps of Fractional-Order Cumulative Discrete Grey Model. The modeling steps for $\text{DGM}^{p/q}(1,1)$ are as follows:

Step 1. The cumulative sequence of order p/q is obtained by calculation: $X^{(p/q)} = |x^{(p/q)}(1), x^{(p/q)}(2), \ldots, x^{(p/q)}(n)|$

Step 2. Substitute $x^{(p/q)}(k)(k = 1, 2, \ldots, n)$ into step (4) to estimate the parameter $\begin{bmatrix} \widehat{\beta}_2 \\ \widehat{\beta}_1 \end{bmatrix}$ by the least square method

Step 3. We can use $x^{(p/q)}(k) = (x^{(0)}(1) - \widehat{\beta}_2/1 - \widehat{\beta}_1)\widehat{\beta}_1^{(k-1)} + \widehat{\beta}_2/1 - \widehat{\beta}_1\,(k = 2, 3, \ldots, n)$ to predict that $\widehat{x}^{(p/q)}(1), \widehat{x}^{p/q}(2), \ldots$

Step 4. So, let us subtract $X^{(p/q)} = |\widehat{x}^{(p/q)}(1), \widehat{x}^{(p/q)}(2), \ldots, \widehat{x}^{(p/q)}(n)|byp/q$, which is $\alpha^{(p/q)}X^{(0)} = |\alpha^{(1)}\widehat{x}^{(1-(p/q))}(1), \alpha^{(1)}\widehat{x}^{(1-(p/q))}(2), \ldots, \alpha^{(1)}\widehat{x}^{(1-(p/q))}(n), \alpha^{(1)}\widehat{x}^{(1-(p/q))}(n+1), \ldots|$

4. Case Analysis

The above model $\text{DGM}^{p/q}(1,1)$ was applied to the forecasting research of agricultural water consumption. The agricultural water consumption of Handan region in Hebei Province and Jingzhou region in Hubei Province from 2011 to 2020 was used as the basic data to predict the agricultural water consumption of the two regions from 2021 to 2025, and the GM (1, 1) model was used to make a comparison.

4.1. Overview of the Study Area. In this paper, Handan region (36°20′~36°44′N, east longitude 114°03′~114°40′E) and Jingzhou region (29°26′~31°37′N, 111°15′~114°05′E) of Hebei Province are selected as the study areas.

Handan is a large agricultural region with 9.95 million mu of arable land and is plotted in Figure 1. It is an important commodity grain production base and grain production core area in China and a major cotton, egg, and vegetable production base in China. It is one of the five pilot cities (regions) in China to promote high-yield production known as “grain warehouse in the north,” “cotton sea in the south of Hebei,” and “Beijing Tianjin Vegetable Garden” of reputation.

Jingzhou is a large agricultural region, is the famed based on grain, cotton, oil, fish, meat, eggs production base, and is plotted in Figure 2. The agricultural production of Jingzhou occupies an important position in Hubei Province. The output of main agricultural products ranks the top in the province. Perennially, the output of cotton accounts for 1/3 of the province, the output of aquatic products accounts for 1/4, the output of grain and oil, respectively, accounts for 1/6, the output of pigs accounts for 1/10, and the added value of agriculture, forestry, animal husbandry, and fishery accounts for 1/9 of the province, especially the rapeseed and freshwater products occupy an important position in the country. The area and output of freshwater aquaculture have ranked first in China for 18 consecutive years.

It can be seen that the agricultural planting in both places wins a place in the whole country. Handan region is one of the main bases of corn and wheat in Hebei Province, and Jingzhou region is the main base of rice and cotton production in Hubei Province. Due to the great difference of planting varieties between the two places, the demand for agricultural water consumption is also different. It has the typical representative significance for us to select the two places as the research area.

4.2. Agricultural Water Consumption in the Study Area. According to “Hebei Province water resources communique,” “Handan water resources communique,” “Hubei Province water resources communique,” and “Jingzhou water resources communique” from 2011 to 2020, the agricultural water consumption data of Handan region and Jingzhou region from 2011 to 2020 are collected, as shown in Table 1. It can be seen from Table 1 that agricultural water consumption is the main water users of the two regions, accounting for about 70% of the total water consumption. However, with the development of social economy, other industries are crowding out agricultural water, and water pollution is becoming more and serious. Therefore, it is necessary to predict the agricultural water consumption of the two regions in order to provide the basis for the overall planning of agricultural water supply.

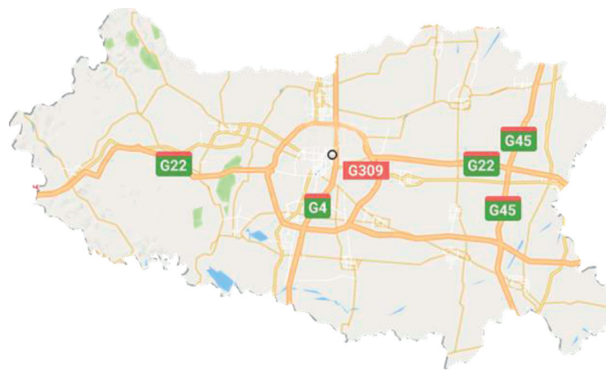

Figure 1: Location map of research area—Handan.

Figure 2: Location map of research area—Jingzhou.

Table 1: Agricultural water consumption in Handan and Jingzhou from 2011 to 2020.

	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Agricultural water consumption in Jingzhou region	26.28	24.62	29.55	26.49	25.11	24.01	26.31	26.7	27.68	—
Proportion of water occupied	71%	69%	77%	75%	71%	69%	71%	72%	73%	—
Agricultural water consumption in Handan region	12.86	14.96	14.02	14.62	14.14	12.72	12.98	12.75	12.96	12.61
Proportion of water occupied	69.9%	72.2%	71.2%	72.6%	73.0%	68.9%	69.6%	67.5%	67.5%	67.2%

4.3. Model Comparison and Test. The procedure of data preprocess is illustrated as follows:

Step 1. Normalize the data: Taking the observation data of Handan region from 2011 to 2020 as the modeling sample, the original data sequence was obtained as follows:

$$X_H(0) = \{12.86, 14.96, 14.02, 14.62, 14.14, 12.72, 12.98, 12.75, 12.96, 12.61\}. \tag{11}$$

The observation data of Jingzhou from 2011 to 2019 were taken as modeling samples, and the original data sequence was as follows:

$$X_J(0) = \{26.28, 24.62, 29.55, 26.49, 25.11, 24.01, 26.31, 26.7, 27.68\}. \tag{12}$$

Step 2. Find the optimal order of the model and build a model: In order to illustrate the advantages of the fractional-order cumulative grey model in national economic forecasting, the commonly used order $R = 1/2$ and $R = 1/4$ are selected to compare with GM (1, 1) [15, 16].

However, in order to accurately predict the agricultural water consumption of Handan and Jingzhou in the future, the fractional-order discrete grey optimal model should be constructed, which requires the optimal order number. The optimal order $R = 0.1025$ was obtained by MATLAB software programming. The fractional discrete grey DGM (1, 1) model established according to the observed data is as follows:

$$x^{(0.1025)}(k+1) = 1.2865x^{(0.1025)}(k) + 21.7806, \quad k = 1, 2, \ldots, n-1. \tag{13}$$

Step 3. Solve the model: In order to test the performance of the model proposed in this paper, the prediction effect of the model compared with that of the GM (1, 1) model is shown in Table 2.

Table 2: Comparison of prediction effect of the model.

Study area	Year	Original value	GM (1, 1) model		$DGM^{p/q}(1, 1)$ model	
			Predicted value	Relative error	Predicted value	Relative error
Handan region	2011	12.86	12.86	0.00%	12.86	0.00
	2012	14.96	14.73	1.51%	14.49	3.16
	2013	14.02	14.42	2.84%	14.41	2.76
	2014	14.62	14.11	3.51%	14.04	3.98
	2015	14.14	13.80	2.38%	13.68	3.23
	2016	12.72	13.51	6.18%	13.39	5.24
	2017	12.98	13.22	1.82%	13.14	1.25
	2018	12.75	12.93	1.43%	12.94	1.47
	2019	12.96	12.65	2.37%	12.76	1.53
	2020	12.61	12.38	1.81%	12.61	0
	Mean			2.38%		2.26
Jingzhou region	2011	26.28	26.28	0.00%	26.28	0.00
	2012	24.62	26.07	5.91%	25.53	3.70
	2013	29.55	26.147	11.53%	25.50	13.71
	2014	26.49	26.21	1.06%	25.69	3.03
	2015	25.11	26.27	4.64%	26.98	3.48
	2016	24.01	26.34	9.71%	26.34	9.72
	2017	26.31	26.41	0.38%	26.74	1.65
	2018	26.7	26.48	0.84%	27.17	1.78
	2019	27.68	26.54	4.11%	27.63	0.19
	Mean			4.24%		4.14

Table 3: Forecast value of agricultural water consumption in the study area in the next five years.

Region	2020	2021	2022	2023	2024	2025
Handan region	12.61	12.48	12.35	12.25	12.15	12.05
Jingzhou region	28.10	28.58	29.07	29.58	30.09	30.61

Step 4. Contrast and analyze: It can be seen from Table 2 that under the GM (1, 1) model established when the order $r = 1$, the average prediction error of test set water consumption in Handan City and Jingzhou City is 2.38% and 4.24%, respectively. However, the average prediction error of the $DGM^{p/q}(1, 1)$ model in Handan region and Jingzhou region is 2.26% and 4.14%, respectively, which is small, indicating that the model in this paper is significantly improved compared with the GM (1, 1) model.

4.4. Forecast of Agricultural Water Consumption in the Study Area in the Next Five Years. The fractional discrete grey GM (1, 1) power model is constructed according to the characteristics of the original data series, which plays an important role in enriching and developing the theory and method of grey prediction. In general, the model in this paper can predict agricultural water consumption well. In order to further test the performance of the model, the model in this paper is used to forecast and analyze agricultural water consumption in Handan region and Jingzhou region in the next five years. The predicted results are shown in Table 3.

5. Conclusion

In this paper, the basic data of agricultural water consumption from 2011–2020 in Hebei Province and Hubei Province were selected to compare the differences between the GM (1, 1) model and the fractional-order discrete grey model, verify the effectiveness of fractional-order discrete grey model, expand the application range of the grey prediction model, and provide a new method for demand prediction of small sample data. It also contributes to the policy formulation and risk control of water resources protection in the two places, so as to ensure the rational use of water resources and provide water resources guarantee for the sustainable development of agriculture in the two places.

(1) In view of the oscillation characteristics and data requirements of agricultural water series, this paper introduces the discrete idea and fractional-order accumulation idea into the grey model and constructs the fractional-order discrete grey model. Compared with the GM (1, 1) model, this model eliminates the error caused by the traditional grey model jumping directly from the differential equation to the difference equation, improves the modeling accuracy of the model, and can be used as an effective method for the prediction of agricultural water consumption.

(2) With the adjustment of agricultural industrial structure, the popularization of water-saving irrigation technology is slow, and the agricultural water consumption will increase year by year. Jingzhou has vigorously developed rice and crayfish industry in

recent years. In 2019, the area of shrimps and rice in Jingzhou is 2.51 million mu, and the output of crayfish is 400,000 tons, which ranks first among cities and states in China. The demand for water is obviously increasing. Handan has made great efforts to carry out high-efficiency water-saving irrigation project and the agricultural project to stabilize the overdrawing of groundwater, and the agricultural water consumption has shown a downward trend. Therefore, the water management department should improve the existing irrigation system and accelerate the promotion of water-saving irrigation to improve the water use efficiency and realize the transformation from traditional agriculture to modern agriculture.

(3) Agricultural water consumption is affected by many factors, especially when the climate conditions change significantly, which will affect the consistency of agricultural water consumption data before and after climate change so that the historical data will show different patterns before and after climate change. To some extent, considering the influence of different meteorological conditions on agricultural water consumption, the prediction of agricultural water consumption is more accurate. Therefore, climate factors should be considered in the future model research to establish a more reasonable prediction model of water consumption.

Data Availability

The relevant data are included within the paper or in Supplementary Information.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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