Research on the Optimal Water Level Evaluation of the Great Lakes Based on Entropy Weight Method and Particle Swarm Algorithm

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Abstract. The hydrological conditions of the Great Lakes have undergone significant changes due to climate variation and human activities, impacting the ecological environment and multiple stakeholders. Therefore, scientific assessment and management of lake water levels are crucial. This study employs the entropy weight method and Particle Swarm Optimization (PSO) algorithm to optimize the water levels. By integrating multiple data sources that affect water level changes, an indicator system encompassing water level - related factors is constructed. The entropy weight method is utilized to determine the weights of natural factors, the Analytic Hierarchy Process is applied to quantify the weights of stakeholders, and a comprehensive scoring model is established. The PSO algorithm is adopted to solve for the optimal water level. The results indicate that the weights of each factor are clearly defined, and the monthly optimal water levels from 2011 to 2020 show an upward trend, and the scoring coefficients of stakeholders can be maximized. This study provides a scientific basis for the water level management of the Great Lakes, and the constructed method framework is helpful for dealing with complex water resource challenges, which has important practical significance for water resource management.

Keywords: Great Lakes, Particle Swarm Optimization, Hydrological Network, Sensitivity Analysis, Decision matrix.

1. Introduction

The Great Lakes, as the largest freshwater lake system in the world, play a crucial role in the ecological, economic, and social spheres. However, due to climate change and human activities, the hydrological conditions of the Great Lakes have undergone significant changes, affecting both the ecological environment and various stakeholders. Therefore, scientifically managing the water levels of the Great Lakes is vital for maintaining ecological stability and ensuring the sustainable development of the surrounding regions.

In the existing research on water level prediction and management. Li et al proposed a grey prediction model optimized by Particle Swarm Optimization (PSO), focusing on the dynamic characteristics of water level fluctuations and the accuracy of predictions [1]. Liu Hongyu studied the application of the entropy weighting method in water environment assessment, improving the scientific accuracy of evaluation results by determining the objective weights of various assessment indicators [2]. Tang et al optimized the scheduling strategy of the Chengbi River Reservoir, examining the dynamic relationship between water level control and flood scheduling [3]. Zhou et al used an improved PSO algorithm to precisely control water levels in the Feiyunjiang River Basin reservoir group, reducing downstream flood pressure [4]. Qi et al explored water exchange optimization based on the RBF surrogate model and PSO algorithm, with the focus on improving water exchange efficiency and the feasibility of optimization schemes [5]. Song et al constructed a health assessment system for Li Lake using the Analytic Hierarchy Process (AHP) and entropy weighting methods, enhancing the scientific accuracy of the results [6].

These studies have promoted technological innovations in water level prediction and management, but they have not fully addressed the uncertainty and complexity of hydrological conditions. Future research should focus on water resource scheduling under changing hydrological conditions, optimizing water environmental protection, and developing flexible and adaptive water resource management systems to cope with complex hydrological environments.

In the field of water level prediction, various algorithms have demonstrated their respective advantages and limitations. The Long Short - Term Memory (LSTM) model proposed by Wang et al performs excellently with time series data, but its parameter tuning is complex [7]. The Singular Spectrum Analysis - Radial Basis Function (SSA - RBF) neural network model used by Zheng et al excels in denoising and trend extraction, but it is highly dependent on data quality [8]. The Dynamic Nonlinear Grey Model (DNGM (1,1)) studied by Chen et al provides accurate predictions in specific scenarios, but may face limitations when dealing with nonlinear data [9]. The Convolutional Neural Network - Long Short - Term Memory (CNN - LSTM) model proposed by Li et al offers high prediction accuracy but comes with a high computational cost [10]. These studies show that although the proposed algorithms hold potential in the field of water level prediction, they still share common shortcomings such as limited generalization ability, sensitivity to outliers, the need for improved prediction accuracy, long training times, and strong dependence on parameter settings. Further research is needed to improve their practicality and accuracy.

This paper proposes an optimal water level evaluation model for the Great Lakes based on the entropy weight method and Particle Swarm Optimization (PSO) algorithm, aiming to optimize water level management by integrating natural factors and the demands of various stakeholders. Under different climatic conditions, the model improves the efficiency and accuracy of water level management, with simulation results confirming its effectiveness. The findings demonstrate the efficacy and practicality of the entropy weight method and PSO algorithm in water level optimization, providing a scientific basis for the sustainable management of water resources in the Great Lakes region, while also offering theoretical support for addressing similar water resource management challenges.

2. Data Preprocessing and Model Preparation

In the research on the optimal evaluation of lake water levels, data preprocessing, and model preparation are indispensable steps, laying a solid foundation for subsequent analysis and calculations.

2.1. Data Sources

The data was from https://www.contest.comap.com/undergraduate/contests/mcm/register.php, as well as datasets from the Great Lakes region spanning over two decades. This dataset encompasses comprehensive information on lake water levels, inflow and outflow rates, river flow data, and stakeholder feedback on various aspects of lake management. Incorporating data from different years allows us to capture seasonal variations, extreme weather events, and long-term trends, which are crucial for developing a robust and adaptable model.

2.2. Data Processing

Before model construction, preprocessing the data to ensure its accuracy, consistency, and analytical suitability is essential. This includes the following key steps:

Data standardization is crucial due to the different scales and units of the data. In our context, it is of particular importance as we need to integrate features such as lake water levels, inflow rates, and stakeholder satisfaction levels into a unified evaluation framework for comparison and integration. Meanwhile, handling data consistency is essential for accurate modeling. For example, rainfall and runoff data for the same lake must be coordinated when input into the evaluation model to maintain consistency.

2.3. Indicator Construction

Establishing the evaluation index system should follow the principles of systematicity, consistency, scientificity, and comparability. Based on the above principles, three important factors, namely, water loss, water gain, and other values, were taken into account in constructing the first-level evaluation indexes of the water level of the lakes. Through research and analysis, the indicators were refined by combining the current actual situation of the Great Lakes, and the influencing factors of the first-level indicator layer were used as the influencing factors of the second-level indicator layer, as shown in Figure 1:

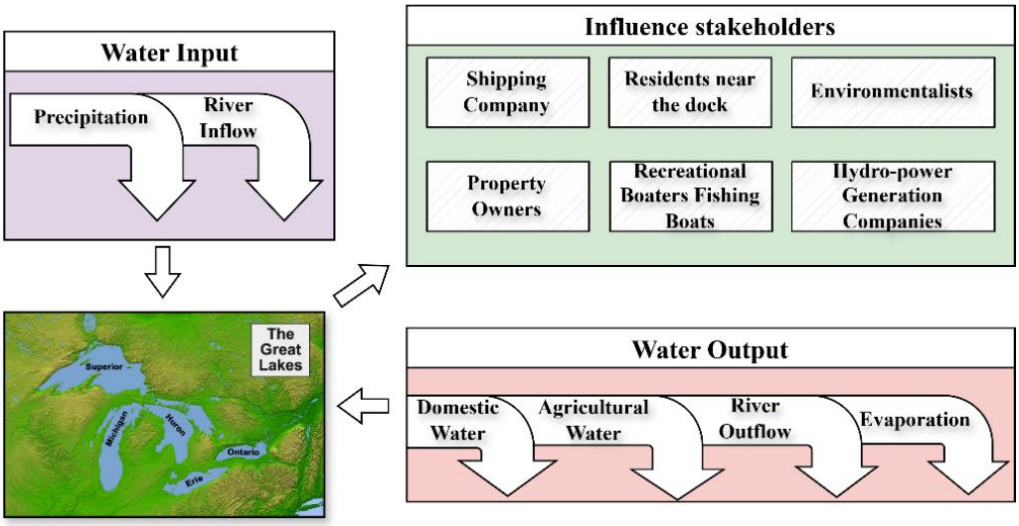

Figure 1. Schematic diagram for establishing indicators

2.4. Model Preparation

In the model preparation stage, this study employed various methods such as the entropy weight method and particle swarm optimization (PSO) to construct an optimal evaluation model for lake water levels.

Firstly, this study utilized the entropy weight method to calculate the weights of various influencing factors. The entropy weight method is an objective weighting method based on information entropy, which determines the weight of each indicator according to its information entropy value. In this study, we first calculated each indicator's information entropy value. Then, we converted it into a weight value through a formula, obtaining the relative importance of each influencing factor in lake water level changes.

Finally, we prepared the particle swarm optimization algorithm to solve for the optimal lake water level. PSO is an optimization algorithm based on swarm intelligence that searches for the optimal solution to a problem by simulating natural behaviors such as birds foraging. In this study, we set the range of lake water level changes as the search space and the demands of various stakeholders as the objective function. By continuously iterating and updating the positions and velocities of particles in the search space using PSO, we aimed to find the optimal lake water level solution that satisfies the needs of all stakeholders.

3. Entropy Weight Method Modeling for Lake Hydrological Factors

Considering the lake's factors, such as precipitation, evaporation, and other six indicators for the lake's impact on the degree of difference, cannot be directly added to the establishment of the subsequent scoring model system, so at this time it is necessary to use the six historical data for the integration of the assessment, the use of entropy weighting method for the six indicators to assign a weight.

3.1. Modeling of the entropy weight method

Firstly, calculate the entropy weights for the environmental evaluation model.

As far as the entropy weighting method is concerned, when the probability of the occurrence of a certain indicator is high or consistently at a high value, it indicates that the indicator has a greater impact and has a greater surface weight in this paper.

First, for the historical value of the indicator, the proportion of the individual in the whole can be derived as the importance of the indicator p_{ij} .

$$p_{ij} = \frac{x_{ij}^{"}}{\sum_{j=1}^{5} x_{ij}^{"}} \tag{1}$$

Secondly, with p_{ij} the derived above, the exact information entropy value of each indicator can be obtained through the following equation (5):

$$e_i = -k\sum_{j=1}^{5} p_{ij}\ln(p_{ij}) \tag{2}$$

Take note of: $k = \frac{1}{\ln n} = \frac{1}{\ln 5} > 0$ meet $e_i \geq 0$; When $p_{ij} = 0$, define: $\lim_{p_{ij}\to 0} p_{ij}\ln(p_{ij})$.

Subsequently, calculate the weight of each indicator W_i .

Since the sum of the resulting information entropy values is not equal to unit 1, to standardize the criteria, this paper will probabilistically distribute the weights of each information entropy value so that the sum of their final weights is equal to 1.

$$W_i = \frac{1-e_i}{n-\sum_{i=1}^{4} e_i} \tag{3}$$

3.2. Solving the entropy weight method model

Our step of averaging using the Great Lakes' metrics over the past 20 years culminates in the Figure 2:

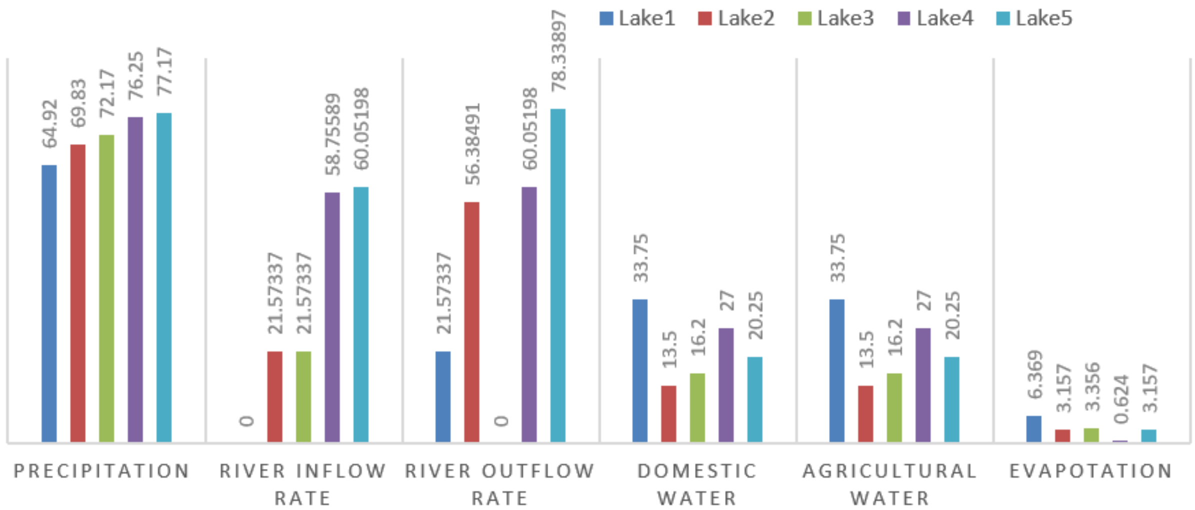

Figure 2. Average values of indicators

Through the above steps from the data of each indicator for the last 20 years, the corresponding weights of the lake's indicators were finally obtained as follows:

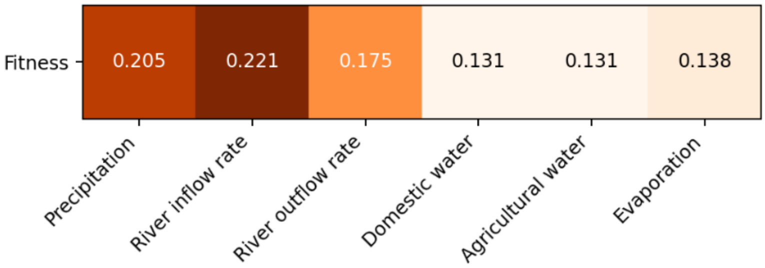

Figure 3. Weighted coefficients of natural factor indicators

From the Figure 3, it can be seen that among the six indicators included in the lake's factors, the river flow into the lake has the largest weight value, i.e., the largest degree of influence, and the two indicators of domestic water use and agricultural water use have the smallest degree of influence on the change of the lake's water level.

4. Quantitative Analysis of Stakeholder Importance

Due to the different social value, economic value, and degree of influence brought by the stakeholders' respective interests, to distinguish their respective degrees of importance and quantify the indicators more accurately and reasonably in the subsequent establishment of the comprehensive scoring model, this paper is based on the standardized data, integrating its various factors, and quantifying the corresponding indicators. Utilizing the construction of decision matrices.

Firstly, the scale method is utilized to compare the needs of each of the six categories of stakeholders in conjunction with the relevant scale values and meanings in Figure 4.

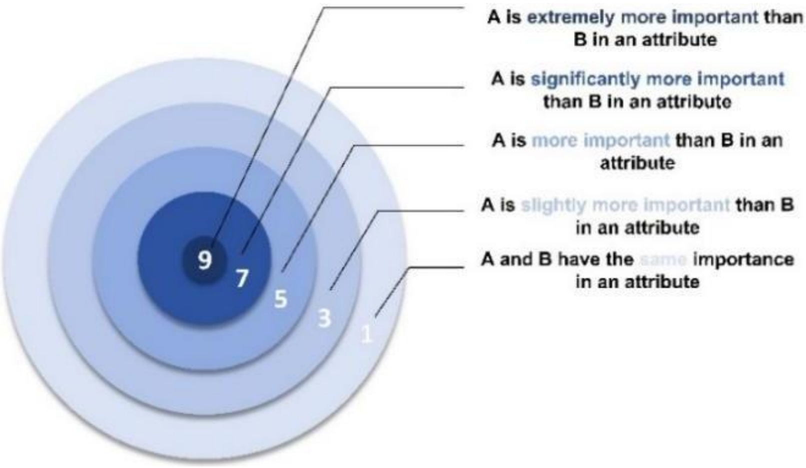

Figure 4. Specific scale values and meanings of the scale method

Establishment of fuzzy method judgment matrix:

$$A=\begin{bmatrix} \frac{\omega_1}{\omega_1} & \frac{\omega_1}{\omega_1} & \cdots & \frac{\omega_1}{\omega_9} \\ \frac{\omega_2}{\omega_1} & \frac{\omega_2}{\omega_2} & \cdots & \frac{\omega_2}{\omega_9} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\omega_9}{\omega_1} & \frac{\omega_9}{\omega_2} & \cdots & \frac{\omega_9}{\omega_9} \end{bmatrix} \tag{4}$$

Firstly, a fuzzy method judgment matrix A is created to maximize the economic benefits brought by each stakeholder.

$$A=\begin{bmatrix} 1 & 3 & 3 & 1 & 3 & 0.2 \\ 1/3 & 1 & 1 & 1 & 1/3 & 0.2 \\ 1/3 & 1 & 1 & 1 & 1/3 & 0.2 \\ 1 & 1 & 1 & 1 & 1/3 & 0.2 \\ 1/3 & 3 & 3 & 3 & 1 & 1/3 \\ 5 & 5 & 5 & 5 & 3 & 1 \end{bmatrix} \tag{5}$$

Subsequently, calculate the weight values for each criterion. This step is to determine the importance of each criterion in the evaluation system. Next, based on the matrix created above based on the principle of maximum economy, the sum of each row in the matrix is calculated as the total comparison value of the criteria. This is then summed and divided by the sum of the total comparison values of all the criteria to obtain the initial program weight C_{Wi} for each criterion.

$$C_{Wi}=\frac{\sum_{i=1}^{6} x_{ij}}{\sum x_{ij}} \tag{6}$$

Then, create an alternative fuzzy method judgment matrix to analyze and compare each criterion from different perspectives. To be able to think more comprehensively, this paper then based on the social value that can be generated as the basis for the establishment of the judgment matrix, the final establishment of the judgment matrix is shown in the following table:

$$B=\begin{bmatrix} 1 & 1 & 1/3 & 1/3 & 1 & 1/3 \\ 1 & 1/3 & 1 & 1 & 3 & 1/3 \\ 3 & 1 & 1 & 1 & 3 & 1 \\ 3 & 1 & 1 & 1/3 & 1 & 1 \\ 1 & 1/3 & 1/3 & 1 & 1 & 1/3 \\ 3 & 3 & 1 & 1 & 3 & 1 \end{bmatrix} \tag{7}$$

Next, calculate the weighting values for each criterion under different options based on this matrix, further refining the weight situation of the criteria in different contexts. Based on the above matrix B established under the principle of sociality, the method is the same as that of solving the fuzzy judgment matrix A under the principle of economics, and finally, the weights of the alternatives for each indicator can be solved to obtain the value of A_{Wi}.

$$A_{Wi}=\frac{\sum_{i=1}^{6} x_{ij}}{\sum x_{ij}} \tag{8}$$

Finally, calculate the final weight values. By comprehensively considering the results of the previous steps, the most accurate and comprehensive weight values of each criterion are obtained, providing a reliable basis for subsequent decision-making or analysis. Multiply the weight values of each element based on maximum economic and maximum social respectively to get the final weight value of each element combining economic and social, due to the small weight value of the output elements at this time, it is normalized.

$$F_{Wi}^{'}=C_{Wi}\cdot A_{Wi} \tag{9}$$

$$F_{Wi}=\frac{F_{Wi}^{'}}{\sum_{i=1}^{6} F_{Wi}^{'}} \tag{10}$$

Based on the above steps, the results of the weight coefficients of each stakeholder can be obtained as Figure 5:

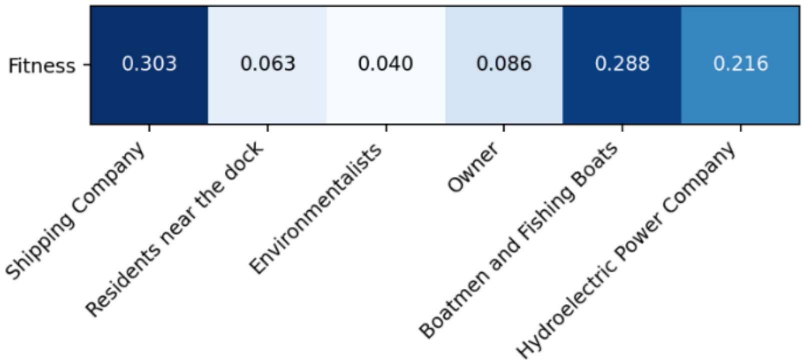

Figure 5. Weighting coefficients for each equity stakeholder

The weights of the solved indicators show that shipping companies bring the highest economic and social value and that environmentalists bring the least overall benefit compared to others.

5. Stakeholder-Based Water Level Optimization in Great Lakes

5.1. Steps in building a comprehensive scoring model

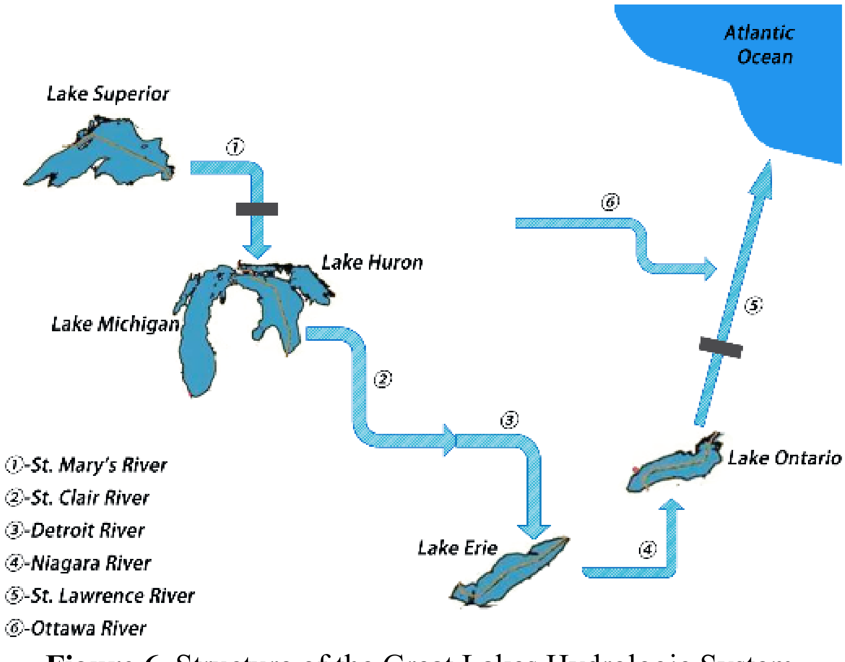

Figure 6. Structure of the Great Lakes Hydrologic System

In this paper, based on the structure of the Great Lakes water system, the lakes are numbered from east to west as Lakes 1 to 5, with rivers numbered from 1 to 6. As shown in figure 6. The first step involves calculating a composite score for water level conditions in each lake. The objective function consists of several components, each reflecting the benefit score of a particular stakeholder. The model aims to find the optimal solution that maximizes these scores, essentially maximizing the total value of benefits received by all stakeholders.

First of all, shipping companies prefer higher water levels in the lakes, as a larger change in water levels typically correlates with higher ratings. Therefore, the following formula can be obtained:

$$P_1^{'} = (\Delta H - C_{\min})^3 \tag{11}$$

Second, conversely, those managing shipping terminals or living near the Port of Montreal desire lower water levels. They favor smaller changes in water levels, especially when these fluctuations are smaller than the maximum historical changes, resulting in higher ratings when the level change is less dramatic. Therefore, the following equation can be obtained:

$$P_2^{'} = (C_{\max} - \Delta H)^2 \tag{12}$$

Then, environmentalists, on the other hand, prefer seasonal fluctuations in water levels, with a focus on achieving higher water levels during the flood season. The more the current levels exceed the average historical changes during this period, the better. Therefore, the following formula can be obtained:

$$P_3^{'} = (-1)^i (C_{average} - \Delta H) \tag{13}$$

Where: or the month of t, $i = 0$ when $11 \le t \le 12, 1 \le t \le 5$; $i = 1$ when $6 \le t \le 10$

Next, homeowners around Lake Ontario prefer moderate and stable water levels, with deviations from historical averages resulting in point deductions from the overall score. so the following formula is derived:

$$P_4^{'} = -|(C_{average} - \Delta H)| \tag{14}$$

Then, similarly, recreational boaters and fishing boat operators on the lake also favor stable water levels, with preferences aligning closely with those of homeowners. Similar to model 4, the following equation is obtained:

$$P_5^{'} = -|(C_{average} - \Delta H)| \tag{15}$$

In the end, Hydroelectric companies, however, prefer the water level to be as high as possible, similar to the needs of the shipping companies, which further emphasizes the desire for higher levels. Similar to model 1, the following equation equation can be obtained:

$$P_6^{'} = (\Delta H - C_{\min})^3 \tag{16}$$

The second step is the evaluation of water levels in each lake, which mainly includes the following two aspects.

The first aspect is domestic water use. Residents around the Great Lakes will have water for domestic use and industrial production on the lakes, and the solid will consume the water of the Great Lakes to reduce the water level of the lakes:

$$h_1 = 0.356\gamma N_p Q_{live} + GQ_{industry} \tag{17}$$

Where γ the guaranteed rate of urban water supply; N_p is the number of urban population; Q_{live} is the annual urban per capita water quota; G is the regional industrial added value; $Q_{industry}$ million yuan of industrial added value of water demand.

The second aspect is agricultural water. The people around the Great Lakes use water for farming, which consumes water from the Great Lakes and reduces the water level of the lakes.

$$h_2 = K_C \cdot ET_O \tag{18}$$

Where K_C is the crop coefficient and ET_O what is the water requirement of the reference crop.

The natural factors mainly include precipitation, evaporation, and river inflows and outflows in the natural environment, which are analyzed in detail as follows.

The natural factors mainly include precipitation, evaporation, and river inflows and outflows in the natural environment, and it is mainly represented by the following characters in the subsequent text. Precipitation is represented by h_3; For river inflow, when river z flows into lake j, its quantitative indicator h_4 is determined by the formula $h_4 = C_{ijz}\frac{v_i t}{s}$; For river outflow, when river z flows out of lake j, its quantitative indicator h_5 is determined by the formula $h_5 = b_{ijz}\frac{v_o t}{s}$; Evaporation is represented by h_6.

According to the establishment of the above model, as well as the analysis of the river's factors, it can be concluded that ΔH is mainly composed of natural and anthropogenic factors, because this paper simulates the lake into a cylindrical model, so according to the cylindrical volume equation:

$$V = S \cdot \mathrm{h} \tag{19}$$

Therefore, based on the above analysis, the expression function of the change in lake level ΔH can be finally obtained as:

$$\Delta H = \frac{k_1 v_i - k_2 v_o + \sum_{i=1}^{6} h_i}{S} \tag{20}$$

To summarize, the total scoring formula for a separate year is the sum of the monthly scoring formulas:

$$\begin{aligned} P = \sum_{i=1}^{12}[\sum_{j=1}^{6}\sum_{z=1}^{6}\omega_{ijz}h_{ijz} + (\omega_{i1}^{'} + \omega_{i3}^{'})(\Delta H_i - C_{\min}) + \omega_{i2}^{'}(C_{\max} - \Delta H_i) + \\ \omega_{i3}^{'}(-1)^i(C_{average} - \Delta H_i) + (\omega_{i4}^{'} + \omega_{i5}^{'})(-\left|C_{average} - \Delta H_i\right|] \end{aligned} \tag{21}$$

Where: ω is the weighting factor for each lake, and ω' is the stakeholder weight share.

Of course, the model also has certain limitations, which are mainly as follows:

First since the amount of water level change in each lake can cause irreversible damage to littoral residents when the amount of water level change in each lake can cause irreversible damage to littoral residents, theΔHof each lake should not exceed 2 to 3 feet, i.e., the formula is as follows:

$$\Delta H = \frac{k_1 v_i - k_2 v_o + \sum_{i=1}^{6} h_i}{S} < 2 \tag{22}$$

Second since each lake has its own maximum and minimum water levels, i.e., the formula is as follows:

$$H_{\min} < H_i + \Delta H_i < H_{\max} \tag{23}$$

Then, to meet the most basic water needs, it is required:

$$H_i + \Delta H_i > h_{i1} + h_{i2} \tag{24}$$

Finally the rate of change of the flow rate of a river does not increase indefinitely, so the following expression is obtained:

$$0 < k < 5 \tag{25}$$

5.2. Solving the model

The particle swarm algorithm searches for the optimal solution in the solution space by a group of particles, and through cooperation and communication, constantly updates their search direction and speed, until the global optimal solution or near-optimal solution is found.

In this paper, the rate of change of velocity k will be determined for each river each month from a randomly generated initial position and initial velocity. Then, for each particle, the adaptation value corresponding to its position is calculated. If the adaptation value of the current position is better than the adaptation value of the individual best position (pbest), the current position is used as the individual's best position. Meanwhile, in the particle swarm, the particle with the best adaptation value has its position set as the global best position (gbest). Next, according to the pbest and gbest of each particle, its velocity and position are updated. Then, repeated iterations are performed, and after each iteration, it is checked whether the constraints are satisfied:

If they are satisfied, the iteration continues, updating the velocity and position of the particles and continuing the search for the optimal solution. When the termination condition is satisfied, the particle swarm algorithm ends and outputs the optimal.

Solution results:

The rate of change of velocity k_{ij} values for each river under the December 2011 to November 2019 values are shown in the figure 7:

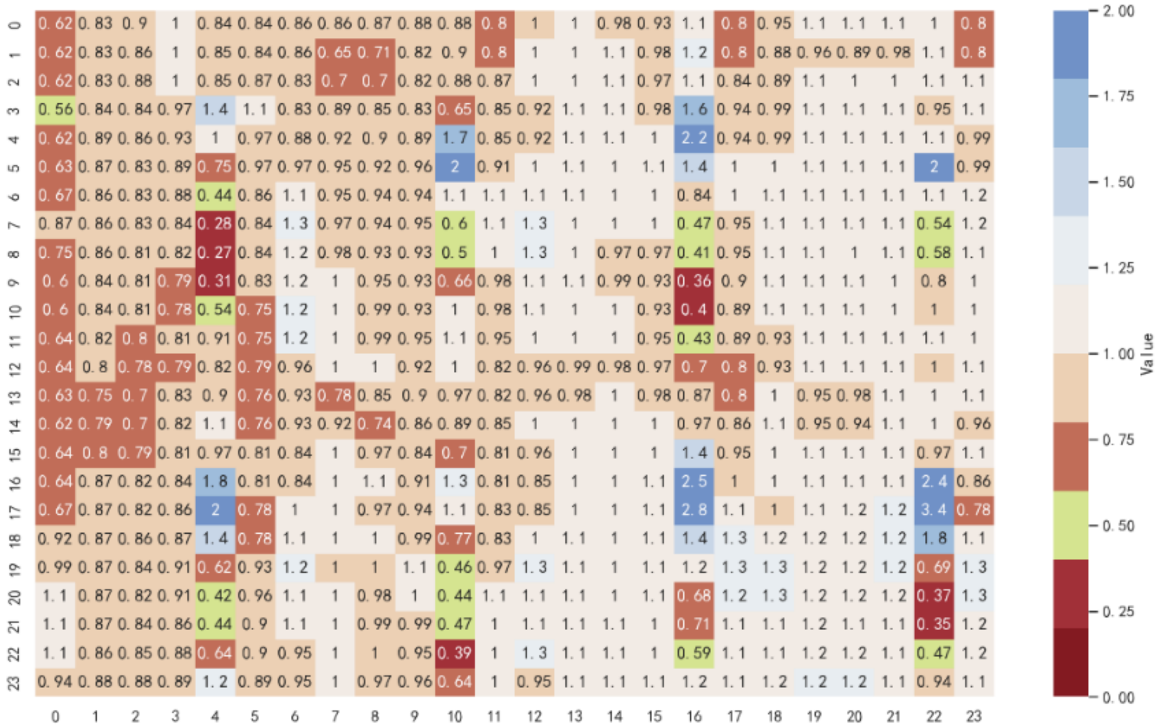

Figure 7. k_{ij} value from December 2011 to November 2019 value

Based on Equation (23), the optimum water level values for the Great Lakes can be obtained as shown below:

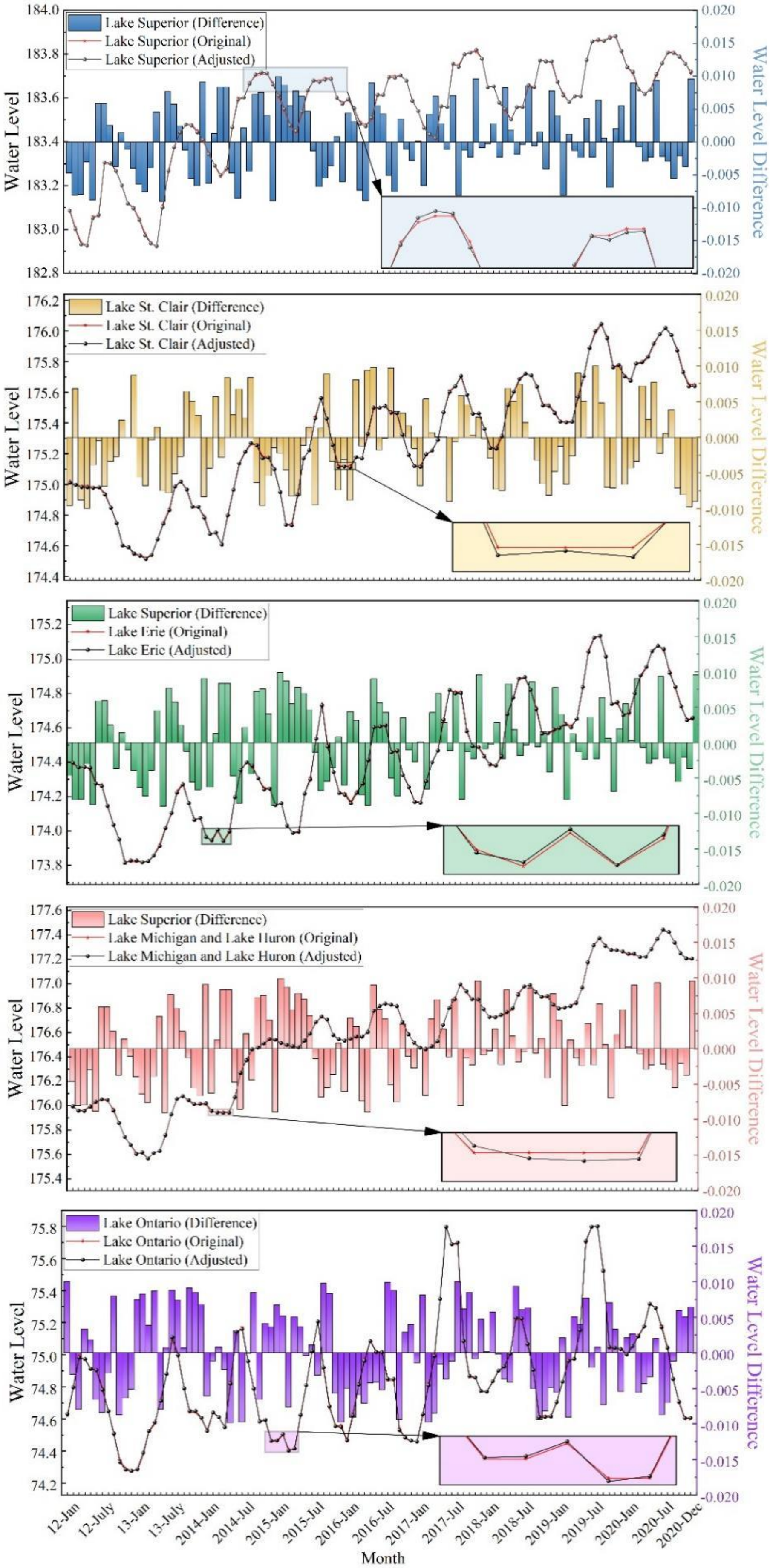

Figure 8. Map of optimal water levels in the Great Lakes

Figure 8 above shows the best monthly lake level results from 2011 to 2020, with an overall upward trend. The red lines represent the original water levels of each of the Great Lakes, while the black lines indicate the optimized monthly best water levels of the Great Lakes after the evaluation system in this paper, with the left vertical coordinate as the reference axis. The bar graphs in other colors represent the differences between the monthly best water levels and the original water levels, with the right vertical coordinate as the reference axis.

6. Conclusion

The conclusions of this study focus on the hydrology of the Great Lakes following the implementation of the 2014 policy and provide several significant insights. A comprehensive hydrological network model has been successfully developed, encompassing key hydrological elements within the Great Lakes basin. This model lays a solid foundation for subsequent analyses and enables a detailed understanding of the water dynamics in the region. By applying the entropy weighting method, scientific weights have been calculated for various natural factors influencing the water levels, such as precipitation, evaporation, and river flow. These weights reveal the relative importance of each factor in determining lake level variations, contributing to a more precise evaluation framework.

Additionally, this study constructs a decision matrix to quantify and analyze the demands of various stakeholders involved in lake-level management. The matrix integrates economic and social benefits, reflecting the expectations and preferences of different interest groups, such as shipping companies, agricultural users, and environmental organizations. By combining these stakeholder demands with the intrinsic value of the lakes and natural influencing factors, the particle swarm algorithm is employed to solve for the optimal water levels of the Great Lakes on a monthly basis. This optimization is achieved under constraints such as specified river flow rates and limits on water level change heights, using the rate of change of river velocity as a variable.

Overall, this research presents a robust approach and framework for hydrological science applications. By comprehensively integrating stakeholder demands, natural factors, and the intrinsic value of lakes, the study offers a practical solution for determining the optimal water levels of the Great Lakes. The findings provide a scientific basis for lake management and scheduling while demonstrating the feasibility and effectiveness of the proposed methods in addressing complex water resource challenges.

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