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Research Article

Suitability Evaluation and Analysis of the Human Settlement-Environment-Energy Coupling System Based on Information Entropy and Artificial Intelligence Algorithms

Wenjie Qi, Xiaohua Yang*, Weiqi Xiang

State Key Laboratory of Wetland Conservation and Restoration, School of Environment, Beijing Normal University, Beijing, China

Abstract

To address the issues of insufficient granularity and ambiguous identification of key driving factors in the evaluation of the Human Settlement-Environment-Energy (HSEE) coupling system, this study takes 30 Chinese provinces as research objects and constructs an interpretable coupling evaluation model based on "information entropy + artificial intelligence" using panel data from 2003 to 2023. Using classic AI algorithms (BP neural network, PCA, and SVM) combined with the entropy weight method, the model was constructed. The entropy weight method and PCA respectively calculated the system suitability scores, and the robustness was validated by the Spearman correlation test (r = 0.9392). Indicator importance was identified via BP neural network, SVM, and the Garson algorithm, and comprehensive weights were determined using the rank average method. The results show that: during the study period, the national average system suitability continuously increased with an average annual growth rate of 3.8%; eastern coastal provinces significantly outperformed western and northeastern regions; per capita water resources, per capita local fiscal revenue, and residential consumption level are the core driving factors; infrastructure indicators exhibit diminishing marginal returns; energy consumption and environmental protection indicators show nonlinear differentiation characteristics. This study integrates objective weighting and machine learning interpretability to provide a standardized methodological framework for evaluating the HSEE coupling system, offering data support for regional human settlement quality improvement and sustainable development policy making.

Keywords

Human Settlement-Environment-Energy Coupling System, Information Entropy, Garson, Artificial Intelligence Algorithms

1. Introduction

With economic development and social progress, people increasingly value the comfort of human settlements. The complex coupling among human settlement systems, environmental systems, and energy systems has become a research hotspot. Comprehensive evaluation models for the Human Settlement-

*Correspondence: Xiaohua Yang (xiaohuayang@bnu.edu.cn)

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Energy-Environment (HSEE) coupling system for system coupling analysis (Xiang et al., 2025) have gained increasing attention. For instance, artificial intelligence algorithms such as principal component analysis and the entropy weight method are now widely applied to quantitative assessments of system suitability across provinces. However, fine-grained evaluation of HSEE coupling system suitability and identification of its key driving factors remain lacking. To address this gap, this study takes 30 Chinese provinces as examples, uses PCA and the entropy weight method to calculate provincial system suitability scores, conducts Spearman correlation analysis to verify the feasibility of the evaluation results, and then introduces machine learning algorithms (SVM and BP neural network) to identify key driving factors.

2. Materials and Methods

2.1. Overview of the Research Area

China has a vast territory with significant regional differentiation, presenting distinct spatial disparities in system suitability. Climatically, China spans five temperature zones from south to north: tropical, subtropical, warm temperate, mid-temperate, and cold temperate, and also includes a unique plateau climate zone, forming five climate types: tropical monsoon, subtropical monsoon, temperate monsoon, temperate continental, and plateau mountain climate, resulting in diverse regional water-heat combinations. Socioeconomically, provincial economic development levels are uneven, and population distribution patterns and urbanization processes show significant gradient differences. In energy consumption and ecological environment, regional development conflicts are also prominent: northern regions have strong winter heating demand and relatively high shares of fossil energy consumption, accompanied by prominent air pollution issues; southern regions have more diversified energy structures with relatively higher proportions of clean energy such as hydropower and biomass, and the forms and degrees of environmental pressure differ significantly from those in northern regions. Given the regional imbalance characteristics of human settlements, ecological quality, and energy consumption, studying the coupling coordination of human settlement-environment-energy systems across Chinese regions from the perspective of residents' subjective well-being has important theoretical value and practical significance [1].

2.2. Theoretical Framework

The comprehensive evaluation method combining information entropy and artificial intelligence algorithms is an important tool that can effectively handle multi-dimensional indicator dimensionality reduction, objective weighting, and identification of key driving factors. This combined approach integrates linear dimensionality reduction, information entropy weighting, and ensemble learning algorithms. It can extract core features from high-dimensional system indicators, provide transparent and interpretable evaluation results, facilitate communication between interdisciplinary researchers and policy makers, and support data-driven regional sustainable development strategies and resident well-being improvement policy design.

Therefore, this study takes 30 Chinese provinces as examples, uses PCA and the entropy weight method to calculate provincial system suitability scores, conducts Spearman correlation analysis to verify the feasibility of the evaluation results, and then introduces BP neural network and SVM models to identify key driving factors. The indicator system uses the HSEE framework (Table 1) [1], which consists of three subsystems: human settlement, environment, and energy. Indicators are classified into positive and negative types for subsequent evaluation. Positive indicators mean that larger values indicate higher system suitability; negative indicators mean that larger values indicate lower system suitability. Using PCA and the entropy weight method separately ensures objectivity of scoring. Spearman correlation analysis between the two methods guarantees the stability of results. The introduction of multiple machine learning models overcomes the bias of single models in driving factor identification. Finally, the rank average is used as the comprehensive weight ranking to further enhance result accuracy.

Table 1. *HSEE Coupling System Suitability Evaluation Indicator System.*

Target Layer	System Layer	NO.	Indicator Layer	Indicator Type
Human Settlement-Environment-Energy Coupling System Suitability	Human Settlement Subsystem	I1	Climate Comfort (UTCI) (℃)	Positive
		I2	Number of Medical and Health Institutions (units)	Positive
		I3	Per Capita Disposable Income of Residents (RMB)	Positive
		I4	Number of Beds in Medical and Health Institutions (units)	Positive
		I5	Education Level (%)	Positive
		I6	Per Capita Local Fiscal Revenue (RMB/person)	Positive

Target Layer	System Layer	NO.	Indicator Layer	Indicator Type
		I7	Resident Consumption Level (RMB)	Positive
		I8	Population Density (persons/km^2)	Negative
		I9	Per Capita GDP (RMB)	Positive
		I10	Urban Registered Unemployment Rate (%)	Negative
		I11	Per Capita Residential Floor Space (m^2)	Positive
		I12	Per Capita Park Green Area (m^2)	Positive
		I13	Green Coverage Rate of Built-up Areas (%)	Positive
		I14	Harmless Treatment Rate of Domestic Waste (%)	Positive
	Environment Subsystem	I15	Sewage Treatment Rate (%)	Positive
		I16	Number of Urban Road Lighting Lamps (thousand units)	Positive
		I17	Forest Coverage Rate (%)	Positive
		I18	Per Capita Urban Road Area (m^2)	Positive
		I19	Population Affected by Natural Disasters (10,000 persons)	Negative
		I20	Number of Wastewater Treatment Facilities (sets)	Positive
		I21	Total Water Consumption (10^8 m^3)	Negative
		I22	Per Capita Water Resources (m^3/person)	Positive
		I23	Total COD Emissions (tons)	Negative
		I24	CO_2 Emissions (10^6 tons)	Negative
	Energy Subsystem	I25	Total Energy Consumption (10,000 tons of SCE)	Negative
		I26	Total Ammonia Nitrogen Emissions (10,000 tons)	Negative
		I27	Urban Gas Penetration Rate (%)	Positive
		I28	Electricity Consumption (10^8 kWh)	Negative
		I29	Urban Water Penetration Rate (%)	Positive
		I30	Hazardous Waste Generation (10,000 tons)	Negative

2.3. Input and Output Data

This study takes 30 Chinese provinces as research objects. Based on the HSEE model, 30 indicators covering three subsystems (human settlement, environment, energy) are selected. The selected 30 human settlement-environment-energy coupling system suitability indicators are used as input data, and suitability scores and indicator weights are used as output data. Data sources: China Statistical Yearbook (2003-2023); China Urban-Rural Construction Statistical Yearbook (2003-2023); China Environmental Statistical Yearbook (2003-2023); China Social Statistical Yearbook (2003-2023).

2.4. Artificial Intelligence Methods

2.4.1. Scoring Methods

Principal Component Analysis (PCA) [2, 3]: PCA is an important data dimensionality reduction method. Its core idea is to map high-dimensional data to a low-dimensional space through linear space transformation, where the low-dimensional data are uncorrelated and their linear combinations can reflect most of the information of the high-dimensional data, thus achieving data compression and redundancy removal.

Entropy Weight Method [4, 5]: The entropy weight method is an objective weighting approach. Its core lies in automatically determining weights using the dispersion of each indicator: calculating the information entropy of each indicator; a smaller entropy value indicates greater variation and more information contained in the indicator; then weights are determined based on the coefficient of difference (1 – entropy); finally, the normalized values of each indicator are weighted and summed to obtain a comprehensive score for each sample. This method is completely data-driven, avoids subjective weighting bias, and higher scores indicate better system suitability for that region in that year.

2.4.2. Weight Analysis Methods

BP (Back Propagation) neural network is a feedforward artificial neural network proposed by Rumelhart and McClelland [6, 9]. The BP neural network approximates arbitrarily complex functional relationships through nonlinear mapping, making it particularly suitable for modeling and prediction of complex systems. Its adaptive learning ability, strong fault tolerance, and wide applicability also provide theoretical foundations for comprehensive evaluation and system prediction. This study uses the BP neural network combined with the Garson algorithm to quantify the relative importance of the 30 input indicators on suitability scores. This method analyzes the connection weights of the BP neural network to measure the contribution of each indicator to the output. The calculation process is as follows:

Extract network weights: Obtain two weight matrices from the trained network: W1 (weight matrix from input layer to hidden layer) and W2 (weight matrix from hidden layer to output layer).

Calculate initial importance for each indicator: For the i-th input indicator, iterate over all hidden neurons j, take the absolute value of the product of the input weight and output weight, and accumulate:

$$Imp_i = \sum_j^H \left| W1_{j,i} \times W2_j \right| \tag{1}$$

Normalize to percentage: Sum the initial importance of all indicators, then calculate the percentage for each indicator:

$$Weight_i = \frac{Imp_i}{\sum_{k=1}^{30} Imp_k} \times 100\% \tag{2}$$

Support Vector Machine (SVM): SVM maps data to a high-dimensional feature space via a kernel function and finds the optimal hyperplane for class separation, making it especially suitable for small-sample classification problems [7, 10, 15]. Its advantages include theoretical completeness, a unique global optimal solution, and good robustness to sample noise. In prediction tasks, the radial basis function (RBF) kernel is most commonly used for flexibly capturing nonlinear relationships. However, its performance highly depends on hyperparameter selection, and computational complexity increases significantly with sample size, limiting its application in large-scale data [8].

2.4.3. Correlation Analysis Method

Spearman correlation coefficient [11-14]: The Spearman rank correlation coefficient is a nonparametric statistical method used to measure the strength of a monotonic relationship between two variables, without requiring normal distribution or linear relationship. It is calculated based on the ranks of the variables rather than the original values, by applying Pearson correlation to the ranks. Its range is [-1,1], with absolute values closer to 1 indicating a stronger monotonic association.

2.5. Analysis Process

(1) Data preprocessing: Handle unit rows, clean missing values, and standardize the data for the entropy weight method and PCA scoring.

(2) System suitability scoring: Use the entropy weight method and PCA separately to score system suitability for each province and each year, then perform Spearman correlation analysis on the two model results. If the results are highly consistent (Spearman correlation coefficient > 0.8), the evaluation results of the two models are considered robust, and the entropy weight method results can be selected as the final evaluation results for subsequent weight analysis.

(3) Indicator weight analysis: Use SVM and BP neural network models to analyze indicator weights for provincial system suitability scores, combine them with the weights generated by the entropy weight method during scoring, and finally take the rank average of the three methods as the comprehensive weight ranking

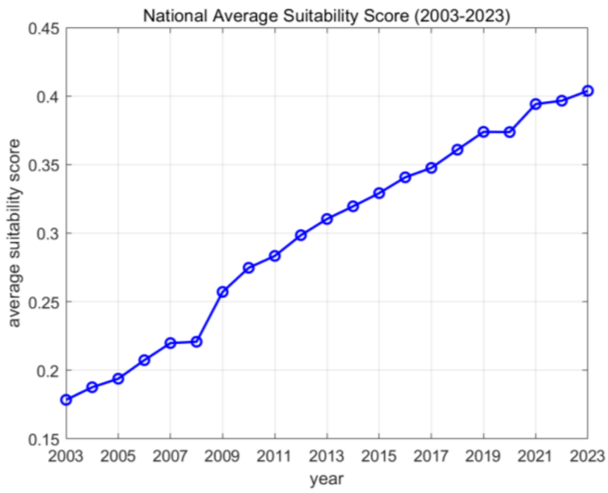

Figure 1. *National Average Suitability Score from 2003 to 2023.*

3. Result Analysis

3.1. Scoring Results

This study used the entropy weight method and PCA to score national system suitability. Spearman correlation analysis between the two model scores yielded a coefficient of 0.9392, indicating high consistency between the two models (correlation coefficient > 0.8). Either can be selected. Since the HSEE evaluation framework includes multiple dimensions, the entropy weight method scores were used for feature importance analysis to preserve dimensional interpretability.

From the evaluation results: between 2003 and 2023, the national average suitability score (Figure 1) increased from 0.18 to 0.41, with an average annual growth rate of approximately 3.8%. As shown in Figure 2, eastern coastal provinces consistently maintained a leading position in residential suitability, while western and northeastern regions scored relatively lower.

Specifically, from the 2023 suitability scores (Figure 2(d)):

The top five provinces in 2023: Guangdong (0.566), Zhejiang (0.553), Jiangsu (0.541), Beijing (0.511), Shanghai (0.515).

The bottom five provinces: Gansu (0.288), Ningxia (0.300), Xinjiang (0.319), Qinghai (0.351), Heilongjiang (0.339).

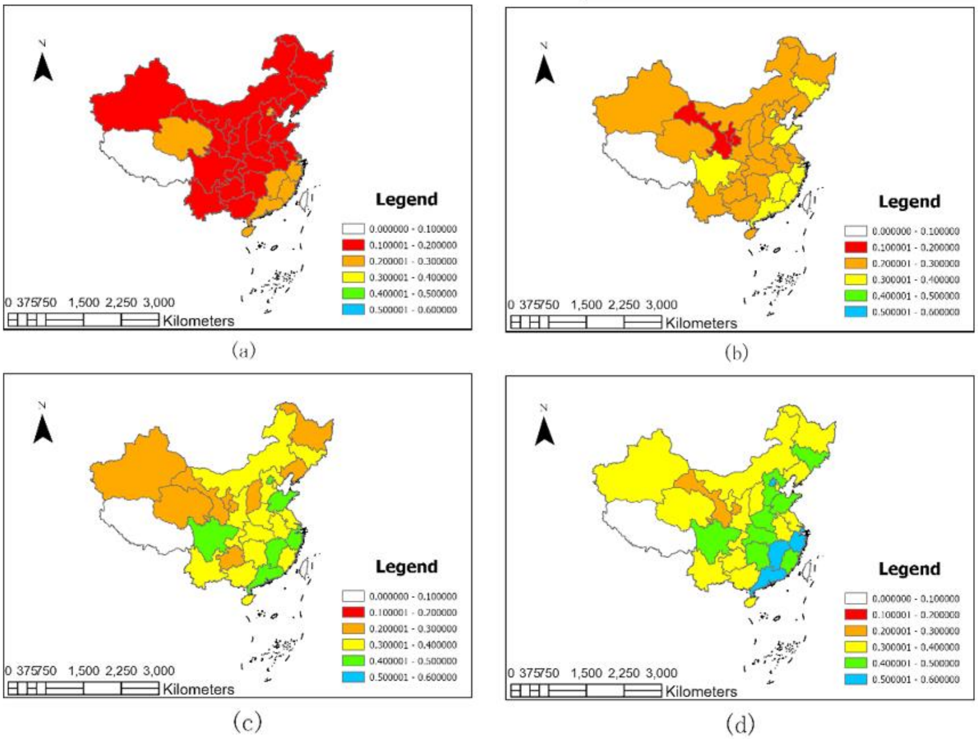

Figure 2. Suitability Scores of Each Province from 2003 to 2023: (a)year 2003; (b)year 2010; (c)year 2017; (d)year 2023.

3.2. Weight Analysis Results

The core indicators identified by the three artificial intelligence algorithms—entropy weight method, SVM, and BP neural network—showed high consistency.

For each indicator, the arithmetic mean of its entropy weight rank, SVM rank, and BP neural network rank was calculated, and then indicators were sorted by average rank (a smaller average rank indicates higher comprehensive importance). The ranking results (Table 2) show:

(1) Economic foundation and resource endowment are primary driving factors: per capita water resources, per capita local fiscal revenue, resident consumption level, and per capita GDP rank high. Resident consumption level ranks first in the BP neural network, indicating that consumption vitality has a strong nonlinear positive effect on improving human settlements.

(2) Returning indicator weights to each subsystem and re-ranking: In the energy subsystem, the top three indicators by average rank are per capita water resources, total energy consumption, and total COD emissions. In the human settlement subsystem, the top three are per capita local fiscal revenue, resident consumption level, and number of medical and health institutions. In the environment subsystem, the top three are forest coverage rate, number of wastewater treatment facilities, and per capita urban road area.

(3) Infrastructure investment exhibits nonlinear saturation characteristics: the number of wastewater treatment facilities and the number of urban road lighting lamps show prominent

importance in the entropy weight method and SVM but drop sharply in the BP neural network, indicating diminishing marginal benefits after facility numbers exceed thresholds. Therefore, efficiency rather than quantity expansion should be emphasized.

(4) Total energy consumption shows methodological divergence: total energy consumption has low importance in the entropy weight method and SVM but jumps to third in the BP neural network, suggesting complex interactions with industrial structure and energy efficiency, with nonlinearly amplified impacts in high-energy-consumption regions.

Table 2*. Weight Analysis Using Rank Average Method of Three Models.*

Comprehensive Rank	Indicator	Entropy Weight Rank	SVM Rank	BP Neural Network Rank	Average Rank
1	Per Capita Water Resources	1 (0.1141)	2 (0.0900)	13 (0.03243)	5.333333333
2	Per Capita Local Fiscal Revenue	2 (0.0933)	4 (0.0822)	12 (0.0364)	6
3	Resident Consumption Level	9 (0.0582)	9 (0.0577)	1 (0.0603)	6.333333333
4	Forest Coverage Rate	11 (0.0406)	8 (0.0584)	2 (0.0530)	7
5	Number of Medical and Health Institutions	4 (0.0770)	1 (0.0972)	17 (0.0307)	7.333333333
6	Per Capita GDP	8(0.0595)	10 (0.0539)	4 (0.0441)	7.333333333
7	Number of Wastewater Treatment Facilities	3(0.0787)	3 (0.0884)	25 (0.0255)	10.33333333
8	Per Capita Disposable Income of Residents	6(0.0666)	7 (0.0596)	20 (0.0286)	11
9	Per Capita Urban Road Area	13(0.0309)	12 (0.0371)	8 (0.03889)	11
10	Number of Urban Road Lighting Lamps	5(0.0748)	6 (0.0665)	23 (0.0272)	11.33333333
11	Per Capita Park Green Area	14(0.0179)	16 (0.0171)	6 (0.0411)	12
12	Education Level	10(0.0493)	11 (0.0426)	16 (0.0314)	12.33333333
13	Number of Beds in Medical and Health Institutions	7(0.0633)	5 (0.0678)	28 (0.0218)	13.33333333
14	Total Water Consumption	17(0.0140)	17 (0.0169)	7 (0.0389)	13.66666667
15	Sewage Treatment Rate	19(0.0128)	19 (0.0162)	5 (0.0414)	14.33333333
16	Total Energy Consumption	20(0.0127)	20 (0.0143)	3 (0.0450)	14.33333333
17	Per Capita Residential Floor Space	12(0.0315)	13 (0.0278)	21 (0.0285)	15.33333333
18	Total COD Emissions	18(0.0134)	18 (0.0165)	18 (0.0305)	18
19	Green Coverage Rate of Built-up Areas	22(0.0102)	22 (0.0082)	11 (0.0369)	18.33333333
20	Population Density	15(0.0157)	15 (0.0176)	27 (0.247)	19
21	Harmless Treatment Rate of Domestic Waste	16(0.0144)	14 (0.0198)	30 (0.0132)	20
22	Urban Gas Penetration Rate	27(0.0050)	27 (0.0038)	10 (0.0383)	21.33333333
23	Electricity Consumption	23(0.0067)	23 (0.0063)	19 (0.0303)	21.66666667
24	Total Ammonia Nitrogen Emissions	26(0.0058)	25 (0.0053)	14 (0.0324)	21.66666667
25	Climate Comfort (UTCI)	21(0.0117)	21 (0.0118)	24 (0.0267)	22

Comprehensive Rank	Indicator	Entropy Weight Rank	SVM Rank	BP Neural Network Rank	Average Rank
26	CO_2 Emissions	29(0.0034)	29 (0.0024)	9 (0.0384)	22.33333333
27	Urban Registered Unemployment Rate	25(0.0060)	26 (0.0043)	22 (0.0282)	24.33333333
28	Urban Water Penetration Rate	30(0.0027)	30 (0.0013)	15 (0.0317)	25
29	Population Affected by Natural Disasters	24(0.0062)	24 (0.0060)	29 (0.0183)	25.66666667
30	Hazardous Waste Generation	28(0.0039)	28 (0.0031)	26 (0.0252)	27.33333333

*Values in parentheses after ranks are the original weights for that indicator under the respective evaluation method. When average ranks are equal, the order is fine-tuned by original importance values: an indicator is ranked ahead of another if any two of its model ranks are smaller.

4. Conclusion

4.1. Spatiotemporal Evolution Characteristics

The national average suitability score increased steadily from 0.18 in 2003 to 0.41 in 2023, with an average annual growth rate of about 3.8%, showing a sustained upward trend. Notably, growth was particularly significant during the late period of the "Eleventh Five-Year Plan" (2008–2010) and the middle-late period of the "Thirteenth Five-Year Plan" (2018–2020), corresponding respectively to the strengthening of energy-saving and emission-reduction policies and the acceleration of ecological civilization construction. It is worth noting that the score growth rate slowed slightly after 2020, possibly related to the short-term impact of the COVID-19 pandemic on economic activities and public services, but the overall upward trend remained unchanged, indicating that China has achieved sustained results in improving human settlements, optimizing energy structures, and environmental governance.

Although national system suitability shows a continuous increasing trend over time, the spatial pattern of "high in the east, low in the west, north-south differentiation" has not fundamentally changed. Future policy support and resource investment should be strengthened in western and northeastern regions.

4.2. Comparison with Existing Studies

The results of this study are consistent with previous research: per capita GDP, income level, and medical resources are core factors affecting livability, confirming the supporting role of economic and social foundations on human settlement quality. Compared with traditional single evaluation methods, this study further reveals that the importance of wastewater treatment facilities and urban road lighting lamps changes significantly in nonlinear models, indicating that after infrastructure reaches a certain threshold, its improvement effect on livability exhibits diminishing marginal benefits rather than simple linear growth. This finding enriches the theoretical understanding of human settlement science and provides more precise targets for policy formulation. Furthermore, this study introduces interpretable machine learning into coupling system weight analysis, breaking through the limitation of traditional methods that can only characterize linear relationships, enabling quantitative identification of nonlinear impacts of driving factors.

4.3. Hybrid Strategy

This study adopts a hybrid strategy of "information entropy + artificial intelligence algorithms", balancing the objectivity of comprehensive evaluation and the nonlinear identification capability of driving factors. Compared with single methods, the cross-validation framework can effectively avoid weight bias and model overfitting. The Garson algorithm is used to analyze BP neural network connection weights, achieving interpretability of the black-box model. The rank average method integrates importance rankings from multiple models to enhance result stability and reliability. This methodological system can provide a standardized and generalizable technical path for complex coupling system evaluation.

4.4. Limitations and Future Research

This study still has the following limitations:

(1) The weight calculation results heavily depend on the accuracy of the scoring system. If the entropy weight method and PCA calculations are incorrect, the subsequent weight analysis will be significantly affected.

(2) The model does not fully account for time lag effects, such as the long-term cumulative impacts of pollution emissions and energy consumption on human settlements.

(3) The cluster analysis is based on scores from the recent three years and does not fully utilize the dynamic evolution information from the 20-year time series. Future research can introduce Long Short-Term Memory (LSTM) networks for

spatiotemporal prediction and combine causal machine learning algorithms (e.g., causal inference methods) to verify causal relationships among driving factors.

Abbreviations

HSEE	Human Settlement-Environment-Energy
AI	Artificial Intelligence
SVM	Support Vector Machine
BP Neural Network	Back Propagation Neural Network
PCA	Principal Component Analysis
UTCI	Universal Thermal Climate Index
COD	Chemical Oxygen Demand

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Author Contributions

Wenjie Qi: Conceptualization, Data curation, Methodology, Visualization, Writing – original draft
Xiaohua Yang: Funding acquisition, Supervision
Weiqi Xiang: Data curation, Methodology, Visualization, Writing – review & editing

Conflicts of Interest

The authors declare no conflicts of interest.

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