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Water Use Attribution Analysis and Prediction Based on the VIKOR Method and Grey Neural Network Model: A Case Study of Zhangye City

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Abstract: Water consumption forecasting is a critical aspect of the increasingly strained water resources and sustainable water management processes. It is essential to explore the current status of water use patterns and future development directions in Zhangye City. In this study, 17 factors affecting water consumption in Zhangye City were selected to analyze changes in water consumption and to predict values from 2003 to 2022, utilizing the entropy weight–VIKOR model and the grey neural network model. The results indicate that agricultural water consumption and annual rainfall are the factors with the largest weights among the social and natural attribute indicators, respectively, significantly influencing water consumption in Zhangye City. As the proportions of water consumption for forestry, animal husbandry, fishery, livestock, urban public use, and ecological environment increase, while agricultural water consumption continues to decline, the overall water consumption trend in Zhangye City from 2003 to 2022 shows a positive trajectory. Each water consumption factor is tending toward greater balance, and the relationship between water supply and distribution is improving. The multi-year average relative error of the water consumption predictions for Zhangye City from 2003 to 2022 using the grey neural network model was 4.28%. Furthermore, the relative error values for annual predictions ranged from 0.60% to 5.00%, achieving an accuracy rate of 80.00%. This indicates a strong predictive performance. Ultimately, the model was used to predict a water consumption of 20.18 $\times$ 10^8 m^3 in Zhangye City in 2027. The model can serve as a theoretical reference for short-term water consumption forecasting and for establishing a basin water resource allocation system in Zhangye City.

Keywords: water consumption prediction; grey neural network; entropy weight–VIKOR model; Zhangye City; attribution analysis

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1. Introduction

Rapid urbanization has led to a dramatic increase in water consumption across various sectors. However, the limited availability of water resources, coupled with the need for rational planning and sustainable management, presents a significant challenge to socio-economic development [1,2]. Effective management of water resources and accurate prediction of water demand are crucial not only for ensuring the safety of urban water supply but also for the optimal allocation and efficient use of these resources [3–5]. Nonetheless, water usage is influenced by a multitude of factors, including population changes, economic development status, industrial activities, and climatic conditions. The complexity and uncertainty inherent in these factors complicate the forecasting of water use [6,7]. Common methods for water use forecasting include time series analysis [8], statistical modeling [9], and machine learning [10]. Among these, grey system theory is a theoretical method used to solve the problem of incomplete and uncertain information, by generating a regular sequence of data to reveal the inner connection and development law of things.

As a valuable mathematical tool for addressing small sample sizes and unbalanced data, this offers distinct advantages in water use prediction [11]. The grey neural network model, which integrates the robustness of grey system theory with the self-learning capabilities of artificial neural networks, is particularly effective in managing the non-linearity and uncertainty present in urban water use systems [12,13]. For instance, Wang et al. [14] demonstrated that the combination of the grey prediction GM(1,1) model and the Elman neural network yielded relative prediction errors of less than 3.5% when forecasting water consumption in Nanjing, thus enhancing the model's accuracy. Furthermore, the grey neural network model has also been successfully applied in predicting geological disasters; for example, Yue et al. [15] found that the grey BP neural network model provided more accurate predictions of landslide displacement values. As a data-driven prediction tool, the grey neural network model has shown its powerful prediction ability in many fields, but its integrated application in water resources prediction is still underexploited.

Zhangye City is traversed by the Heihe River, with river runoff, primarily consisting of meltwater from the snowy mountains, serving as the main source of regional water supply. As a significant city in the western part of the Hexi region of China, the sustainable utilization of water resources in Zhangye City is essential for ensuring the economic and social development of the area. According to statistics, the annual water supply for Zhangye City in 2022 was projected to be 19.43×10^8 m^3. Of this total, 14.08×10^8 m^3 was sourced from surface water, accounting for 72.46% of the overall water supply [16,17]. Additionally, the annual water consumption is expected to match the water supply. Rapidly changing socio-economic conditions complicate the relationship between water use and supply, making effective water resource management a critical component of sustainable development in Zhangye City. However, the interplay of natural conditions and human activities results in a complex and variable water demand in the city, introducing numerous uncertainties in the prediction and management of water consumption. Consequently, this study examines 17 factors influencing water consumption in Zhangye City and employs the entropy weight–VIKOR method to analyze the current status of water consumption and identify the key influencing factors. Additionally, utilizing water consumption statistics from 2003 to 2022, a grey neural network is applied to predict future water consumption in Zhangye City. The objective is to conduct an in-depth analysis of the factors influencing water consumption and to develop a prediction model characterized by robust generalization capabilities and high accuracy, which can provide valuable decision support for the rational planning and scientific management of water resources in Zhangye City, while also serving as a significant reference for water resource management in similar regions.

2. Materials and Methods

2.1. Study Area

The target area of this study is Zhangye City, located in the middle reaches of the Heihe River Basin, within the central part of the Hexi Corridor (between 97°12′–102°12′ E and 37°28′–40°00′ N). The city encompasses a total area of 3.86×10^4 km^2 and is administratively divided into five counties and one district. As of the end of 2022, the total population was approximately 112.11×10^4, with an urbanization rate of about 53.49%. The region experiences an average multi-year rainfall of 118.20 mm and an average annual temperature ranging from 4.1 to 8.3 °C. The primary water source for all units within the study area is the Heihe River and its tributaries, providing a total water supply of approximately 17.49×10^8 m^3. Of this supply, agricultural irrigation accounts for 85.74%, while water consumption for forestry, animal husbandry, fishery, and livestock constitutes 8.49%. Industrial water consumption is 0.88%, public water consumption in urban areas accounts for 0.42%, residential water usage represents 2.43%, and water allocated for ecological purposes comprises 2.04%. The amount of water supplied to Zhangye City during the year is equal to the total amount of water consumed by all water-using sectors. The per capita water resource availability during the year is estimated at 1.73×10^4 m^3 [17,18]. A schematic overview of the study area is presented in Figure 1.

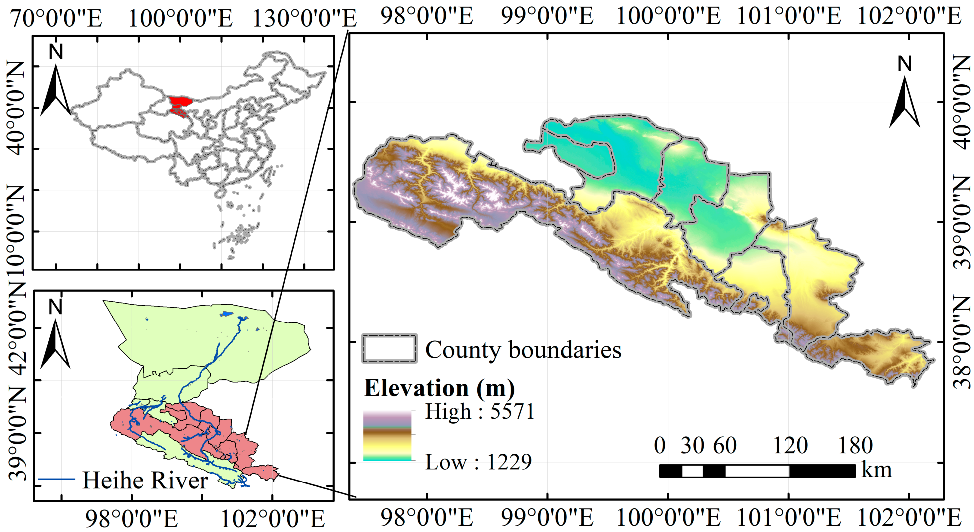

Figure 1. Overview of the study area.

2.2. Data Sources

The data sources for this study primarily include the "Gansu Provincial Statistical Yearbook" [18], the "Gansu Provincial Water Resources Bulletin", and the "Zhangye City Calendar Years Temperature Statistics" for the years 2003–2022. This research examines the factors influencing water resources demand and consumption in various cities across China, with a specific focus on Zhangye City. The selected evaluation index set comprises 17 factors, including agricultural water consumption, industrial water consumption, residential water consumption, FAFW (forestry, animal husbandry, and fishery water use), urban public water consumption, ecological environment water consumption, population density, urbanization rate, AFA value added (agri-forestry–animal husbandry and fishery value added), added value of industry, gross domestic product, annual precipitation, water-saving irrigated area, cultivated land area, the number of water-producing systems, water production modulus, and the average annual temperature [19]. During the modeling process, the dataset for Zhangye City from 2003 to 2021 was utilized as the training set, while each data index for 2022 served as the validation set.

2.3. Research Methods

2.3.1. Entropy Weight–VIKOR Model

(1) Entropy weight method [20]

1. Data standardization:
Positive indicator:

$$x'_{ij} = \frac{X_{ij} - \min(X_{1j}, X_{2j}, \cdots, X_{nj})}{\max(X_{1j}, X_{2j}, \cdots, X_{nj}) - \min(X_{1j}, X_{2j}, \cdots, X_{nj})} \tag{1}$$

Negative indicator:

$$x'_{ij} = \frac{\max(X_{1j}, X_{2j}, \cdots, X_{nj}) - X_{ij}}{\max(X_{1j}, X_{2j}, \cdots, X_{nj}) - \min(X_{1j}, X_{2j}, \cdots, X_{nj})} \tag{2}$$

where X_{ij} is the original data, x'_{ij} is the normalized data, max (X_{nj}) is the maximum value in the original data, and min (X_{nj}) is the minimum value in the original data.

2. Ratio of indicators under each program y_{ij}:

$$y_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{n} x'_{ij}} \tag{3}$$

where y_{ij} is the ratio of indicators under each program.

3. Information entropy for each indicator e_j:

$$e_j = -\ln(n)\sum_{i=1}^{n}(y_{ij} \times \ln(y_{ij})) \tag{4}$$

4. Indicator weights W_j:

$$W_j = \frac{1-e_j}{n-\sum_{i=1}^{n} e_j}(i = 1, 2, \cdots, n) \tag{5}$$

(2) VIKOR model [21]

1. Group utility S_i and individual regret R_i:

$$S_i = \sum_{i=1}^{n} \frac{W_j(b_j^* - b_{ij})}{b_j^* - b_j^-} \tag{6}$$

$$R_i = \max_{1\le j\le n}\left[\frac{W_j(b_j^* - b_{ij})}{b_j^* - b_j^-}\right] \tag{7}$$

where b_j^* and b_j^- are the maximum and minimum values of each column of the matrix after normalization of the data, respectively. Individual regret here refers to the gap between the individual evaluation object and the optimal solution.

2. Indicator values for trade-off decision-making Q_i:

$$Q_i = \frac{v(S_i - S^*)}{S^- - S^*} + \frac{(1-v)(R_i - R^*)}{R^- - R^*} \tag{8}$$

where S^* and R^* are the minimum value of group utility and individual regret, respectively; S^- and R^- are the maximum value of group utility and individual regret, respectively; and v denotes the coefficient of decision-making mechanism, which is 0.5.

2.3.2. Grey Neural Network Model

(1) GM(1,1) model [22]

1. The original data $x^{(0)}$ are accumulated once to obtain a new sequence $x^{(1)}$:

$$x^{(0)} = \left\{x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n)\right\} \tag{9}$$

$$x^{(1)} = \left\{x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)\right\} \tag{10}$$

2. Immediate neighborhood mean sequence of the new sequence $Z^{(1)}(k)$:

$$z^{(1)}(k) = ax^{(1)}(k) + (1-a)x^{(1)}(k-1) \quad k = 2, 3, \cdots, n \tag{11}$$

where a takes the value of 0.5.

3. Establish the time response equation for the GM(1,1) model:

$$\frac{dx^{(1)}(t)}{dt} + \alpha x^{(1)}(t) = \mu \tag{12}$$

where the development factor α and the amount of grey play μ are obtained using the least squares method.

4. Least squares calculation of α and μ:

$$(\alpha, \mu)^T = \left(B^T B\right)^{-1} B^T Y \tag{13}$$

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{14}$$

$$Y = \begin{bmatrix} x^{(0)}(2) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} \tag{15}$$

where B and Y are the data matrix and data vector, respectively.

5. Calculation of predicted values $\hat{x}^{(0)}$:

Solving Equation (12) yields the predicted value of $x^{(1)}$. The reverse cumulative subtraction yields the predicted value $\hat{x}^{(0)}$ of the original data sequence $x^{(0)}$.

$$\hat{x}^{(0)}(t+1) = \hat{x}^{(1)}(t+1) - \hat{x}^{(1)}t \tag{16}$$

6. Residual method to test the accuracy of GM(1,1) model:

$$\varepsilon(k) = \frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)} \tag{17}$$

where $\varepsilon(k)$ is the relative residual, generally required to be $< 20\%$; when $\varepsilon(k) < 10\%$, it indicates that the model is more accurate.

(2) BP neural network model [23]

1. Network initialization:

Weights ω and bias b are usually initialized using a random method to break the symmetry of the network.

2. Forward propagation:

The input data are passed through each layer of the network until the last layer outputs a prediction. For the jth neuron in layer l, output a_j^l:

$$z_j^l = \sum\nolimits_i \left(\omega_{ij}^l a_j^{l-1}\right) + b_j^l \tag{18}$$

$$a_j^l = \phi\left(z_j^l\right) \tag{19}$$

where a_j^{l-1} is the output of the ith neuron in layer $l-1$; ω_{ij}^l is the weight connecting the ith neuron in layer $l-1$ to the jth neuron in layer l; b_j^l is the bias of the jth neuron in layer l; and ϕ is the activation function (identity), with the solver being Ibfgs.

3. Calculation of losses:

This is used to measure the difference between the predicted and actual values of the network and is calculated as follows:

$$L = \frac{1}{n}\sum\nolimits_{k=1}^{n} \left(y_k - \hat{y}_k\right)^2 \tag{20}$$

where n is the number of samples; y_k is the actual output value of the sample; and $\hat{y}_k$ is the predicted output.

4. Backpropagation and parameter updates:

The error gradient of the output layer:

$$\delta_j^L = \frac{\partial L}{\partial z_j^L} = \phi\prime\left(z_j^L\right) \cdot \frac{\partial L}{\partial a_j^L} \tag{21}$$

Error gradient in the non-output layer ($l < L$):

$$\delta_j^l = \frac{\partial L}{\partial z_j^L} = \sum\nolimits_i \omega_{ij}^{l+1} \delta_j^{l+1} \cdot \phi'(z_j^l) \tag{22}$$

where L is the last layer, and ϕ' is the derivative of the activation function.

Update the weights and bias using gradient descent:

$$\omega_{ij}^l \leftarrow \omega_{ij}^l - \alpha \cdot \delta_j^l \cdot a_j^{l-1} \tag{23}$$

$$b_j^l \leftarrow b_j^l - \alpha \cdot \delta_j^l \tag{24}$$

where α is the learning rate.

The above steps may be repeated until the prediction error of the network is reduced to an acceptable level or a preset number of iterations is reached, the preset number of iterations here being 1000; otherwise return to step 2.

(3) Grey neural network model

The grey neural network model is a data prediction model that integrates GM(1,1) and BP neural networks. Its primary advantage lies in effectively leveraging the strengths of both models to enhance prediction accuracy. Previous researchers have conducted various explorations into the combination of these models [24,25]. In this study, we select a superior combination mode, specifically the parallel mode, to construct the grey neural network model. The basic structure of the model is illustrated in Figure 2. The specific calculation steps are outlined as follows.

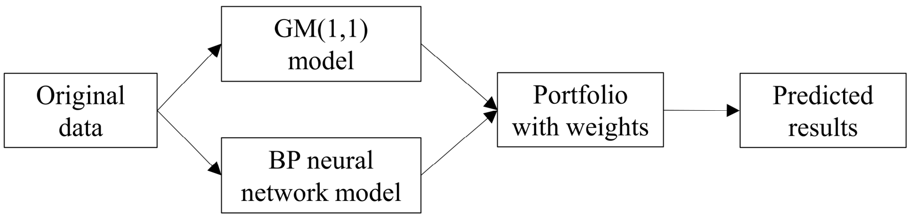

Figure 2. Schematic structure of grey neural network in parallel mode.

1. Determine the sequence of predicted values:

Set the GM(1,1) model prediction result as sequence $Y_i(1)$, the BP neural network model prediction result as sequence $Y_i(2)$, and the expectation of the prediction structure as sequence X_i.

2. Portfolio forecasts:

First determine the root mean square error (ζ_1 and ζ_2) and the mean absolute percentage error (ζ_1 and ζ_2) for $Y_i(1)$ and $Y_i(2)$ versus X_i. The formulas are as follows:

$$\xi = \frac{1}{n}\sum_{i=1}^{n}|X_i - Y_i| \tag{25}$$

$$\zeta = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{X_i - Y_i}{X_i}\right| \cdot 100\% \tag{26}$$

Next, the weights (W_i) of each base model of the combined model are determined through ζ_1 and ζ_2. The formula is as follows:

$$W_i = \frac{\xi_i}{\sum\limits_{i-1}^{n} \xi_i} \quad n = 1,2 \tag{27}$$

Finally, the predicted sequential results of the grey neural network model are obtained by arithmetic averaging.

$$Y_j = W_1 Y_1(1) + W_2 Y_2(1) \tag{28}$$

3. Results

3.1. Status of Water Use in Zhangye City

According to the "Gansu Province Water Resources Bulletin", the annual water consumption of Zhangye City is categorized into seven sectors: agriculture, industry, residential life, forestry, animal husbandry, fishery, and urban public and ecological environment. The variations in water consumption across these sectors from 2003 to 2022 are illustrated in Figure 3. The average annual total water consumption in Zhangye City during this period is 22.02×10^8 m^3, with agriculture representing the largest share among all sectors, and the combined water consumption of each water sector is equal to the total amount of water supplied during the year. Since 2013, the area of water-saving irrigation for arable land in Zhangye City has consistently increased, while public water use in urban areas constitutes the smallest proportion, averaging 0.42%. Industrial water use has exhibited notable fluctuations from 2003 to 2022, characterized by two phases of continuous growth from 2003 to 2006 and 2007 to 2014, followed by a gradual decline from 2015 to 2022, dropping to 71.63% of its 2015 level by 2022, thus ranking the city fifth in terms of industrial water consumption. The water consumption for forestry, animal husbandry, fishery, and livestock surged abruptly in 2013, making it the second-largest consumer of water, with an average consumption of 11.39% from 2013 to 2019, which subsequently decreased to 8.00% during the period from 2020 to 2022. The city's ecological environmental water consumption ranks fourth, having remained above 1.20% during the periods of 2005 to 2012 and 2015 to 2022. In recent years, due to the region's focus on ecological and environmental protection, water consumption in this sector has continued to rise, surpassing 2.00%. Public water use in urban areas holds the smallest share, which increased to between 0.92% and 1.17% from 2013 to 2018, before declining to approximately 0.50% post-2018.

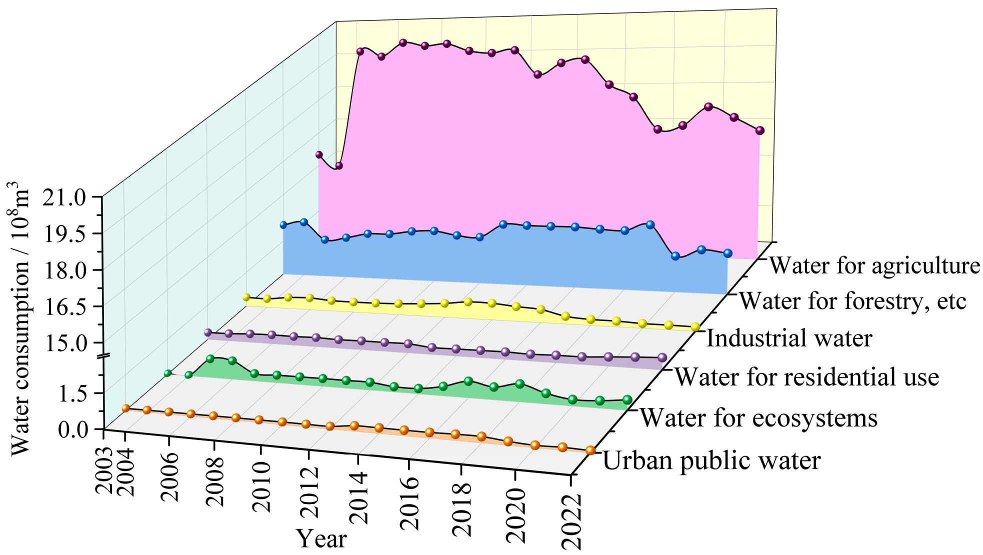

Figure 3. Changes in water consumption by sector in Zhangye City.

3.2. Attribution Analysis of Water Consumption in Zhangye City

To ground the analysis of the status quo and the primary influencing factors of water consumption in Zhangye City, the entropy weight–VIKOR model was employed to identify these factors and assess the current state of water consumption. The calculation results are presented in Table 1. From Table 1, it is evident that among the 17 evaluated factors, agricultural water consumption exerts the greatest influence on regional water consumption, accounting for 11.47%, while the water production modulus (the ratio of groundwater production per unit area per unit time to the decline in the water table) has the least influence at 1.78%. Among the natural attribute indicators, annual precipitation has the smallest weighting and a correspondingly lower degree of influence, whereas the water production modulus indicator has the largest weighting and a higher degree of influence. In terms of social attribute indicators, agricultural water consumption holds the highest weight, while residential water consumption has the lowest. Utilizing the weights of these indicators, the VIKOR model facilitated a comprehensive analysis of the water usage situation in Zhangye City from 2003 to 2022, with results also shown in Table 1. The data indicate a positive trend in overall water usage in Zhangye City during this period, suggesting a more balanced distribution of various water use factors and an improving relationship between water supply and distribution. Although there was a short-term deterioration in the water usage situation from 2010 to 2012, there has been a consistent improvement from 2013 to 2022. This phenomenon may be attributed to an increase in the proportion of water usage for forestry, livestock, fisheries, urban public water use, and ecological environmental needs during this timeframe, while agricultural water use continued to decline, leading to a temporary uneven or irrational distribution of water resources in the study area.

Table 1. Main impact factors and current status of water consumption in Zhangye City.

Evaluation Indicators	Effect	Indicator Weights (%)	Year	Benefit Ratio Value (Q)	Compromise Decision Ordering
AFA value added/(10^4 CNY)	↑ *	8.35	2003	0.513	8
Industrial value added/(10^8 CNY)	↑	4.98	2004	0.559	9
Gross domestic product/(10^8 CNY)	↑	7.55	2005	0.887	17
Annual precipitation/(10^8 m^3)	↑	6.82	2006	0.870	16
Water-saving irrigation area/(10^4 acres)	↑	9.65	2007	0.950	18
Number of water-producing systems	↑	1.83	2008	0.969	20
Modulus of water yield	↑	1.78	2009	0.958	19
Annual average temperature/(°C)	↓	4.04	2010	0.748	13
Water consumption in agriculture/(10^8 m^3)	↓	11.47	2011	0.770	14
Industrial water consumption/(10^8 m^3)	↓	5.58	2012	0.792	15
Residential water consumption/(10^8 m^3)	↓	2.83	2013	0.735	12
FAFW/(10^8 m^3)	↓	6.14	2014	0.690	10
Urban public water consumption/(10^8 m^3)	↓	6.44	2015	0.728	11
Ecosystem water consumption/(10^8 m^3)	↓	4.70	2016	0.465	7
Population density/(person per km^2)	↓	8.67	2017	0.310	5
Urbanization rate	↓	5.63	2018	0.397	6
Cropland area/(10^4 acres)	↓	3.54	2019	0.159	4
—	—	—	2020	0.141	3
—	—	—	2021	0.129	2
—	—	—	2022	0.064	1

* Note: ↑ in the table represents a positive indicator; ↓ represents a negative indicator.

3.3. Water Consumption Prediction Based on GM(1,1) Model and BP Neural Network Model

The GM(1,1) model and the BP neural network model were employed to predict the water consumption of Zhangye City from 2003 to 2022, with the prediction results illustrated in Figure 4. The GM(1,1) model yielded an average relative error of 5.087%, which is below the threshold of 20%, indicating a good fit for the model. Additionally, all class ratio values of the water consumption sequence, after translation and transformation, fell within the interval (0.909, 1.100), suggesting that the sequence is appropriate for constructing a grey prediction model. The post hoc error ratio was determined to be 0.647, further affirming the model's accuracy. As depicted in Figure 4a, the multi-year average relative error between the predicted water consumption of Zhangye City from 2003 to 2022 using the GM(1,1) model and the actual water consumption is 5.087%. The year with the highest relative error was 2008, with relative errors exceeding 5.00% noted in the years 2008, 2014–2015, and 2020–2022, while the remaining years exhibited relative error values ranging from 0.00% to 4.692%, indicating a generally accurate prediction. In Figure 4b, the BP neural network model demonstrated a training set R^2 of 0.982 (indicative of a value close to 1.00), a root mean square error (RMSE) of 0.253 (where a smaller RMSE indicates higher accuracy), and a mean squared error (MSE) of 0.064 (with smaller values correlating to greater model accuracy). The mean absolute error (MAE) was recorded at 0.210, reflecting the average absolute error of the predicted values; again, smaller values suggest a more accurate model.

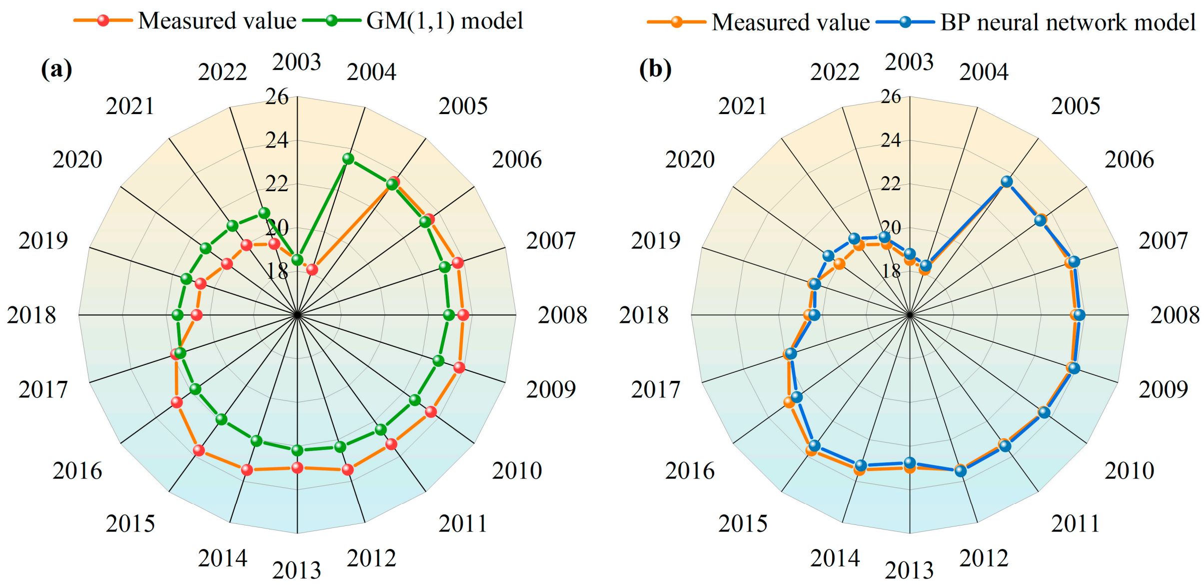

Figure 4. Prediction results of GM (1,1) model and BP neural network model. (**a**) GM(1,1) model; (**b**) BP neural network model.

3.4. Water Consumption Prediction Based on Grey Neural Network Model

The grey neural network model was employed to predict the annual water consumption of Zhangye City from 2003 to 2022, with the accuracy of the model's predictions presented in Table 2. As indicated in Table 2, the predictions made by the grey neural network model closely align with the actual water consumption figures, which demonstrate a trend of decline over the years. The multi-year average relative error between the actual and predicted water usage was 4.28%, with a maximum relative error of 22.12% occurring in 2004. This performance is comparable to the prediction results of the GM(1,1) model and the BP neural network model, suggesting that the grey neural network model offers a higher accuracy in its predictions. In response to the national water conservation policy and the promotion of water-saving initiatives, Zhangye City has been actively developing water-efficient irrigated farmland, resulting in a year-to-year reduction in overall water consumption of 0.075%. Concurrently, the total population of Zhangye City is declining at a rate of 0.579%, which will subsequently reduce water consumption across the agriculture, industry, forestry, animal husbandry, fishery, and livestock sectors, contributing to a gradual decrease in total water consumption. Although total water consumption in 2022 has increased by 4.88% compared to 2003, this can be attributed to a cultivated land area growth rate of 12.39% and the additional water demands due to urbanization for residential and public use. Overall, water consumption in Zhangye City has stabilized in recent years, and it is anticipated that disparities in water consumption will continue to diminish in the coming years. In summary, the grey neural network model was used to predict the water consumption of Zhangye City, and the water consumption was predicted to be 20.75×10^8, 20.61×10^8, 20.47×10^8, 20.33×10^8, and 20.18×10^8 m^3 for the years 2023–2027, respectively.

Table 2. Grey neural network model prediction results (10^8 m^3).

Year	Measured Value	Projected Value	Relative Error/%	Year	Measured Value	Projected Value	Relative Error/%
2003	18.521	18.7940	1.45	2013	22.992	22.3251	2.99
2004	18.176	23.3393	22.12	2014	23.456	22.2114	5.60
2005	23.525	23.3850	0.60	2015	23.655	22.0996	7.04
2006	23.44	23.2601	0.77	2016	22.805	21.9425	3.93
2007	23.708	23.2720	1.87	2017	21.834	21.6521	0.84
2008	23.579	23.1020	2.06	2018	20.606	21.2320	2.95
2009	23.777	22.9110	3.78	2019	20.648	21.2380	2.78
2010	23.541	22.6980	3.71	2020	19.975	20.9875	4.82
2011	23.312	22.5930	3.18	2021	19.948	20.8612	4.38
2012	23.444	22.4150	4.59	2022	19.425	20.6953	6.14

4. Discussion

The quantitative analysis of water use trends in Zhangye City presented in this study indicates that agricultural water use constitutes the predominant component of the overall water use structure. This finding aligns with existing literature and underscores the crucial role of agricultural water management in ensuring regional water security [26,27]. The cyclical fluctuations observed in industrial water use are closely tied to the stages of economic development, reflecting the dynamic equilibrium between industrial water demand and macroeconomic factors. Concurrently, the consistent growth in ecological water consumption highlights the strategic importance of ecological water needs in the allocation of water resources, consistent with contemporary water resource management principles that prioritize ecological considerations and promote green development [28,29]. These findings provide a scientific foundation for the formulation of targeted water resource optimization strategies and emphasize the necessity of considering the coordinated development of agricultural, industrial, and ecological water use in the planning and management of water resources.

Numerous models for analyzing and forecasting water demand are based on more comprehensive datasets and can be utilized for predictive analyses by identifying patterns of change in the data, as well as revealing trends, cycles, and seasonality [30]. However, models such as time series analysis for predicting water demand must meet specific assumptions, including data smoothness and linear relationships. Additionally, these models are significantly influenced by region-specific climatic and hydrological attributes, which may limit the accuracy of predictions [31]. This study presents a novel analytical framework for identifying and quantifying the key drivers of water use by innovatively integrating the entropy weighting method with the VIKOR multi-criteria decision-making model. This approach, which has been utilized less frequently in the field of water resources management, offers a new perspective for assessing the complexity and dynamics of water use structures. Additionally, this study introduces a grey neural network model for predictive analysis of water use, recognized for its high accuracy in non-linear time series prediction [32]. Notably, the significant downward trend in industrial water consumption observed after 2015 contrasts with the continuous growth pattern documented in previous studies. This phenomenon may be closely linked to the implementation of local water conservation measures and the optimization of industrial structures [33]. These findings not only enhance the quantitative analysis tools available for water resource management, but also provide policymakers with empirical evidence regarding improvements in industrial water use efficiency and the adjustment of water conservation strategies.

This study provides a comprehensive analysis of water use dynamics in Zhangye City; however, the influence of external factors such as policy changes and population migration on water use requires further investigation. Additionally, the effects of climate change on water availability, particularly in arid regions, warrant closer examination [34,35]. Furthermore, research on water use efficiency and the potential for water conservation across various sectors should be expanded. In the agricultural sector of Zhangye City, precision irrigation techniques are being promoted to optimize the allocation and utilization of water resources. In the industrial sector, it is essential to enhance water recycling and regulation to ensure the effective reuse of water resources and minimize waste. Simultaneously, a thorough assessment of water use in forestry, animal husbandry, fisheries, and livestock will be conducted to identify sustainable management practices for ecological water use and to safeguard the ecological environment. Additionally, efforts will be made to improve the efficiency of urban and residential water use, while reducing leakage through technical interventions to enhance water resource utilization. Finally, it is crucial to strengthen policy support to foster innovation in water-saving technologies and simultaneously raise public awareness of water conservation, thereby creating a societal atmosphere in which water-saving practices are embraced by all.

5. Conclusions

This study employs the entropy weight–VIKOR model and a grey neural network model to analyze and predict water consumption in Zhangye City, a significant urban area in the middle reaches of the Heihe River, from 2003 to 2022. The findings indicate that the average annual water consumption in Zhangye City during this period was 22.02×10^8 m^3, demonstrating a consistent decline over the years, although this trend has begun to stabilize in recent years. Among the indicators influencing water consumption, the social attribute indicator accounts for the largest share of agricultural water use, while the natural attribute indicator, specifically annual precipitation, significantly affects changes in water consumption levels in Zhangye City. The combined model—integrating the GM(1,1) model with the BP neural network model—was utilized to forecast water consumption from 2003 to 2022, achieving a multi-year average relative error of 4.28%. The maximum relative error recorded was 22.12% in 2004; however, aside from 2004 and 2015, where relative errors exceeded 7.00%, the relative errors for the remaining years ranged from 0.60% to 6.14%. The final prediction of water consumption in Zhangye City in 2027 was 20.18×10^8 m^3. The predictions generated by the grey neural network model in this study demonstrate a high degree of accuracy, suggesting that this model is suitable for forecasting short-term water use in areas akin to Zhangye City within the middle section of the Heihe River Basin.

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