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Trade-Off and Synergy Mechanism of Agricultural Water Resource Spatial Allocation in Monsoon Climate Areas Based on Machine Learning: A Case Study of Reservoir Layout Optimization in Shandong Province, China

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Citation: Zou, M.; Xie, D.; Xu, L.; Dai, K.; Liang, S.; Guo, M.; Qin, X.; Zhao, W. Trade-Off and Synergy Mechanism of Agricultural Water Resource Spatial Allocation in Monsoon Climate Areas Based on Machine Learning: A Case Study of Reservoir Layout Optimization in Shandong Province, China. *Agronomy* **2024**, *14*, 1902. https://doi.org/10.3390/agronomy14091902

Academic Editor: Paul Kwan

Received: 19 July 2024
Revised: 21 August 2024
Accepted: 23 August 2024
Published: 25 August 2024

Abstract: Influenced by increasing global extreme weather and the uneven spatiotemporal distribution of water resources in monsoon climate areas, the balance of agricultural water resources supply and demand currently faces significant challenges. Conducting research on the spatial allocation trade-offs and synergistic mechanisms of agricultural water resources in monsoon climate areas is extremely important. This study takes the spatial layout of reservoir site selection in water conservancy projects as an example, focusing on Shandong Province as the research area. During the site selection process, the concept of water resource demand is introduced, and the suitability of reservoir siting is integrated. It clarifies ten influencing factors for suitability degree and five influencing factors for demand. A bi-objective optimization model that includes suitability degree and demand degree is established. Utilizing machine learning methods such as the GA_BP neural network model and the GA-bi-objective optimization model to balance and coordinate the supply and demand relationship of agricultural water resources in the monsoon region. The study found that: (1) in the prediction of suitability degree, the influencing factors are most strongly correlated with the regulatory storage capacity (regulatory storage capacity > total storage capacity > regulating storage coefficient); (2) compared with single-objective optimization of suitability degree, the difference between water supply and demand can be reduced by 74.3% after bi-objective optimization; (3) according to the spatial layout optimization analysis, the utilization of water resources in the central and western parts of Shandong Province is not sufficient, and the construction of agricultural reservoirs should be carried out in a targeted manner. This study provides new ideas for promoting the efficient use of water resources in monsoon climate zones and the coordinated development of humans and nature, reflecting the importance of supply and demand balance in the spatial allocation of agricultural water resources, reducing the risk of agricultural production being affected by droughts and floods.

Keywords: machine learning; trade-off and coordination mechanism; irrigation management strategy; reservoir siting; monsoon climate zone

1. Introduction

The IPCC AR6 report [1] and the interpretation reports [2–4] point out that the frequency and intensity of extreme weather events will increase significantly due to global warming. According to data from the United Nations Food and Agriculture Organization, the number of people suffering from severe food shortages due to climate change has increased to 345 million worldwide. In monsoon climate zones, changes in the temporal and spatial distribution of precipitation and the occurrence of extreme weather have made the temporal and spatial distribution of water resources increasingly uneven. Coping with the contradiction between water supply and demand caused by climate change has become an urgent issue. Due to the different temporal and spatial distribution of water resources in different climate zones, the spatial allocation and synergy mechanisms of water resources will be fundamentally different. For example, in arid and semi-arid regions where water is generally in short supply, the suitability of the site for the project is the main research topic [5–7]. In the monsoon region of Southeast Asia, the relationship between water supply and demand is a primary research topic in order to address the risk of flooding [8] and ensure economic development [9]. In addition, due to the wide distribution of the population and the high proportion of agriculture in the monsoon climate region of Southeast Asia, it is particularly important to ensure a balance between water supply and demand for agricultural water resources.

The regulation and storage of water resources by reservoirs (dams) in water conservancy projects play a very important role in addressing the problem of uneven spatiotemporal distribution of water resources. The influencing factors and supply and demand relationships in different climatic zones are significantly different, and the purposes and functions of reservoir construction will also be significantly different [5–7,10]. Although there are currently only a few studies on reservoir and dam siting in other climate zones [10], research in other areas of water resources can provide new insights into reservoir siting. For example, Randle, T. J. [11], Wisser, D. [12], Ran, L. [13], Wu Jianchun [14], Peng Fangxu [15], Wei Runchu [9], and others have studied the reservoir capacity calculation and irrigation storage function of reservoirs. The regulatory storage capacity, total storage capacity, and regulating storage coefficient involved in previous studies provide a reliable basis for selecting important research indicators for studying the spatial layout of reservoirs. Therefore, based on the correlation between the aforementioned three indicators and the influencing factors of suitability degree, a machine learning approach can be used to screen for the most correlated suitability prediction model, thereby determining the independent variables and scoring function for the suitability degree score.

Due to the inevitable spatial heterogeneity of water demand in different climate zones, the problem of reservoir siting is particularly prominent in monsoon climate zones, where the spatial and temporal distribution of water resources is uneven. Significant results have been achieved in the study of agricultural water demand measurement in monsoon climate zones. Data charts on the potential evapotranspiration of agricultural water in Shandong Province by Zhao Shen et al. [16] and the calculation method for crop water requirements in the ecological water storage guarantee of the Yellow River region by Pang Aiping et al. [17] provide a scientific basis for the prediction of the irrigation capacity of reservoirs and the calculation of agricultural water requirements, and provide a reference for the collection of data on the demand degree of reservoir siting research and the calculation of crop water requirements. However, there is little reporting on how to effectively reflect water demand in reservoir siting studies. Therefore, we introduce the analysis of demand degree in the genetic algorithm-based garbage station siting in Pengyang [18] into the field of reservoir siting, and establish a scoring function for demand degree. At this point, the reservoir siting bi-objective optimization model that comprehensively considers suitability degree and demand degree becomes the key to solving the problem. By drawing on the bi-objective optimization model for the selection of a waste station site, this study attempts to analyze and optimize the indicators selected by the suitability degree prediction model and the demand degree as the independent variables of the objective function in the bi-objective optimization model.

The methods for reservoir and dam site selection can mainly be divided into the following four categories: traditional specific engineering survey site selection methods, GIS/RS methods, MCDM/MCDM-GIS methods, and machine learning methods [19]. Traditional specific engineering survey site selection methods, such as those by Lashkaripour, G.R. [20], Rajabi, A.M. [21], and Kanik, M. [22], involve methods for site selection surveys for specific reservoir and dam projects. These site selection methods have comprehensive on-site environmental data, allowing for the development of specific strategies tailored to diverse surrounding environments. The GIS/RS method, with its smaller data volume and simpler processing, enables rapid and accurate screening and site selection for individual projects. For instance, IBRAHIM, M.H.J., and others have conducted dam site selection using remote sensing satellite technology [23]. The first two methods mentioned are suitable for site selection of small-scale projects with simple data, but they have limitations when dealing with complex projects with large volumes of data. The MCDM/MCDM-GIS methods can handle the weight relationships of various factors affecting the site selection of reservoirs and dams. For example, studies by Ebrahimi, J., Hamidifar, H., Nzotcha, U., and others [24–26] have used MCDM methods for decision-making and application in reservoir site selection. The MCDM/MCDM-GIS method is currently widely used, but due to the subjectivity in determining the advantages and disadvantages of various influencing factors and the evaluation of weights, as well as the lack of objective conditions to correct the final results, it may lead to significant prediction errors. Machine learning methods can learn from a large amount of data to accurately simulate the relationship between reservoir site selection and various influencing factors, and can precisely predict the site positioning. Compared to the MCDM/MCDM-GIS method, machine learning has a clear optimization direction, avoids the impact of human factors in the MCDM method, and improves the accuracy of decision-making.

At present, in response to the impact of extreme weather and monsoon climate, the government has formulated a series of policies to strengthen water resources security and flood and drought control, and to prevent water and drought disasters [27,28]. Shandong Province is a major agricultural province in China, with agricultural water consumption accounting for more than 60% of total water consumption. Agricultural water security is therefore a top priority in water resources construction [29]. This study takes the optimization of reservoir siting in Shandong Province as an example, and improves the existing evaluation system for reservoir siting. (1) The concept of water demand, namely the degree of demand, and the use of machine learning to test the correlation between the predictor variables of suitability degree and their influencing factors, aims to identify the independent variables that have the best correlation with suitability degree. (2) Conducting bi-objective optimization for suitability degree and demand degree, aiming to promote the improvement of the spatial allocation balance and coordination mechanism for agricultural water resources in Shandong Province, and to improve the supply and demand relationship of water resources and ensure the security of agricultural water use.

2. Materials and Methods

2.1. Study Area

The study area is situated in Shandong Province, located in eastern China (as shown in Figure 1, encompassing a total area of 157,900 square kilometers. Shandong Province, surrounded by the sea on three sides, is dominated by plains and traverses five major river systems, falling under the category of a warm temperate monsoon climate. With a permanent resident population of approximately 102 million, Shandong Province is the second most populous and second largest grain-producing province in China, with agricultural water consumption accounting for more than 60% of the province's total water consumption. According to the survey, the entire province has built approximately 6000 large, medium, small, and micro reservoirs, some of which were constructed from the 1950s to the 1970s. The reinforcement project for dangerous reservoirs within the provincial jurisdiction has commenced at the present stage, with new construction and renovation projects gradually being carried out. Research on the trade-off and coordination mechanisms for reservoir layout has become an important topic.

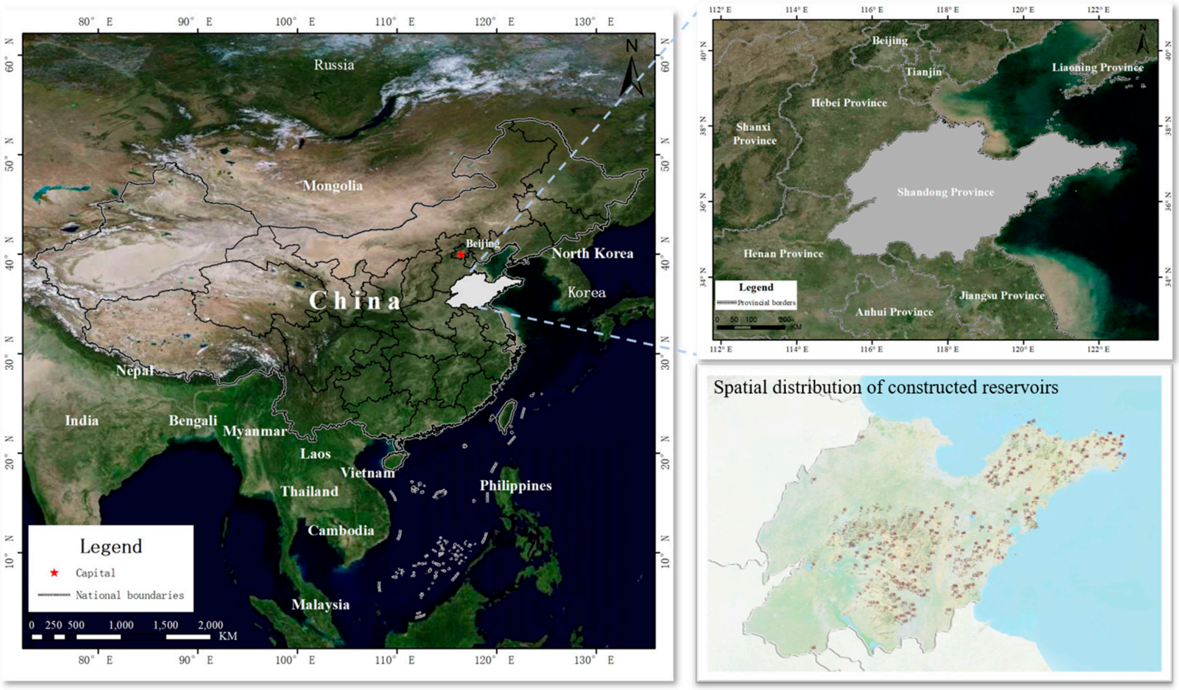

Figure 1. Spatial distribution of the study area and existing reservoirs.

2.2. Data Sources and Processing

2.2.1. Determination of Data Coordinate Points

The allocation of agricultural water supply, the division of irrigation areas, and the optimization of water conservancy facilities in various regions of Shandong Province are all based on city and county-level units. However, there are fewer samples at the city level, and the optimization of reservoirs should also aim to meet the water use and irrigation conditions at the county level to ensure agricultural water security in counties and their subordinate villages. This study is based on the coordinates of 193 publicly reported reservoirs in Shandong Province and the geometric centers of 136 counties in Shandong Province, which together constitute a research system for learning and optimizing reservoir location planning, involving a total of 329 location coordinates.

2.2.2. Data and Processing of Factors Influencing Suitability Degree

In this study, the factors influencing reservoir siting layout are categorized into two primary groups: suitability degree and demand degree, with a focused analysis on the impact of each on the siting decision.

Based on previous studies, by combining the six categories of influencing factors summarized by Wang Yang et al. [19] with the research scheme of reservoir dam site selection by scholars such as Al-Ruzouq, R. [30–32], ten suitability influencing factors were identified, including water resources, precipitation, temperature, evaporation, geological hazards, stratigraphic lithology, hydrogeology, socio-economic factors, land terrain type, and ecologically sensitive areas. Due to the large variety of influencing factors on suitability degree, it is necessary to perform quantitative data assignment for these factors prior to machine learning (Table 1), in order to facilitate the data learning and prediction processes of the GA_BP neural network model.

Table 1. Data sources and processing of influencing factors for suitability degree.

Influencing Factors	Data Source	Data Processing
water resource	Data comes from the vector map of the river basin water system data across China.	Water resources are an important factor influencing the site selection of reservoirs, and the factors of water sources include the basin area upstream of the dam site, the average flow over time, and the peak flow [33,34]. Research has found that the main factor affecting the storage capacity of large and medium-sized reservoirs is the flow of the river flowing into the reservoir. In addition, to facilitate the statistical management of rivers, China has established a set of river grading standards. The hydrological information such as the size of the river flow can be reflected through the river grade; the distance from the river can be used to judge the cost and necessity of building a reservoir. Therefore, this paper uses the river grade and the distance from the river to reflect the richness of the water source.
precipitation	Data comes from the annual precipitation distribution map of Shandong Province.	The values are assigned based on the standardized and transformed rainfall amounts of the coordinate points obtained from the annual precipitation distribution map of Shandong Province, with the assignment scores ranging from 1 to 9.
temperature	Data comes from the annual average temperature distribution map of Shandong Province.	Based on the annual average temperature distribution map of Shandong Province, the temperature values obtained for the coordinate points are standardized and transformed to obtain transformation scores, with the scoring range being [1,9]. The scoring method is the same as that for precipitation.
evaporation	Data comes from the evapotranspiration distribution map of Shandong Province.	Based on the evapotranspiration distribution map of Shandong Province, the values of evaporation obtained for the coordinate points are standardized and converted to obtain transformation scores, with the scoring range being [1,9]. The scoring method is the same as that used for precipitation.
geological hazards	Data comes from the seismic intensity distribution map of Shandong Province.	Based on the research in engineering hydrogeology by Wang Xue et al. [34–38], using the grading standards of seismic intensity [35,36], the intensity of geological disasters is analyzed to assess the impact of geological disasters on the suitability of reservoir construction. The coordinate points within Shandong Province are assigned values, where 0.2 g and 0.3 g represent the seismic acceleration, and g represents the acceleration due to gravity.
stratigraphic lithology	Data comes from the stratigraphic lithology distribution map of Shandong Province.	Based on the types of rock layers and the intensity of water richness displayed in the spatial distribution map of water-rich rock types in Shandong Province, the valuation of rock lithology is evenly divided.
hydrogeology	Data comes from the distribution map of groundwater resources in Shandong Province and the “Surface Water Quality Standards” [37].	Based on the distribution map of groundwater resources in Shandong Province, the richness of groundwater sources is divided into five grades according to the classification standards in the map, with reference to the grading standards of groundwater water richness and the depth of groundwater burial for valuation. According to the degree of pollution of groundwater sources in Shandong Province, the water quality is divided into five categories following the water environmental quality grades defined in the “Surface Water Quality Standards” [37].
socio-economic	Data comes from the GDP data of various counties in Shandong Province that were publicly disclosed in the 2021 Shandong Provincial Government Report.	Based on the GDP data of various counties in Shandong Province from the Shandong Provincial Government Report, standardized valuation is conducted for 329 points, with a valuation range of [1,9]. The valuation method is the same as that for precipitation.

Table 1. *Cont.*

Influencing Factors	Data Source	Data Processing
Land terrain type	Data comes from the land use map and topographic map of Shandong Province.	To reduce the potential flood risks of reservoir construction on land use, relocation, farmland, and urban and rural settlements, minimize the destruction to the natural environment and ecology, ensure agricultural irrigation, and reduce the impact on economic development, this study assigns values to the types of land and terrain based on the land use map and topographic map of Shandong Province.
ecologically sensitive area	Data comes from the "Shandong Province Ecological Protection Red Line Planning" [38].	In accordance with the "Shandong Province Ecological Protection Red Line Planning" [38], the spatial distribution locations of ecological protection areas are determined, and the distance between the planned reservoir sites and ecologically sensitive areas is planned to reduce the impact of reservoir construction on ecologically sensitive areas. This study assigns values to the research coordinate points based on their distance from ecologically sensitive areas.

See Appendix A for data assignment process.

This paper brings the data processing results of the 10 influencing factors of the suitability degree of 329 site selection points into ArcGIS 10.8 software. It uses Kriging interpolation to interpolate and visualize the data. The spatial distribution map of the resulting assignment is shown in Figure 2. The colors of the legend in the figure represent the assignment from low to high from left to right, so that the spatial distribution of the assignment of each influencing factor can be more intuitively seen, which is convenient for data selection and solving of the model.

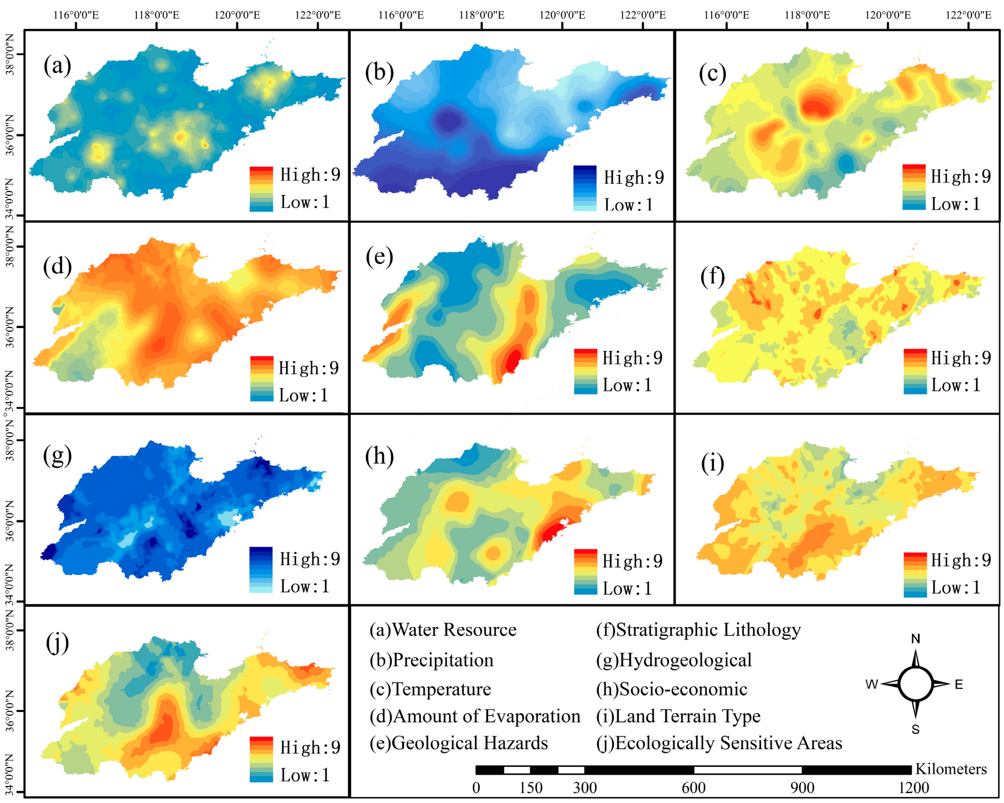

Figure 2. Spatial distribution of scores for influencing factors: (**a**) Water Resources; (**b**) Precipitation; (**c**) Temperature; (**d**) Amount of Evaporation; (**e**) Geological Hazards; (**f**) Stratigraphic Lithology; (**g**) Hydrogeological; (**h**) Socio-economic; (**i**) Land Terrain Type; (**j**) Ecologically Sensitive Areas.

2.2.3. Data and Processing of Influencing Factors of Demand Degree

In terms of demand degree, five influencing factors of demand degree were identified based on studies of evapotranspiration in the agricultural water sector [16,17], including the original regulating storage capacity, the area of the irrigation area, the average annual precipitation at the coordinate point, the potential evapotranspiration, and the distribution coefficient (Table 2). Based on existing studies [16–18], the regulating storage capacity can be used to calculate the specific water supply capacity of the reservoir, fully tap the potential of the reservoir water supply, and solve the problem of high water loss and low water supply guarantee rate in the operation of existing reservoir water supply projects. In contrast, calculating the water supply capacity based on the total storage capacity will lead to a mismatch between the theoretical value of the water supply capacity and the actual water supply capacity, and it is not possible to consider the value of total reservoir capacity as the amount of irrigation water that can be supplied. Although the regulating storage coefficient of the reservoir is related to the regulatory storage capacity of the net flow of the river, the regulating storage coefficient has no direct relationship with the irrigation water requirement, and its correlation with the influencing factors is not significant. Therefore, based on existing research, we selected the regulatory storage capacity as the independent variable of the scoring function for demand degree, combined the water supply capacity of the reservoir with the water demand of the irrigation area, and processed the data on the existing reservoir water supply and agricultural water demand to obtain the scoring function for demand degree for reservoir siting.

1. Source of data

Table 2. Data sources for factors influencing the degree of demand.

Influencing Factors	Data Source
original regulating storage capacity	For the regulating storage capacity of the existing reservoirs adjacent to the coordinate points within the irrigation area, the geographical information data of the reservoirs comes from the team's statistical collection, and the data on the regulating storage capacity comes from the introduction reports of the reservoirs.
irrigation area	For the area of the irrigation district where the coordinate point is located, the data comes from the Shandong Province Irrigation District Directory.
annual average precipitation at the coordinate point P	Data comes from the spatial distribution map of precipitation in Shandong Province.
Potential evapotranspiration	Data sources refer to Zhao Shen's study on the spatiotemporal variation of evapotranspiration and potential evapotranspiration in Shandong Province [16].
distribution coefficient α	Data comes from the proportion of agricultural water allocation to total water demand in various cities of Shandong Province.

2. Data processing

Demand for Reservoir Site Selection: In the existing reservoir layout system, the demand for agricultural irrigation water and the availability of existing reservoirs can meet the supply–demand imbalance of water resources.

$$W_i^D = W_i - \alpha \cdot V_{oi}^R \quad (1)$$

$$W_i = W_{ai} - \frac{P_{ei} \times A}{1000} \quad (2)$$

$$W_{ai} = \frac{PET_i \times A}{1000} \quad (3)$$

W_i^D—Difference between supply and demand for irrigation (m^3), i = 1, 2, 3, . . ., 329;

V_{oi}^R—Original regulation storage capacity: Regulating storage capacity of existing reservoirs adjacent to coordinate points within the irrigation area (m^3), (The value of the original regulating capacity at the coordinates of the unbuilt reservoirs is 0);

α—Distribution coefficient;

W_i—Water demand for agricultural irrigation (m^3);

W_{ai}—Crop water requirements (m^3);

A—Irrigation area (m^2), is the area of the irrigation area where the coordinate point is located;

PET_i—Potential evapotranspiration, is the amount of water evaporated and transported by the crop under conditions of water availability;

P_{ei}—Average annual effective rainfall (mm): Amount of rainfall that is utilized directly or indirectly by crops, and for other essential uses on agricultural land [17,39], is the average annual effective rainfall at the coordinates.

$$P_{ei} = \begin{cases} \frac{P_i\left(4.17 - \frac{0.2P_i}{365}\right)}{4.17} & \mathrm{P}_i < 3029.5 \\ 4.17 \times 365 + 0.1P_i & P_i \geq 3029.5 \end{cases} \tag{4}$$

p_i—Average annual rainfall at coordinates.

The scoring function for demand degree shows the irrigation water requirement for agriculture and the irrigation supply–demand gap for reservoirs (demand degree for reservoir siting) in Figure 3.

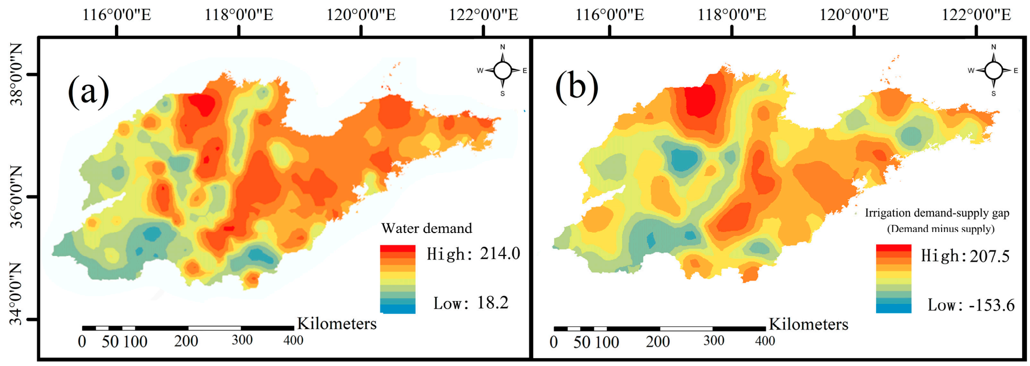

Figure 3. Irrigation water demand and degree of need for reservoir siting: (**a**) Water demand; (**b**) Irrigation demand-supply gap.

2.2.4. Predictor Variables Data and Processing

The predictor variables to be selected in this study are those that need to be determined after screening by the GA_BP neural network model. The establishment of scoring functions requires the determination of predictor variables. In this study, the regulatory storage capacity, total storage capacity, and regulating storage coefficient, which are commonly used in water conservancy research, are selected as the predictor variables for suitability degree. In terms of demand degree, the water supply for agricultural irrigation, power generation, and shipping provided by reservoirs is all studied in terms of regulatory storage capacity [13,40,41]. Therefore, the demand degree can be used as the independent variable for regulatory storage capacity, while there is no unified standard for the selection of independent variables for suitability degree. Machine learning is needed to screen the selected candidate variables. In addition, the two objective functions in bi-objective optimization also need to have the same independent variable as a common measure. Therefore, the predictor variables need to meet the requirements of the three scoring functions for suitability degree, scoring functions for demand degree, and bi-objective optimization functions for the independence of the independent variables.

1. Data Sources

Because machine learning is needed to find the relationship between the predictor variables and the influencing factors, this study collected information on 193 large and medium-sized reservoirs in Shandong Province that have been made public. The data sources are shown in Table 3.

Table 3. Data sources for independent variables to be selected.

Independent Variable to be Selected	Interpretation	Source of Data
Adjustment of storage capacity	Adjustment of storage capacity (also known as regulating storage capacity) is the volume of the reservoir between the normal storage level and the dead level. Used to regulate runoff and provide water supply to reservoirs. Natural runoff is redistributed for use by regulating the capacity of the regulating reservoir in accordance with water demand requirements.	Reservoir regulation capacity data for the study coordinate points were obtained from local reservoir reports.
Total capacity	Total reservoir capacity is the volume of the reservoir below the calibrated flood level. It is the sum of dead storage capacity, regulating storage capacity and flood control storage capacity, and is called total storage capacity. It is the total size of the reservoir construction.	Total reservoir capacity data for the study coordinate points were obtained from local reservoir reports.
Reservoir capacity factor (β)	Reservoir capacity factor (also known as regulating storage coefficient) is a measure of the ability of an artificially constructed water storage project (reservoir) to regulate the amount of water coming from the rain catchment area above the dam site, which is the ratio of the regulating capacity to the average amount of water coming from the reservoir over a number of years.	Reservoir capacity coefficient data for the study coordinate points were obtained from local reservoir reports.

2. Data Processing

Scoring function for the to-be-selected independent variable of suitability: the scoring formulae for regulating capacity, total capacity, and capacity coefficients of the 193 constructed reservoir coordinate points were processed through data conversion.

$$S_{oj}^{q} = \left(\frac{z_{o,max}^{q} - z_{o,min}^{q}}{S_{\max} - S_{min}}\right)\frac{I_{oj}^{q} - \mu_o}{\sigma_o} + \left[z_{o,max} - \left(\frac{z_{o,max}^{q} - z_{o,min}^{q}}{S_{\max} - S_{min}}\right)S_{\max}\right] \quad (5)$$

$$I_{oj}^{q} = \begin{cases} lnV_{oj}^{T} & q = 1 \\ lnV_{oj}^{R} & q = 2 \\ \beta_{oj} & q = 3 \end{cases} \quad (6)$$

S_{oj}^{q}—Raw scores of the independent variables to be selected. q = 1, 2, 3; j = 1, 2, 3, . . ., 193; S_{max}, S_{min} are the maximum and minimum. The values of the scoring interval is [1,9];

$z_{o,max}^{q}$, $z_{o,min}^{q}$—Maximum and minimum values of standard scores for original constructed reservoirs; $z_{oj}^{q} = \frac{\left(I_{oj}^{q} - \mu_o\right)}{\sigma_o}$ is the standardized score of the original independent variable to be selected;

μ_o—Mean value of the index of the original independent variable to be selected;

σ_o—Standard deviation of the index of the original independent variable to be selected;

I_{oj}^{q}—Original dependent variable index to be selected, q = 1, 2, 3; When q = 1 the independent variable to be selected is taken to be lnV_{oj}^{T}, When q = 2 the independent variable to be selected is taken to be lnV_{oj}^{R}, When q = 3 the independent variable to be selected is taken to be β_{oj}; V_{oj}^{T} is the total capacity of the constructed reservoir (m^3), V_{oj}^{R} is the regulating capacity of the constructed reservoir (m^3), β_{oj} is the capacity factor of the constructed reservoir.

2.3. Research Methods

2.3.1. Research Process

First, in order to solve the problems of the diverse influencing factors, complex relationships, and different evaluation criteria in the current reservoir (dam) siting study, this study classifies, collects, and processes the data on the influencing factors. Second, a GA_BP neural network model is used to find the relationship between the influencing factors and suitability degree and to determine the independent variables and scoring functions for suitability degree. Referring to academic research on agricultural irrigation and evaporation [9,11–15], the relationship between demand degree and influencing factors and the independent variables are determined. Furthermore, by employing the GA_dual-objective optimization model to balance and coordinate the spatial layout of reservoirs, a set of solutions for the spatial layout score of reservoirs is derived when the spatial allocation mechanism for water resources is optimized (i.e., when both objective functions are at their optimal). Finally, the top 15% of the spatial positions and scores of the reservoir's regulation reservoir capacity values in this set of solutions are visualized. The spatial distribution map of the trade-offs and synergies in reservoir layout is then output using the Kriging interpolation method, thereby completing the optimization of the spatial allocation mechanism for water resources in Shandong Province. The research process is shown in Figure 4.

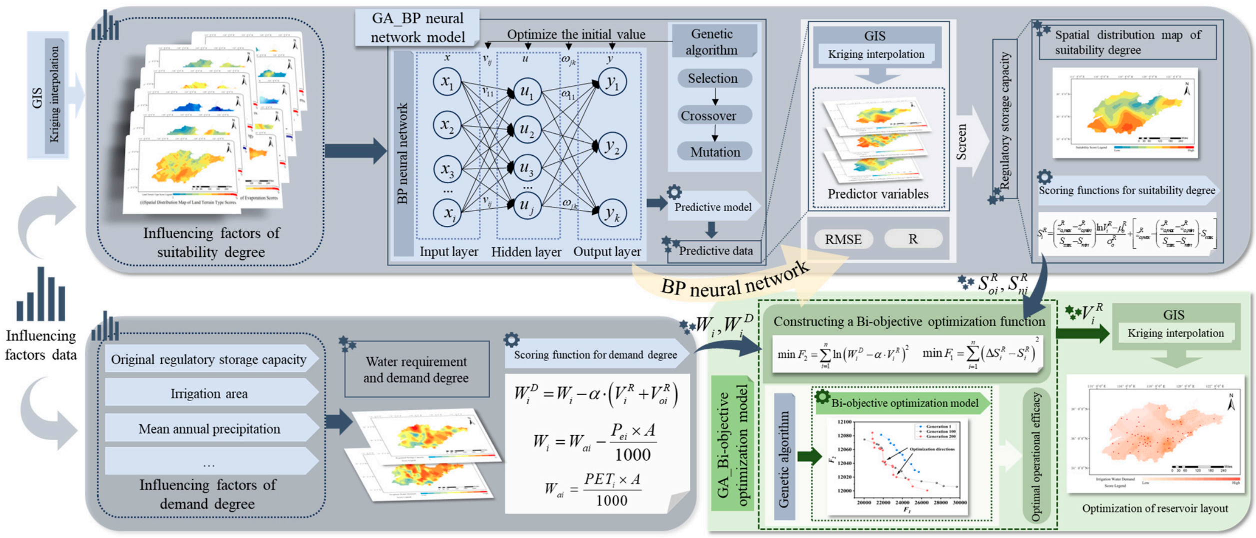

Figure 4. Flow chart of reservoir site selection and layout optimization.

2.3.2. GA_BP Neural Network Model

The GA_BP neural network model is a hybrid model of genetic algorithm (GA) and backpropagation neural network (BP). The BP neural network in the figure has a three-layer topology, and the BP network training process is divided into three steps. First, the 10 influencing factors of the suitability degree are used as the input layer. Then, the output data are compared with the measured data (regulatory storage capacity, total storage capacity, regulating storage coefficient), and the error is calculated using the loss function (also known as the cost function). Finally, the errors are backpropagated to update each weight coefficient in the network. After repeating the above three steps multiple times and learning the weights, the model is applied to new data to predict multiple target values simultaneously. Assuming there is a set of sample data, with the input layer, hidden layer, output layer, and the weight matrices between them as shown in Figure 5a. Genetic algorithms are heuristic search algorithms that mimic the principles of natural selection and genetics to solve optimization and search problems. The process of optimizing the weights and thresholds of neural networks using genetic algorithms is shown in Figure 5b. In summary, the neural network model optimized by the GA algorithm in this study to predict the relationship between suitability degree and its influencing factors is illustrated in Figure 5.

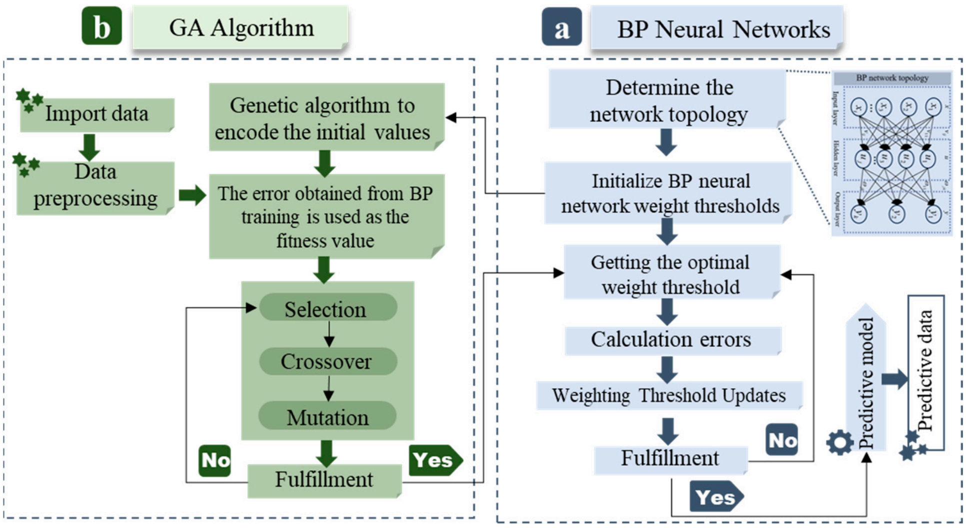

Figure 5. Steps of neural network prediction model optimized by genetic algorithm.

In this study, the neural network model optimized by the GA algorithm predicts the relationship between suitability degree and influencing factors and determines the candidate independent variables, with model parameters shown in Table 4 (See Appendix B for fitness function codes, codes for selection, crossover, and variation).

Table 4. GA_BP neural network model parameters.

Parameter	Value
Number of input neurons	10
Number of neurons in hidden layer	8
Number of output neurons	1
Total number of evolutionary iterations	1000
Population size	100
Crossover probability	0.5
Variation probability	0.1
Train set	80%
Test set	20%

2.3.3. GA_Bi-Objective Optimization Model

There are many current multi-objective optimization algorithms, Kalyanmoy Deb's fast non-dominated sorting genetic algorithm II, NSGA- II with elitist strategies is one of the most widely used of these [42]. This study is based on the NSGA-II multi-objective optimization algorithm in MATLAB R2021b version for the content of this paper. GA_Bi-objective optimization model, i.e., dual-objective optimization model based on genetic algorithm, is a kind of optimization model that can comprehensively analyze two different objectives and carry out directional optimization in accordance with the desired optimization direction for the two objectives. GA_Bi-objective optimization model flow is shown in Figure 6. First, data processing and function modeling were performed. Second, 100 random initial populations were generated by coding (Table 5). Again, non-dominated sorting of populations, race selection of elite strategies, gene manipulation, replacement of the first generation of chromosomes, and entering the next iteration are performed. Finally, the optimization results are derived after the termination conditions are satisfied.

In this study, we carried out the bi-objective optimization of reservoir siting layout through the analysis of the Synergy Mechanism of reservoir water supply and agricultural water irrigation (the parameters of the bi-objective optimization model based on genetic algorithm are shown in Table 5, and the code is shown in Appendix C).

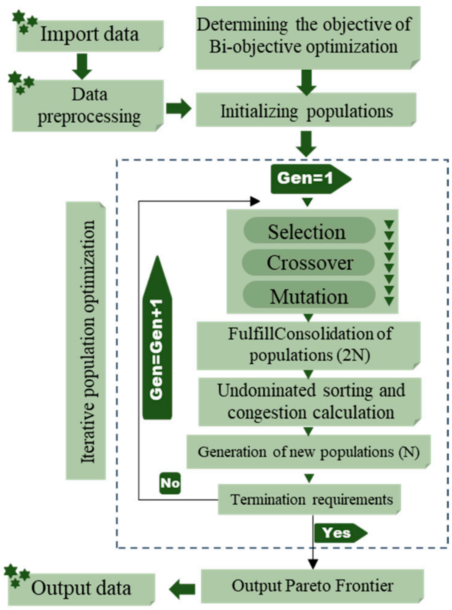

Figure 6. GA_Bi-Objective Optimization Model Flow.

Table 5. Bi-objective optimization parameter values.

Parameters	Value
Number of independent variables	329
Constraints on independent variables	$(0, V_{oi,max})$
Population size	100
Maximum number of iterations	200
Pareto set proportion	0.45
Crossover ratio	0.75
Crossover function	crossoverheuristic
Variation function	mutationadaptfeasible

$V_{oi,max}$ refers to the maximum value of the original reservoir capacity.

2.3.4. Error Analysis

In order to quantitatively assess the effectiveness and accuracy of GA_BP neural network model and GA_Bi-Objective Optimization model, the BA_BP neural network model was analyzed using the metrics Root Mean Square Error RMSE and regression value R. The best individual selected after optimization in the GA_Bi-objective optimization model was analyzed using the indicator root mean square error. The smaller the RMSE, the better the fitting result; the closer R is to 1, the greater the correlation.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[\hat{y}(t) - y(t)]^2} \tag{7}$$

$$R = \left[\sum_{i=1}^{N}(x_i - \overline{x}) \cdot (y_i - \overline{y})\right] \Bigg/ \sqrt{\sum_{i=1}^{N}(x_i - \overline{x})^2 \cdot \sum_{i=1}^{N}(y_i - \overline{y})^2} \tag{8}$$

$\hat{y}(t)$—Projected value;
$y(t)$—Real value;
x_i, $\overline{x}_i$—Target value and average of target values;
y_i, $\overline{y}$—Output values and average of output values.

Both GA_BP neural network model and GA_Bi-objective optimization model in this study are implemented based on MATLAB 2021b software, the data processing map of the model output is from MATLAB, and the spatial distribution map of the scores is obtained by GIS kriging interpolation of the output data. In addition, the screening of the independent variables to be selected and the construction of the bi-objective optimization function are in the results section and will not be repeated here.

3. Results

3.1. GA_BP Analysis of Neural Network Model Results

3.1.1. Prediction Results for the Independent Variable to Be Selected

The scoring data of the three independent variables to be selected, namely, regulated storage capacity, total storage capacity, and storage coefficient, respectively, and the scoring data of the 10 influencing factors of the reservoirs of 193 reservoirs in Shandong Province after data processing were imported into the GA_BP neural network model for learning. The three sets of prediction models of regulated reservoir capacity, total reservoir capacity, and reservoir coefficient learned by the machine are used to predict the 329 coordinate points, i.e., the prediction scores of the independent variables to be selected, i.e., the scores of the regulated reservoir capacity, total reservoir capacity, and reservoir coefficient, which are scored in the interval of [1,9]. The spatial distribution of the ratings of the independent variables to be selected after learning is shown in Figure 5.

Figure 7 shows the spatial distribution of three fitness scores predicted by the GA-BP neural network model. The legend from left to right represents the scores from low to high, assuming that the higher the score, the better the fitness. From Figure 7a, it can be seen that the regions with high suitability scores when using regulated storage capacity as the evaluation index are in the southern and southwestern parts of Shandong Province, while the lower regions are in the central and northern parts of Shandong Province. From Figure 7b, it can be seen that when using the total storage capacity as the evaluation index, the distribution of suitability scores is relatively scattered, and the areas with high scores are mainly concentrated in the western and central northern parts of Shandong. From Figure 7c, it can be seen that the high scoring areas for suitability when using the storage capacity coefficient as the evaluation index are mainly located in the northwest of Shandong Province. By comparing the three graphs in Figure 7, it is found that although the influencing factors are the same, there is basically no similarity between their suitability scores. Therefore, it can be seen that the selection of the independent variables has a significant impact on the suitability scoring function.

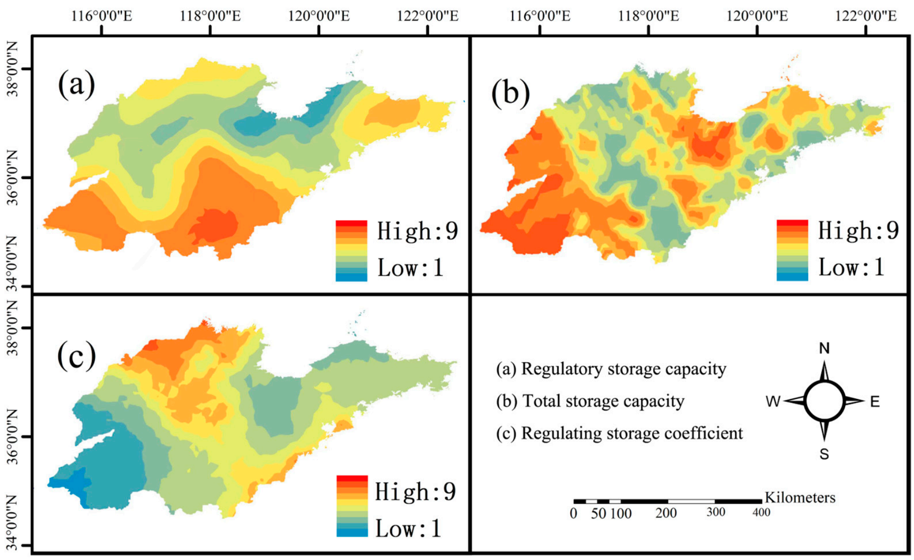

Figure 7. Spatial distribution of the ratings of the independent variables to be selected: (**a**) Adjustment of storage capacity; (**b**) Total storage capacity; (**c**) Reservoir capacity factor.

3.1.2. Correlation Analysis of Independent Variables to Be Selected

Use the root mean square error (RMSE) and regression value (R) output by the GA-BP neural network model to conduct a correlation test on the scoring model of the three selected independent variables. The following table shows the range of RMSE and R values for the three candidate independent variables recorded (Table 6).

Table 6. Data Obtained from Machine Learning.

Category\Standard	RMSE	R
Adjustment of storage capacity	0.10~0.14	0.65~0.94
Total capacity	0.19~0.25	0.23~0.61
Reservoir capacity factor	0.58~0.65	0.18~0.51

The optimal case of RMSE and R reached in machine learning after many machine learning sessions is shown in Figure 8. The horizontal coordinate in the RMSE plot indicates the sample ordinal number, the vertical coordinate indicates the score value of the data of the independent variable to be selected, the green dots are the predicted data, and the blue line is the real data. The R-graph represents correlation, which refers to the degree of fit of the prediction model. It includes the data correlation of all sets of results from the training set, validation set, and prediction set. The horizontal axis represents the target output, and the vertical axis represents the predicted output and the fitted rating function. The solid line in the graph represents the fitted prediction function, and the stronger the correlation, the closer the slope of the solid line.

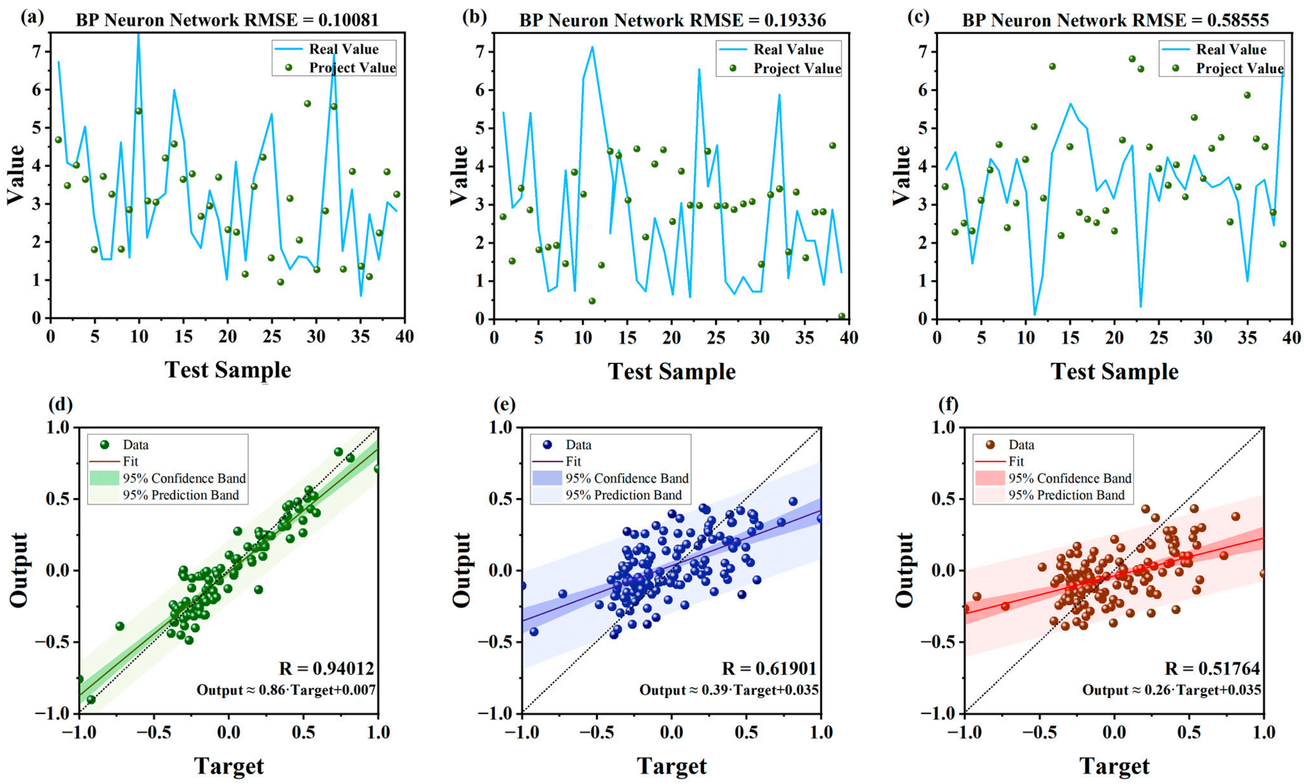

Figure 8. Root mean square error and regression values: Regulatory storage capacity (**a**,**d**); Total storage capacity (**b**,**e**); Regulating storage coefficient (**c**,**f**).

According to the analysis of data, the root mean square error of the three groups of prediction models, regulating storage capacity < total storage capacity < storage capacity coefficient, in the fitting degree R of the prediction model, regulating storage capacity > total storage capacity > storage capacity coefficient, indicating that regulating storage capacity has the greatest correlation with the 10 influencing factors. Therefore, the regulating storage capacity was selected as the independent variable for the suitability rating function. Specifically, the independent variable with q = 2 was chosen from the data processed in Section 2.2.4 to construct a suitability rating function based on regulating storage capacity. The spatial distribution of the predicted suitability is illustrated in Figure 8a, and the scoring function is presented in Formula (11).

3.2. GA-Bi-Objective Optimization Model and Result Analysis

3.2.1. Construction of Bi-Objective Optimization Function

1. Suitability Objective Function F_1:

Using the total suitability deviation as the objective function F_1, calculate the sum of the squared differences between the regulating capacity of the proposed reservoir and the suitability vacancy index for all coordinate points. The overall suitability deviation can reflect the matching situation between the suitability of the proposed reservoir and the actual suitability. When the overall suitability deviation is small, the suitability of the proposed reservoir site is better, and vice versa.

$$minF_1 = \sum_{i=1}^{n}\left(\Delta S_i^R - S_i^R\right)^2 \tag{9}$$

$$\Delta S_i^R = S_{ni}^R - S_{oi}^R \tag{10}$$

$$S_i{}^R = \left(\frac{z_{o,max}^R - z_{o,min}^R}{S_{\max} - S_{min}}\right)\frac{lnV_i^R - \mu_o^R}{\sigma_o^R} + \left[z_{o,max}^R - \left(\frac{z_{o,max}^R - z_{o,min}^R}{S_{\max} - S_{min}}\right)\cdot S_{\max}\right] \tag{11}$$

F_1—Total suitability deviation (n = 329);

ΔS_i^R—Suitability gap indicator; The difference in coordinate evaluation scores before and after prediction optimization for machine learning, i = 1, 2, 3, . . ., 329;

S_i^R—Suitability score; means the suitability score of the regulating capacity (of the proposed reservoir), i = 1, 2, 3, . . ., 329;

S_{oi}^R—Scoring of suitability before optimization, is the suitability score for regulating reservoir capacity through data processing, (Only 193 coordinates of existing reservoirs were involved in the pre-optimization data processing. For the 136 coordinate points not covered, the suitability score is taken as 0);

S_{ni}^R—Scoring of optimized predicted regulating reservoir capacity, is the predicted score after machine learning.

V_i^R—Independent variables for bi-objective optimization, which is the regulating capacity of the proposed reservoir (m^3), refers to the regulating capacity of a reservoir that has not been constructed or will be constructed at the coordinates.

2. Demand Degree Objective Function F_2:

Taking the total deviation of reservoir irrigation coverage as the objective function F_2, the smaller the total deviation of reservoir irrigation coverage is, the easier it is to achieve a balance between supply and demand between water supply in the reservoirs and agricultural water demand. The logarithmic value of the difference between irrigation supply and demand was chosen for the calculation, and keeping the same data distribution pattern as the total suitability deviation reduces the skewness and tail thickness of the dataset. Considering the influence of the existing reservoirs adjacent to the coordinate points in the same irrigation area on the irrigation demand, this paper considers the water supply of the proposed reservoirs and the existing reservoirs together with the water demand, and calculates the value that best suits the size of the reservoir.

$$minF_2 = \sum_{i=1}^{n} ln\left(W_i^D - \alpha \cdot V_i^R\right)^2 \quad (12)$$

F_2—Total deviation in irrigation coverage of reservoirs (n = 329).

V_i^R—Independent variables for bi-objective optimization; regulating capacity of the proposed reservoir (m^3).

W_i^D—Irrigation supply–demand gap (See Equation (1) for details);

3.2.2. Analysis of Bi-Objective Optimization Results

Figure 9 shows the two-objective optimization Pareto frontiers for the 1st, 100th, and 200th generations of the two-objective function. The horizontal coordinate represents the value of the objective function F_1, the vertical coordinate represents the value of the objective function F_2, and the arrow is the direction of population optimization. As can be seen from the figure, the progression trajectory of the population systematically converges to the lower left quadrant of the graph. After 200 iterations, a superior subset of the population is selected among the Pareto frontiers of the screened populations to represent the optimal reservoir siting layout.

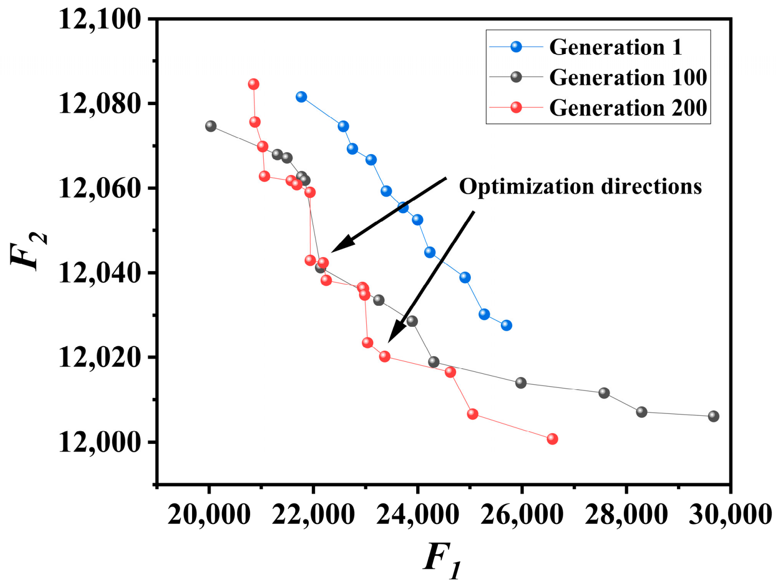

Figure 9. Dual-objective optimization Pareto front graph.

3.2.3. Testing the Effectiveness of the Dual-Objective Optimization Model

By using the method of controlling variables to test the dual-objective optimization model, the root mean square error of irrigation supply and demand difference was verified by comparing the use of suitability single-objective optimization and dual-objective optimization to determine whether the impact of demand on water resources supply and demand relationship was considered. Upon verification, it was found that the root mean square error of the irrigation supply–demand difference (demand degree) data for the top 15% of the optimized reservoir site selection and layout decreased from 87.76782298 million cubic meters to 22.56676997 million cubic meters. Compared to using only suitability as a single-objective optimization, the supply–demand difference of water resources can be reduced by 74.3%, significantly improving the utilization efficiency of water resources.

3.3. Optimization Analysis of Spatial Layout for Reservoir Site Selection

Extract the solution set for optimizing the spatial layout of the reservoir selected from the dual-objective optimization model for reservoir site selection. Visualize the regulation capacity score and spatial position of the solution set, and take the top 15% of the data in the solution set as the final site selection point for the proposed reservoir. Finally, this study compares and analyzes the suitability of reservoir site selection, the demand for reservoir site selection, and the site selection results after dual-objective optimization (Figure 10).

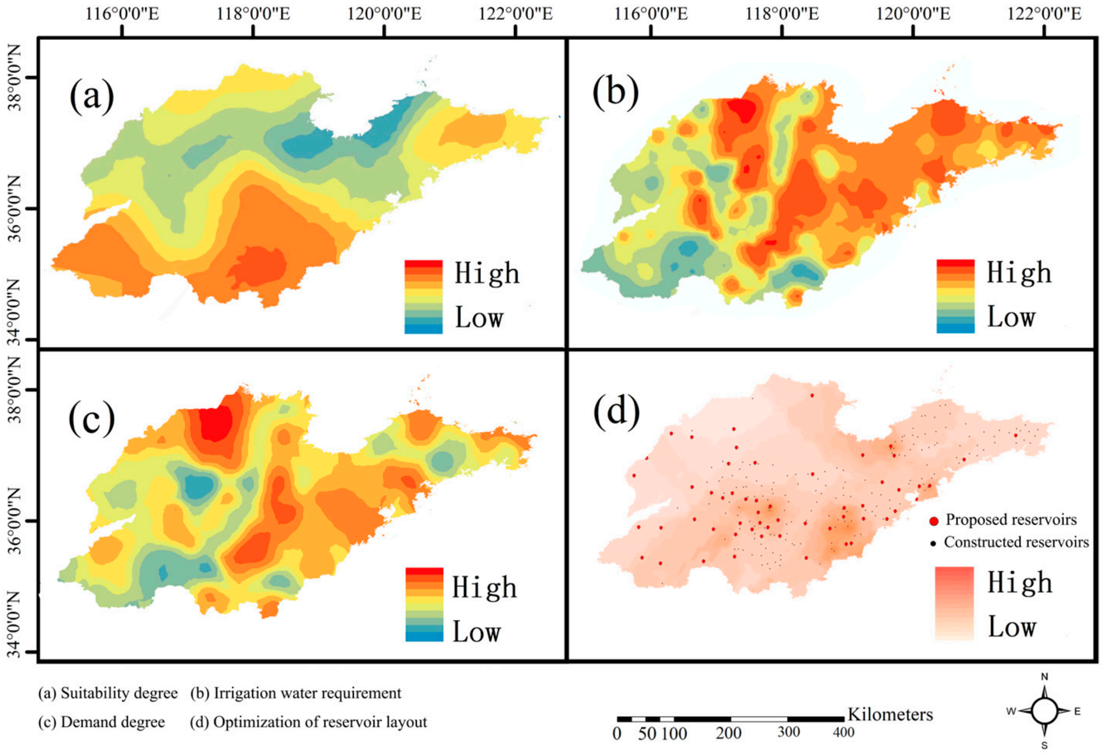

Figure 10. Shandong Province Reservoir Site (**a**) Suitability degree, (**b**) Irrigation water requirement, (**c**) Demand degree, (**d**) Optimization of reservoir layout.

Figure 10a shows the spatial distribution of suitability scores for reservoir site selection in Shandong Province. The legend indicates from left to right that the suitability score for reservoir construction ranges from low to high, and the environmental conditions range from poor to good. The suitability of reservoir site selection is relatively high in the southern part of Shandong Province (35°00′00″ N, 115°00′00″ E)~(35°00′00″ N, 119°30′00″ E) and the eastern Shandong Peninsula (37°00′00″ N, 121°30′00″ E). Comparing the spatial distribution map of factors affecting site selection, it can be found that the region has more precipitation, better terrain and geological conditions, and abundant water sources. However, the northern and central parts of the Shandong Peninsula (37°00′00″ N, 119°00′00″ E) have poor suitability due to low precipitation, high evaporation, and water scarcity in the region.

Figure 10b shows the spatial distribution of irrigation water demand in Shandong Province. By analyzing the supply–demand gap between existing reservoir water supply and agricultural water demand, the current demand for reservoir site selection has been determined. As shown in the figure, the high water demand in Shandong Province is mainly concentrated along the southeast coast.

Figure 10c shows the spatial distribution of demand for reservoir site selection in Shandong Province. The demand degree refers to the current difference between the supply and demand of water resources for reservoir water supply and agricultural irrigation. The higher the demand, the greater the water supply gap of the reservoir in that area. From the graph, it can be seen that the water demand in Shandong Province is mainly concentrated in the southeast coast and the northwest of Shandong Province.

Figure 10d shows the optimized layout of reservoir site selection in Shandong Province. The depth of colors in the figure indicates the potential for reservoir construction in various regions of Shandong Province. The darker the color, the larger the scale of potential reservoirs to be built. The selected locations in the figure represent the spatial distribution of optimized existing and planned reservoirs. As shown in the figure, the areas with larger and more concentrated reservoirs are mainly located within the geographical coordinate range (36°0′0″ N, 117°0′0″ E)~(36°0′0″ N, 120°0′0″ E). Due to the fact that the northern region of Shandong Province is located in the northwest plain of Shandong and has relatively scarce water resources, the distribution of reservoir points is limited. The large and medium-sized reservoirs that have been built in Shandong are mainly distributed in the southern part of Shandong (35°0′0″ N, 117°0′0″ E)~(36°45′0″ N, 122°30′0″ E). The demand for reservoir construction is high in the eastern Shandong Peninsula area, but there are already many reservoirs built, which reduces the demand for reservoir construction.

As shown in Figure 10, by comparing a, b, and d, it can be seen that in the eastern region of Shandong (119°0′0″ E) to (122°30′0″ E), the environmental suitability scores for the site selection of most existing reservoirs are not the highest. By analyzing the planning of reservoir site selection in Shandong Province based on the comprehensive figures a and b, it can be seen that the reservoir site selection in Shandong Province considers both the suitability of reservoir site selection and the demand for reservoir water resources. As a result, 98.04% of the selected locations in the optimized spatial layout of the reservoir based on suitability and demand are located above the yellow area of the suitability or demand rating chart, and 62.82% of the optimized locations are located above the yellow area of suitability and demand.

4. Discussion

Through research results, it was found that the suitability and demand evaluation models established after introducing demand can establish a good relationship with influencing factors after machine learning optimization, and solve the current water resource supply–demand contradiction between reservoir water supply and agricultural water demand. It also reduces the risk of drought and flood disasters in vacant areas, providing a guarantee for the safety of agricultural water use.

In the process of improving the suitability scoring model, the correlation test method was used to select the optimal model by comparing RMSE and R values. The R of the regulated storage capacity was more than 30% higher than the total storage capacity and storage coefficient, which reduced the impact of the evaluation model on the experimental results, providing evidence for the current research method of using regulated storage capacity to analyze the role of reservoirs in the fields of reservoir irrigation, regulation and storage, power generation [13,40,41], which is consistent with the research results of [9] the relationship between regulated storage capacity and water demand in the study of spatial matching relationship between reservoirs and drought in Hunan Province. In addition, the analysis results of the already built reservoirs in a, b, and d of Figure 10 further confirm that the suitability of reservoir site selection in monsoon regions cannot determine the direct location of the reservoir site. Comparing and analyzing the layout points of the reservoir in Figure 10d with Figure 10a,c, we can also see that 98.04% of the combined reservoir layout points correspond to the height of the areas with higher suitability and demand scores in both figures. This spatial consistency indicates that the mountainous areas in central and southern Shandong have good natural conditions and agricultural irrigation needs, and building reservoirs in these areas can effectively reduce agricultural water pressure and cope with flood disasters in the region. Although the location conditions for reservoirs in the northwest of Shandong are harsh, a small number of reservoirs also need to be built due to the agricultural demand for water resources. For more additions, in the Yellow River Basin area in the northwest of Shandong Province, although the demand is high, the suitability is low, resulting in a limited distribution of optimized reservoirs. This is also the main reason why there are fewer reservoirs distributed in this area in Shandong Province, and provides evidence for the high irrigation water pressure in the Yellow River Basin in western Shandong Province proposed by Pang Aiping et al. [17].

The GA_BP neural network model we adopt has a clear optimization direction compared to traditional evaluation methods (such as the Analytic Hierarchy Process) [43,44], which reduces the interference of subjective factors on the results. In addition, although we only confine the water demand to the field of agricultural irrigation, this method can carefully examine the relationship between agricultural water demand and reservoir water supply, without being affected by other water demand situations, ensuring the authenticity of the data and results. Current research mainly focuses on the site selection of reservoirs in arid and semi-arid areas [5–7]. The conclusions of this paper may need further exploration in the application of reservoir siting in some arid climate areas, but they can supplement and improve the current research mechanism of trade-offs and coordination of water resource spatial allocation in the monsoon climate area [8], providing new ideas for reservoirs siting in the monsoon climate area.

This study focuses on the environmental context of uneven spatiotemporal distribution of precipitation in the monsoon climate zone, innovatively introducing the concept of "demand degree" into the evaluation system for the optimization of reservoir siting. It uses both "suitability degree" and "demand degree" as two optimization directions for the spatial layout of reservoirs, thereby supplementing the research methods for reservoir site selection in monsoon climate areas. Additionally, after analyzing the suitability degree and demand degree, we did not simply superimpose the data of the two scoring functions. Instead, we used a genetic algorithm to perform a bi-objective optimization on the reservoir site coordinates. Furthermore, in Amanuel Kumsa Bojer's "Water Collection Site Selection": Geographical space and multi-criteria decision analysis [45], as well as Maria Macchiarol's multi-criteria decision-making and water infrastructure [46], have all adopted multi-criteria optimization methods. This study opts for bi-objective optimization within multi-criteria optimization, which can make the forecast results more precise and practical, better ensuring agricultural water security. Through the verification of the optimization results, it was found that considering the demand degree can significantly improve the efficiency of water resource utilization and the irrigation function of reservoirs while ensuring suitability. This also provides a new solution for the spatial layout optimization of water conservancy facilities in other water demand areas.

5. Conclusions

The research results indicate that the optimized reservoir water supply model can effectively alleviate the contradictions in the allocation of agricultural water resources in the monsoon climate zone, while also reducing the risk of drought and flood disasters. Through correlation testing and error analysis, this study has selected the optimal model with high accuracy, providing empirical support for the functions of reservoirs in irrigation, regulation, and power generation. This study found that the R value of the regulated reservoir capacity increased by about 30% compared to traditional indicators, and the RMSE was also the smallest in the model, confirming the key role of regulated reservoir capacity in water resource allocation. In addition, the application of bi-objective optimization based on the genetic algorithm further enhanced the model's optimization capability, reducing the supply–demand gap by 74.3%, ensuring the maximization of water resource utilization efficiency. The images processed through visualization also reflect that the proportion of site selection points in areas with high suitability degree or demand degree scores is as high as 98.04%, and the proportion in areas with high scores for both suitability and demand degree is 62.82%, demonstrating the accuracy of the water resource allocation model. Although the study mainly focuses on the allocation of agricultural water resources, the methods and models used have broad applicability, providing a new optimization direction for the trade-off and coordination mechanisms in water resource allocation for other fields such as industrial and domestic water use. Future research will continue to explore water resource optimization strategies under different water demand scenarios, thereby achieving sustainable development in agriculture and other fields on the basis of harmonious coexistence between humans and nature. In summary, this study provides an innovative optimization method for reservoir site selection and water resource management in the monsoon climate zone, which has important theoretical and practical value for addressing climate change, ensuring agricultural water security, and promoting the collaborative development of humans and nature.

Author Contributions: Conceptualization, D.X. and M.Z.; methodology, M.Z. and W.Z.; software, M.Z.; validation, L.X.; formal analysis, L.X.; investigation, M.G. and X.Q.; data curation, M.G. and X.Q.; writing—original draft preparation, M.Z.; writing—review and editing, D.X.; visualization, K.D. and S.L.; funding acquisition, D.X. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (41907050) and the Natural Science Foundation of Shandong Province (ZR2023QD030).

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Acknowledgments: The authors thank Cheng Wang for his help in data collection.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Grading table of influencing factors of suitability degree.

1	**water resources**	**Distance\River Level**	**Level 5**	**Level 4**	**Level 3**	**Level 2**	**Level 1**
		>2000	1	1	1	1	1
		1500~2000	1	2	3	4	5
		1000~1500	2	3	4	5	6
		500~1000	3	4	5	6	7
		0~500	5	6	7	8	9
2	**Precipitation**	$S_i^{rain} = \left(\frac{z_{max}^{rain} - z_{min}^{rain}}{S_{\max} - S_{min}}\right) z_i^{rain} + \left[z_{o,max} - \left(\frac{z_{max}^{rain} - z_{min}^{rain}}{S_{\max} - S_{min}}\right) S_{\max}\right]$ (A1) $z_i^{rain} = \frac{f_i^{rain} - \mu}{\sigma}$ (A2)					
		S_i^{rain}—Conversion fraction of precipitation; $i = 1, 2, 3, \ldots, 329$ $S_{\max}$, $S_{\min}$—Are the maximum and minimum values of the assignment interval for the conversion score, and the assignment interval is [1,9]; μ—Averages; this is the average precipitation in Shandong Province; σ—Standard deviation; this is the standard deviation of precipitation in Shandong Province; z_i^{rain}—The standard score of precipitation is the score obtained after data accuracy, $z_{max} - z_{min}$ is the maximum and minimum values of the standard score. Here are the maximum and minimum values of the standard score of precipitation in Shandong Province; f_i^{rain}—Precipitation at coordinate points.					
3	**Temperature**	The method of assigning values is the same as that for precipitation.					
4	**Evaporation**	The method of assigning values is the same as that for precipitation.					
5	**Geological hazards**	**Seismic Intensity**				**Score**	
		Six-degree				9	
		Seven-degree				7	
		Eight-degree (0.2 g)				5	
		Eight-degree (0.3 g)				3	
		Nine-degree				1	
6	**Stratigraphic lithology**	**Rock Type\Water-Richness**	**Extremely Low Water Richness**	**Very Low Water Richness**	**Moderate Water Richness**	**High Water Richness**	**Extremely High Water Richness**
		unconsolidated porous rocks	1.0~1.4	1.4~1.8	1.8~2.2	2.2~2.6	2.6~3.0
		Fractured and porous fine-grained rocks	3.0~3.4	3.4~3.8	3.8~4.2	4.2~4.6	4.6~5.0
		Fractured and karstified carbonate rocks	5.0~5.4	5.4~5.8	5.8~6.2	6.2~6.6	6.6~7.0
		Fracture-hosted igneous rocks	7.0~7.4	7.4~7.8	7.8~8.2	8.2~8.6	8.6~9.0
7	**Hydrogeology**	**Water quality\Abundance of underground water resources**	**V**	**VI**	**III**	**II**	**I**
		Class I	9	8	7	6	5
		Class II	8	7	6	5	4
		Class III	7	6	5	4	3
		Class IV	6	5	4	3	2
		Class V	5	4	3	2	1
8	**Socio-economic**	The method of assigning values is the same as that for precipitation.					
9	**Land terrain type**	**Land/Terrain**	**Mountainous**		**Hilly**		**Plain**
		Water areas	9		7		5
		Grassland and woodland	7		5		3
		Agricultural land	5		3		1
		Tideland, Gobi, etc.	3		1		1
		Urban land	1		1		1
10	**Ecologically sensitive areas**	**Distance from ecologically sensitive areas**			**Score**		
		≥2000			9		
		1501~2000			7		
		1001~1500			5		
		501~1000			3		
		0~500			1		

Appendix B

The GA_BP neural network model code is as follows:

(1) GA_BP algorithm main function: (xunhuan_GA_BP_other1)
https://kdocs.cn/l/cftWYHbiB8Uw (accessed on 22 August 2024)
(2) Fitness function: (fitness1)
https://kdocs.cn/l/ceoeK7BVtS9V (accessed on 22 August 2024)
(3) The select function (select)
https://kdocs.cn/l/chEyjic8T8Sa (accessed on 22 August 2024)
(4) The crossover function: (Cross)
https://kdocs.cn/l/cbpOA5vZUPAO (accessed on 22 August 2024)
(5) The variational function: (Mutation)
https://kdocs.cn/l/cfBjNq2Q9jL1 (accessed on 22 August 2024)

Appendix C

GA_Bi-objective optimization model code is as follows:

(1) GA_Bi-objective optimization function: (GA_Bi_objective)
https://kdocs.cn/l/ccquscpr04GC (accessed on 22 August 2024)

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