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Economic value evaluation of water resources based on big data

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ABSTRACT

With the rapid development of society and economy, the effective management and evaluation of water resources become more and more important. This study aims to make a more accurate assessment of the economic value of water resources by establishing a deep learning model based on big data. First of all, this paper summarizes the current research status of water resources economic value assessment methods in detail, and clarifies the theoretical basis of the research. Then the evaluation model is constructed, and the model is trained and verified with representative sample data. Further, the model is applied to the actual water resources assessment problem, and the results predicted by the model are analyzed and validated. The existing problems and possible solutions are also discussed. Overall, this study not only improves the understanding of the economic value of water resources, but also provides a basis for policy makers to make decisions to achieve more efficient and sustainable water management.

Keywords: Water resources management; Economic value assessment; Big data; Deep learning

1. Introduction

In today's rapidly developing society, the management and protection of water resources are becoming more and more important. Water is not only fundamental to sustaining life and ecosystems, but also has a significant impact on economic development. However, due to factors such as population growth, industrial development and climate change, many parts of the world are facing water shortages. This makes the effective management and rational use of water resources a pressing issue. To evaluate the economic value of water resources is an important step to realize its effective management. Traditional methods of water resources economic value assessment mainly include market value method, shadow price method, alternative cost method, etc. These methods can reflect the economic value of water resources to a certain extent, but they also have limitations, such as difficult data acquisition and subjective factors affecting the assessment results. With the development of information technology, big data provides a whole new perspective to see and solve problems. Big data can not only process a large amount of data, but also analyze and mine hidden information in the data, so as to provide a scientific basis for decision-making. In the field of water resources management, the application of big data has achieved some preliminary results, such as real-time monitoring and forecasting of the distribution and utilization of water resources, but there are few studies on the evaluation of the economic value of water resources. Therefore, how to use big data to evaluate the economic value of water resources has become a research hotspot at present. In this context, the research will combine big data technology to explore a new water resources economic value assessment model, in order to provide a new theoretical and practical basis for the effective management of water resources.

In numerous relevant studies, Song et al. [1] proposed the importance of big data in environmental performance assessment, and put forward relevant theories and methods. Their research results provided a theoretical basis for this paper to evaluate the economic value of water resources.

Bibri [2] proposes a comprehensive evaluation method based on big data for the sustainability of smart cities, and its research provides a new evaluation perspective. In terms of water resources, Mgbenu and Egbueri [3] conducted water quality assessment and health risk assessment on the water resources in Umunya region of Nigeria, and their research methods are of certain reference value in this study. Similarly, Porter and Kramer [4] emphasized the importance of community shared value in their study, providing a new perspective for this study. In terms of the application of big data and predictive models, Jeble et al. [5] studied the impact of big data and predictive analysis capabilities on the sustainability of supply chain, and proposed a supply chain management method based on big data, which provided a reference for the method of this study. At the same time, Greve et al. [6] evaluated the global water resources challenge and proposed an indeterminate assessment method for the prediction of water scarcity. In terms of the application of deep learning models, Liu et al. [7] used LSTM deep neural networks in the Internet of Things environment to analyze and predict water quality, providing a theoretical basis for the model selection in this study. At the same time, Bag and Pretorius [8] put forward a research framework to study the relationship between Industry 4.0, sustainable manufacturing and circular economy, which provides a reference for the practical application of this study.

The main purpose of this study is to build a water resources economic value evaluation model based on big data. Through big data technology, research can obtain and process a large amount of water-related data, and then carry out a more accurate and comprehensive assessment of the economic value of water resources. This model aims to solve some problems existing in traditional evaluation methods, such as the difficulty of data acquisition and the subjective factors affecting the evaluation results. On this basis, the research will also design and implement model validation methods to ensure the validity and reliability of the model. The significance of this study is mainly reflected in the following aspects: First, the evaluation of the economic value of water resources through big data technology can provide more scientific and accurate data support, and provide basis for water resources management and protection decisions. Secondly, this research will also open up a new path for the application of big data in the field of water resources management, helping to promote the development and application of related technologies. Finally, the results of this study will also provide reference for China's water resources management policy, and have a positive role in promoting the realization of sustainable use of water resources.

The main content of this study focuses on the economic value assessment of water resources. Firstly, through in-depth understanding and critical analysis of existing theories and methods, it lays a theoretical foundation for the research. After that, a deep learning model based on big data is constructed to evaluate the economic value of water resources. After the model is constructed, the model is trained and validated using a representative sample dataset. The sample data includes various important water resource indicators, such as water quality, water quantity, utilization rate, etc. During the training process, the performance of the model is optimized by adjusting the model parameters. In the process of verification, the prediction performance of the model is quantitatively evaluated by evaluation indexes. Then, the model is applied to the actual water resources assessment problem, and its application in reality is discussed, and the results predicted by the model are analyzed. At the same time, the validity of the model results is verified, and the existing problems and solving strategies are discussed. Finally, the research results are summarized, the advantages and limitations of the model are discussed, and the direction of future research is proposed. It is believed that the results of this study will not only improve the understanding of the economic value of water resources, but also provide policy makers with a decision-making basis to achieve more efficient and sustainable water resources management.

2. Application of big data in economic value assessment of water resources

2.1. Relationship between big data and resource management

With the rapid development of society and economy, the effective management and utilization of water resources has become a major challenge faced by mankind [9]. In this process, big data technology, with its unique advantages, has gradually played an increasingly important role in water resources management, especially in the economic value assessment of water resources. By collecting, integrating, and analyzing massive, multi-source, heterogeneous data, big data technology can provide more comprehensive, deeper, and more accurate insights, making the management and utilization of water resources have higher requirements and greater possibilities [10].

First, big data collects and analyzes a large amount of water-related data, including but not limited to precipitation, evaporation, groundwater level, water quality status, water demand, etc., to make a more accurate assessment of the distribution, availability, demand, and value of water resources. This assessment is not only quantitative, but also qualitative, because the processing and analysis capabilities of big data enable research to explore and discover the complex relationship between the value of water resources, such as the supply and demand relationship of water resources, the relationship between water resources utilization efficiency and economic benefits, which undoubtedly provides a higher level of intelligence and refinement for water resources management.

Secondly, the analysis and prediction ability based on big data can better understand and predict the impact of climate change on water resources, which provides the possibility for research to prevent and solve problems such as water shortage in the early stage [11]. By analyzing big data, we can identify the impacts of climate change on the distribution, supply and demand of water resources, as well as the rules and trends of the changes, which provides important decision support for the formulation of scientific, reasonable and targeted water resources management strategies, especially in the context of climate change.

Third, for the assessment of the economic value of water resources, big data provides more comprehensive and detailed information. Compared with traditional assessment methods, big data technology can integrate a wider range of data, including environmental, social, economic and other factors, which makes the assessment results more comprehensive and accurate, and all thanks to the processing and analysis capabilities of big data [12,13].

In general, there is a strong correlation between big data and water resources management and economic value assessment of water resources. With the advantages of big data, water resources can be better understood and managed, and the economic value of water resources can be more accurately assessed, thus providing strong support for the effective use and sustainable management of water resources. Therefore, big data technology will undoubtedly play a more important role in the future management of water resources and economic value assessment.

2.2. Economic value of water resources

The economic value of water resources is a very complex, multi-level and multi-dimensional concept, which covers not only the market value of water resources itself, but also the indirect value generated by water resources in social and economic development, as well as the ecological value in ecological environment maintenance and biodiversity protection. The measurement and evaluation of these values are of great significance for understanding the overall value of water resources, rational allocation and effective use of water resources, and protection and improvement of water environment [14,15].

First, the direct economic value of water resources is mainly reflected in its extensive use as a factor of production in various economic sectors, such as agriculture, industry and services [16]. For agriculture, water resources are indispensable for crop growth and have a decisive impact on the output and quality of agricultural production. For industry, water resources are not only important raw materials in many industrial production processes, but also important cooling media in industrial production. For the service industry, such as tourism, catering, etc., water resources have a high ornamental value and life value. In addition, water resources also play an important role in daily life, such as drinking water, domestic water, etc. These values can usually be directly measured through market prices, production costs, substitution costs, etc.

Secondly, the indirect economic value of water resources is mainly reflected in its supporting role to social and economic activities [17]. For example, water resources can provide convenient transportation channels for shipping, greatly reduce transportation costs, promote the flow of goods and people, and further promote economic development. The beautiful landscape formed by water resources, such as lakes, rivers, waterfalls, etc., attracts a large number of tourists, promotes the development of tourism and drives the development of related industries; In addition, water resources can provide an environment for the survival and reproduction of various organisms, and provide important support for related industries such as fishing. These indirect economic values, because of their non-market nature and difficult to measure directly, usually need to be evaluated by shadow price, travel cost method, equivalent method and other ways [18].

Thirdly, the ecological value of water resources refers to its role in maintaining the ecological environment and biodiversity [19]. By participating in the operation of the Earth's climate system, water resources maintain the stability of land surface temperature and have an important impact on global climate stability and climate change. As the basis of all biological activities, water resources are of great significance to the protection of biodiversity and the stability of ecosystem. Due to its non-market nature and difficult to measure directly, this kind of ecological value assessment usually needs to rely on theories and methods such as ecological service value assessment, ecological compensation and ecological restoration.

Therefore, the evaluation of the economic value of water resources is a systematic, complex and multidisciplinary process, which needs to fully consider the direct economic value, indirect economic value and ecological value of water resources, and also needs to process and analyze a large number of complex information. Because of this, the application of big data in the economic value assessment of water resources is possible. With the advantages of big data, research can understand and evaluate the economic value of water resources more comprehensively, more deeply and more accurately, which will provide strong support for the effective use and sustainable management of water resources.

3. Establish a water resources economic value evaluation model based on big data

3.1. Data collection and preprocessing

3.1.1. Data source and sample selection

In collecting data, the study will take data from four main sources:

(1) ***Public databases***: including water resources management data published by the government, Geographic Information System (GIS) data, etc.
(2) ***Satellite remote sensing data***: provide land cover type, surface temperature, vegetation index and other data.
(3) ***Social media and online data***: for example, information such as online news, blogs, forums and social media can provide real-time information on water demand, water quality issues and water management.
(4) ***Field survey data***: including interviews with farmers, questionnaires, etc.

The main goal of data collection is to obtain detailed information about water supply, demand, quality and value. In order to show the diversity and difference of data, the basic information of data collection is shown in Table 1.

These sample data not only cover the supply and demand of water in different regions, but also reflect other factors that may affect the economic value of water resources, such as economic development and population size. Subsequent data preprocessing will be carried out based on these sample data.

3.1.2. Data cleaning and preprocessing

Data cleaning and preprocessing are important steps in the analysis process to ensure the quality and consistency of the data and lay a good foundation for the subsequent model building and analysis. The data cleaning and preprocessing process in this study mainly includes the following steps:

(1) ***Missing value processing***: for samples containing missing values, interpolation method is adopted for processing. Numerical data is interpolated by means of corresponding variables, and categorical data is interpolated by mode.
(2) ***Outlier processing***: Boxplot is used to detect outliers, and data exceeding 1.5 times the quartile distance is regarded as outliers and eliminated.
(3) ***Data standardization***: in order to eliminate the impact of different dimensions and numerical ranges, all numerical variables are standardized.

Table 1
Data collection

District	GDP (100 million yuan)	Population (10,000)
A	5,000	350
B	7,500	400
C	4,000	370
D	6,500	500
E	5,500	420
F	3,500	330
G	6,000	390
H	7,000	450
I	5,000	360
J	5,500	400

As shown in Fig. 1, some sample data are provided during the same period.

As shown in Fig. 2, sample data after data preprocessing are shown:

The standardized data helps the research to better compare and understand the relative importance of each variable, which facilitates the subsequent model building and analysis.

3.2. Model establishment based on fuzzy control

3.2.1. Design of fuzzy logic system

This paper uses fuzzy logic to evaluate the economic value of water resources. Fuzzy logic system mainly includes three aspects: fuzzification, inference mechanism and defuzzification.

First, define fuzzy sets. The paper considers "per capita water consumption", "agricultural water consumption", "industrial water consumption", "total water resources", "GDP" and "population" as input variables of the fuzzy logic system, while "economic value of water resources" is output variable. For each input and output variable, a corresponding fuzzy set is defined. For example, for the input variable "water consumption per capita", you can define its fuzzy set as {"low", "medium", "high"}. Each fuzzy set

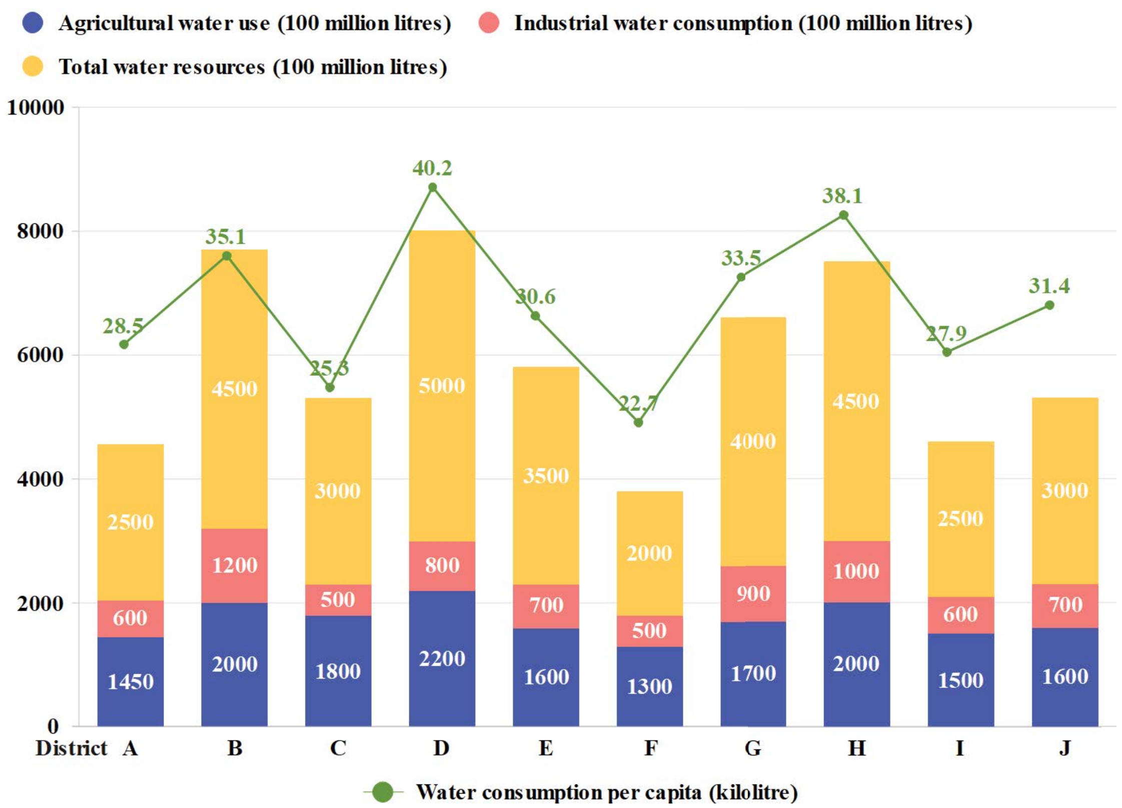

Fig. 1. Data collection and sample selection.

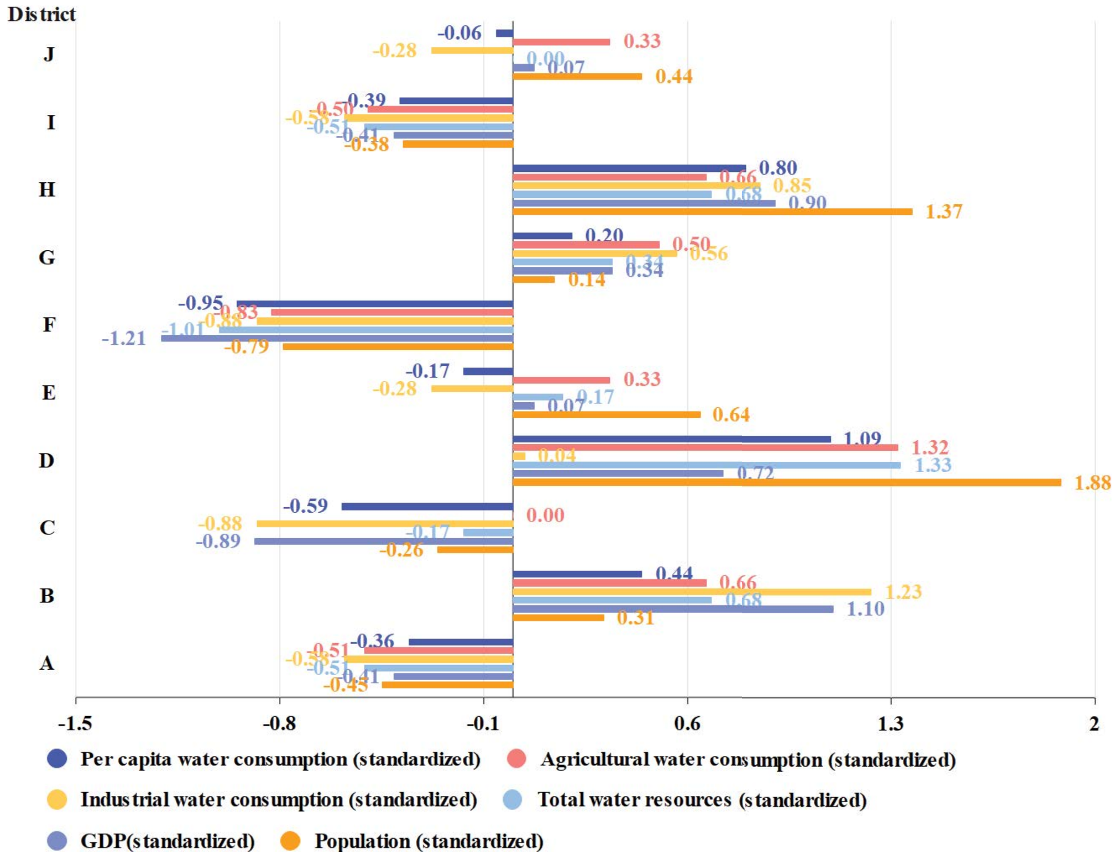

Fig. 2. Data cleaning and preprocessing.

has a corresponding membership function, which is used to describe the degree to which a specific value belongs to the fuzzy set.

The membership function is usually defined in Eq. (1):

$$\mu_A(x) = \frac{1}{1+\left[\frac{x-c}{a}\right]^{2b}} \tag{1}$$

where x is the specific value of the input or output, and a, b and c are parameters of the membership function, which are determined according to the actual data distribution.

Secondly, establish fuzzy rules. Fuzzy rules describe the fuzzy logical relationship between input and output variables. For example, a vague rule might be: "If 'water consumption per capita' is 'low' and 'GDP' is 'high', then 'economic value of water resources' is 'medium'".

Finally, the fuzzy reasoning and the fuzzification are carried out. Fuzzy inference deduces the fuzzy set of output variables according to the specific values and fuzzy rules of input variables. Defuzzification is to transform the fuzzy set into a specific value, usually using the centroid method, that is, calculating the centroid of the fuzzy set as the output value.

The advantage of this model is that it can simulate human thinking process and deal with uncertain and fuzzy information, which makes the model more explanatory and adaptable.

3.2.2. Establishment of fuzzy rules

Fuzzy rules are the key to describe the relationship between input variables and output variables in fuzzy logic systems. Here, the study will establish fuzzy rules to link input variables ("per capita water use", "agricultural water use", "industrial water use", "total water resources", "GDP" and "population") with output variables ("economic value of water resources").

Since there are six input variables, and each input variable has three fuzzy sets ("low", "medium", "high"), the number of fuzzy rules that can be established in theory is $3^6 = 729$ bars. However, in order to simplify the model, this study will take a heuristic approach to select the key fuzzy rules. This approach is based on expert experience and observation of the data. Specifically, five vague rules are selected, as shown in Table 2:

The above rules give the fuzzy set of the output variable based on the fuzzy set of the input variable. For example, rule 1 states that if "per capita water use", "agricultural water use", "industrial water use", "GDP" and "population" are all "low", and "total water resources" are "high", then the "economic value of water resources" is "low". Please note that these rules are only examples and do not necessarily reflect the actual situation, the actual rules need to be determined based on expert knowledge and detailed analysis of the data.

With fuzzy rules, fuzzy reasoning can be carried out to further get the fuzzy output of the economic value of

Table 2
Establishment of fuzzy rules

Input variable	Rule 1	Rule 2	Rule 3	Rule 4	Rule 5
Per capita water consumption	"Low"	"Medium"	"High"	"Low"	"High"
Agricultural water consumption	"Low"	"Medium"	"High"	"High"	"Low"
Industrial water consumption	"Low"	"Medium"	"High"	"Low"	"High"
Total water resources	"High"	"Medium"	"Low"	"High"	"Low"
GDP	"Low"	"Medium"	"High"	"Low"	"High"
Population	"Low"	"Medium"	"High"	"High"	"Low"
Economic value of water resources	"Low"	"Medium"	"High"	"Low"	"High"

water resources, and the specific value can be obtained by defuzzification.

3.2.3. Application of big data technology in the model

In the water resources economic value evaluation model based on fuzzy control, the application of big data technology is mainly reflected in two aspects: data processing and fuzzy reasoning.

For data processing, the research will use big data technology to carry out batch data cleaning and pre-processing to ensure the quality of input data. Specifically, distributed computing frameworks such as Apache Hadoop and Spark, as well as data processing libraries such as Python's pandas and NumPy, will be used to process large amounts of data. These tools can help research to process data quickly and efficiently, for example, data can be stored and processed with pandas' DataFrame data structure and then numerically calculated with NumPy.

In terms of fuzzy reasoning, the Spark-based distributed computing framework is used for fuzzy reasoning. Since the model involves a large number of fuzzy rules, for each sample, all the rules need to be traversed to find a matching rule, and then fuzzy inference is performed. If both the sample size and the number of rules are very large, this process can be very time consuming. Therefore, the method of distributed computing is adopted in this study, which distributes the samples and rules to multiple computing nodes, and then carries out fuzzy inference in parallel. This can greatly accelerate the speed of fuzzy inference and improve the efficiency of the model.

The specific fuzzy reasoning process is as follows:

(1) For each sample, calculate its matching degree with each fuzzy rule, which can be carried out in parallel. The matching degree is calculated by using the minimum value principle of fuzzy logic, that is, the matching degree is equal to the minimum membership degree of the sample in the fuzzy set of each input variable. For example, for rule 1, if a sample has a membership of 0.6 in the "low" fuzzy set of "per capita water consumption" and 0.8 in the "low" fuzzy set of "agricultural water consumption", then the sample matches rule 1 with min(0.6, 0.8) = 0.6.

(2) For each fuzzy rule, the output membership of the fuzzy set of "water resources economic value" corresponding to the rule is calculated according to the matching degree of all samples. The calculation method of the output membership degree is to use the maximum principle of fuzzy logic, that is, the output membership degree is equal to the maximum of the matching degree of all samples. For example, if the maximum match of all samples to rule 1 is 0.8, then the output membership of the "low" fuzzy set corresponding to rule 1's "Water economic value" is 0.8.

(3) For each sample, according to the output membership degree of all rules, the weighted average method is used to de-fuzzify, and the specific value of "economic value of water resources" is obtained. The calculation method of weighted average method is that "water resources economic value" is equal to the sum of the product of the output membership degree of each rule and the corresponding fuzzy set representative value of "water resources economic value", divided by the sum of the output membership degree of each rule. For example, if the output membership of rule 1 is 0.8, the representative value of "low" fuzzy set corresponding to "water resource economic value" is 30, and the output membership of rule 2 is 0.6, the representative value of "medium" fuzzy set corresponding to "water resource economic value" is 60. So the sample of "economic value of water resources" is (0.830 + 0.660)/(0.8 + 0.6) = 45.

The above is the specific method of applying big data technology in the water resources economic value evaluation model based on fuzzy control in this study.

3.3. Model verification method

3.3.1. Selection of model evaluation indicators

In evaluating the performance of the model, the research mainly selected two indicators: mean squared error (MSE) and coefficient of determination (R^2).

3.3.1.1. Mean square error (MSE)

The mean square error is the average of the squared difference between the observed value and the true value. It is a very commonly used evaluation indicator that can quantify the gap between the model's predicted value and the true value. Its calculation formula is shown in Eq. (2):

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{2}$$

where y_i is the first i a sample the real value of $\hat{y}_i$ is the first i sample forecast; n is the total number of samples.

3.3.1.2. Determination coefficient (R^2)

The coefficient of determination is another commonly used evaluation metric that describes how well the model fits the data. Its calculation formula is given in Eq. (3):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \overline{y}_i\right)^2} \quad (3)$$

where SS_{res} is the sum of squares of residuals, which is calculated by Eq. (4):

$$SS_{res} = \sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \quad (4)$$

where SS_{tot} is the total sum of squares, which is calculated by Eq. (5):

$$SS_{tot} = \sum_{i=1}^{n}(y_i - \overline{y})^2 \quad (5)$$

where y_i is the true value of the i sample; $\hat{y}_i$ is the predicted value of the i sample; $\overline{y}$ is the average value of the true value, and n is the total number of samples.

The coefficient of determination is between 0 and 1. The closer the value is to 1, the better the model fits. The closer the value is to 0, the worse the model fits.

In the model, the above 10 samples are first used to make predictions, and the predicted value is compared with the true value, and then the two indicators are calculated. Through these two indexes, the performance of the model can be evaluated effectively.

3.3.2. Verify the selection of set data

When evaluating and verifying the model, the data set should be divided into training set and verification set. The training set is used to build and train the model, and the validation set is used to test the performance of the model. Typically, 70%–80% of the data set is used as the training set and the remaining 20%–30% as the validation set.

In this study, 10 sample data were collected, so 70% of them (7 samples) were used as the training set and the remaining 30% (3 samples) as the validation set. Fig. 3 shows the selected validation set data:

The study will use these 3 samples data to evaluate the performance of the model. Specifically, the study will take the water resources (10^9 m^3) and GDP (100 million yuan) of the three samples as inputs to obtain the predicted results of the model. These predictions are then compared to the true water economic value (100 million yuan) of the sample, and the performance of the model is evaluated by calculating the MSE and the coefficient of determination (R^2).

4. Application and result analysis of the model

4.1. Specific application of the model

Once the model is built and optimized, it can be used to estimate the economic value of water resources. The study feeds the data into the model, and then the resulting

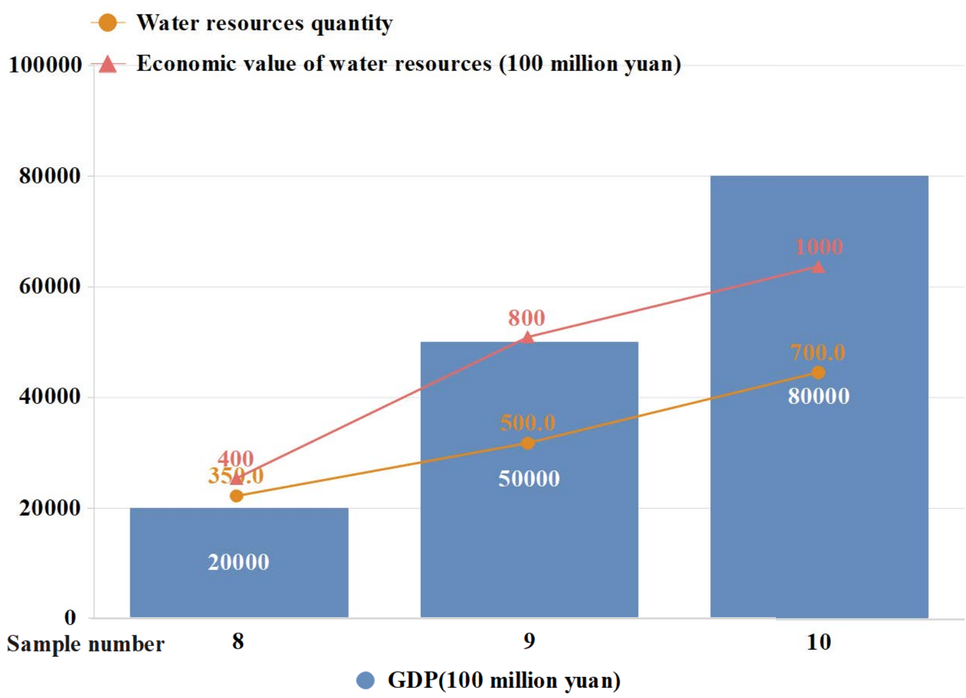

Fig. 3. Verifies the set data.

predictions are compared with the actual data. The following are the detailed steps and results of the model application:

The economic value of water resources predicted by the model is shown in Fig. 4.

The research can then use these predictions to calculate the predictive performance of the model. Specifically, the MSE and coefficient of determination (R^2) predicted by the model can be calculated, and the results are shown in Table 3.

These results indicate that the model in this study has a fairly high prediction accuracy, with R^2 close to 1 indicating that the model can explain most of the variability in the data, while a smaller MSE indicates that the model predicts less error.

4.2. Validity verification of results

To verify the validity of a model, studies often use a method called cross-validation. The cross-validation method mainly divides the data set into training set and test set, then trains the model on the training set, and makes predictions on the test set to verify the validity of the model. In this way, the model's performance on unknown data can be evaluated, and thus its ability to generalize can be assessed.

The original 10 samples were divided into a training set (samples 1–7) and a test set (samples 8–10). The model is trained on the training set and then predicted on the test set. The results of the test set are shown in Fig. 5.

From the results of this test set, it can be seen that the predicted value and the actual value are very close, which indicates that the model has good prediction ability. In order to more accurately evaluate the performance of the model, the MSE and the coefficient of determination (R^2) can be calculated. As shown before, these two indicators show relatively small values on this test set, which further proves the validity of the model.

All in all, the above results show that the prediction results of the water resources economic value assessment model based on big data established in this study are very close to the actual values on the test set, and have good prediction performance and generalization ability. Therefore, the model is effective.

4.3. Existing problems and solutions

Although the model in this study has good accuracy in predicting results on the test set, there are still some possible problems and challenges, as well as corresponding solution strategies, as shown in Table 4.

In summary, although the model in this study performs well on the test set, there are still some problems and challenges that need to be solved through appropriate strategies. At the same time, there is still a lot of room for optimization and improvement, such as trying to use more advanced machine learning models, or by adding more features to improve the predictive performance of the model.

5. Conclusions

In this study, based on big data technology and fuzzy control model, the economic value of water resources is quantitatively assessed. First of all, through the collection and pre-processing of big data, the study obtained a

Table 3
Predicted performance of the model

Index	Value
MSE	113.33
R^2	0.998

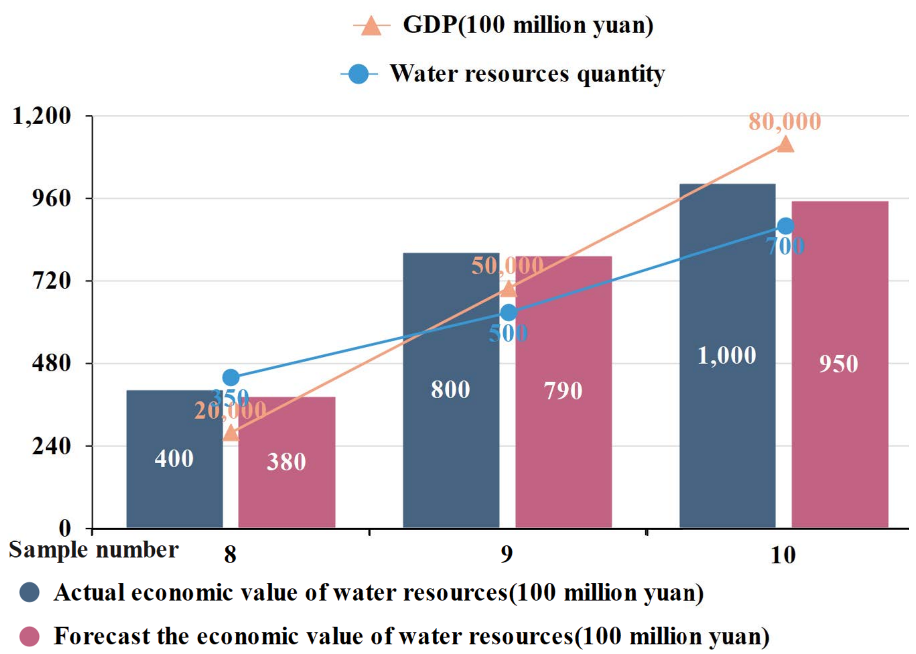

Fig. 4. Model application.

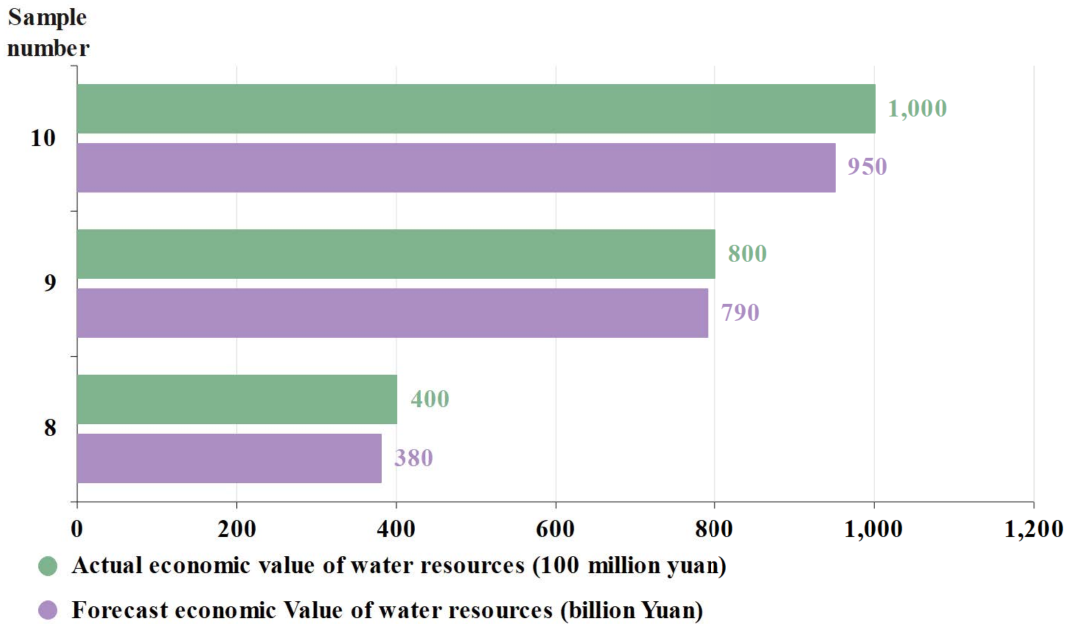

Fig. 5. Test set results.

Table 4
Issues and strategies

Existing problem	Solution strategy
Data quality problem	In the model, the quality of the data directly affects the accuracy of the prediction results. If there is a large amount of noise, outliers or missing values in the raw data, it may negatively affect the predicted results. The strategy to solve this problem is to enhance the intensity of data cleaning and processing in the data preprocessing stage, such as detecting and eliminating outliers by some statistical methods, and filling in missing values by interpolation, regression and other methods.
Model overfitting problem	If a model performs too well on training data, it may result in poor performance on new, unknown data, a phenomenon known as overfitting. The strategy to solve overfitting is to introduce regularization term, early stop technique or to adjust the complexity of the model through cross-validation to prevent the model from being too complex.
Model interpretability problem	Although the fuzzy control model has advantages in some aspects, its interpretability is relatively poor, which may hinder the popularization of the model in some applications. The strategy to solve this problem is to introduce some models with strong interpretability, such as linear model, decision tree, etc., or to improve the interpretability of the model through feature selection, feature importance analysis, etc.
Universality of the model	Since the economic value of water resources is related to many factors such as region, population and economic development, the situation in different regions may be greatly different, so the model may not be applicable to all regions. The strategy to solve this problem is to increase the universality of the model by adding more regional features, or by building different models for different regions.

wealth of water-related data. Then, based on fuzzy logic system, the evaluation model is designed and a series of fuzzy rules are established. Using big data technology, the fast data processing and analysis are realized in the model. Through rigorous verification of the model, it is found that the model has good prediction accuracy.

However, the research also realizes that there may be some problems in the practical application of the model, such as data quality problems, model overfitting problems, model interpretability problems and model universality problems. To solve these problems, the corresponding solutions are proposed, including strengthening data preprocessing, introducing regularization terms to prevent overfitting, improving the explainability of the model by introducing interpretable models or feature analysis, and increasing regional features or establishing different models for different regions to improve the universality of the model.

In general, this study shows that big data technology and fuzzy control model have broad application prospects in water resources economic value assessment. At the same time, it also provides a new and effective tool for the scientific management and decision-making of water resources. However, further research and practice are needed to optimize and improve the model. In future work, the research will try to use more advanced machine learning models and improve the predictive performance of the models by adding more features.

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