

Article

Framework for Comprehensive Risk Assessment and Factor Diagnosis from the Perspective of the Water–Energy–Food–Ecology–Carbon Complex System: A Case Study of the Yellow River “Ji” Bay

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Abstract

The ecological protection and high-quality development of the Yellow River Basin is a major national strategy in China. The Yellow River “Ji” Bay is an important part of the basin. This study evaluates the comprehensive risk of the water–energy–food–ecology–carbon (WEFEC) complex system within the “Ji” Bay. Using 2004–2023 panel data from nineteen regional cities, this study develops a 24-indicator WEFEC index system that assesses reliability, synergy, and resilience. A comprehensive evaluation method based on the game theory–cloud model is employed to determine the risk levels. The study results show the following: (1) the multi-year average comprehensive risk of the WEFEC complex system in the “Ji” Bay from 2004 to 2023 was at a high alert level; (2) the overall synergy of the “Ji” Bay was moderate; (3) spatially, the number of cities in extreme and high alert states decreased, whereas the number of cities in no alert and light alert states increased; and (4) indicators such as per capita water resources, water production modulus, and water area ratio are the main factors restricting the comprehensive risk of the WEFEC complex system. Based on these findings, this paper proposes policy recommendations using the following three aspects: criterion layers, risk factors, and different regions.

Keywords: “Ji” Bay; water–energy–food–ecology–carbon (WEFEC); cloud model; risk assessment



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1. Introduction

There is a high degree of interdependence among water resources, energy, food, ecology, and carbon emissions [1–3]. Research focusing solely on one or two of these systems may result in resource depletion, environmental damage, and vicious competition among systems. Therefore, a comprehensive study of water, energy, food, ecology, and carbon emissions is essential. More than 90% of global freshwater resources are used for agricultural production [4], whereas energy extraction necessitates significant water consumption. Global demand for water, energy, and food is expected to rise by approximately 40%, 50%, and 35%, respectively, by 2030 [5], while the population is expected to reach 8.5 billion, resulting in severe resource shortages. By 2050, energy-related carbon dioxide emissions are expected to rise by 70% [6]. Food production and water resource development and utilization both consume energy and emit carbon dioxide, thereby affecting the ecological environment. Studies have shown that carbon emissions from urban water systems account

for 12% of total emissions [7], while the Intergovernmental Panel on Climate Change (IPCC) reports that agricultural production accounts for approximately 13.5% of global carbon emissions [8]. According to the IPCC's Sixth Assessment Report, global surface temperatures from 2011 to 2020 increased by 1.09 °C compared to the 1850–1900 period. The report further highlights that global warming caused by carbon emissions is irreversible on time scales of hundreds to thousands of years [9], which will pose a serious risk of global warming. Additionally, the annual report of the 2011 World Economic Forum (WEF) listed water, energy, and food, as resource risks; these issues are interrelated, and, specifically, core resource shortages can lead to more conflicts among relevant groups, countries, and industries [10]. In 2015, the United Nations proposed seventeen Sustainable Development Goals (SDGs) [11]; in particular, SDG 2 (End Hunger), SDG 7 (Affordable and Clean Energy), SDG 13 (Climate Action), and SDG 15 (Life on Land) are closely linked to water, energy, food, ecology, and carbon emissions. Thus, research on WEFEC complex system is urgently needed.

In recent years, system analysis frameworks, such as water–energy–food (WEF), water–energy–carbon (WEC), and water–energy–food–ecology (WEFE), have gradually gained prominence in the understanding of the interactions of complex resource systems. Following the Bonn Conference in 2011, numerous theoretical and practical studies on WEF relationships emerged internationally. With the escalation of ecological damage and global warming risks, research on relationships such as WEC, WEFE, and water–energy–food–carbon (WEFC) has emerged. de Amorim et al. argued that water, energy, and food are interdependent and critical resources, and that economic, political, and technological factors can all have an impact on these resources to varying degrees [12]. Zeng et al. used global climate models (GCMs) to simulate real life and found that reservoir operations and water resource allocation can effectively reduce risks in water and food systems [13]. Carbon emissions are clearly present in the energy industry, as well as in all stages of agricultural production, exacerbating climate change risks [14]. Feng et al. revealed the impact mechanism of land use change on the coupling relationship of WEC, and predicted through a system dynamics (SD) model that human settlements and mining/manufacturing land use consume large amounts of water and energy, whereas cultivated land shows high water consumption, low energy consumption, and carbon emissions [15]. Chamas et al. incorporated the carbon cycle into the optimization model of water, energy, and food, revealing the complexity and interconnection of these systems [16]. Liu et al. constructed a complex mega-system focusing on water, energy, food, ecology, and economic, social, and environmental aspects [17]. The framework emphasizes the interdependence of resource sub-systems and the importance of cross-sectoral collaborative management, offering a systematic approach to addressing resource scarcity risks and ecological protection contradictions.

The imbalance of the WEFEC system has resulted in severe resource crises and ecological degradation. In North China, the supply–demand relationship between water resources and food production is out of balance, with extensive groundwater extraction leading to ecological issues such as the shallow groundwater depth in the Taihang Mountain piedmont plain generally reaching 30–50 m, forming multiple groundwater funnels, and 23 out of 27 main rivers in the Haihe River Basin drying up or ceasing flow due to a significant reduction in groundwater recharge [18]. Existing risk studies focus on resource scarcity and supply–demand risks in the three systems of water, energy, and food. For example, Chen et al. used material flow analysis to study the food–energy–water interrelated risks on Jinmen Island, finding that associated risks mainly stem from resource consumption [19]; Cui et al. used a fuzzy comprehensive risk assessment model (FCRAM) to evaluate the sustainable development of water, energy, food, and carbon in agricultural irrigation and

drainage systems [20]. Additionally, methods such as the copula function [21] and Bayesian networks [22] have been used to evaluate complex systems. However, the above studies only consider three or four distinct sub-systems. Failure to integrate the climate effects of carbon emissions with the regulatory functions of ecosystems and the provisioning functions of resource systems into a unified synergistic analysis framework makes it difficult to reflect the chain-like risk transmission mechanism of carbon constraints–ecological responses–resource supply and demand. Research on ecologically fragile regions (such as arid and semi-arid watersheds) often focuses on single resources or isolated ecological issues. It fails to establish integrated assessment frameworks for synergistic risks involving carbon, ecology, and resources that account for regional characteristics. Consequently, evaluation outcomes struggle to support coordinated governance decisions across departments and regions.

As the cradle of Chinese civilization and an important economic belt, the ecological protection and high-quality development of the Yellow River Basin have been elevated to a national strategic level [23]. The Yellow River “Ji” Bay region includes the following four provinces: Gansu, Ningxia, Inner Mongolia, and Shaanxi. It serves as both an ecological barrier in northern China but also an important hub for regional economic collaborative development. It faces multiple challenges, including water resource shortage, an imbalanced energy structure, and food security concerns. This region includes arid and semi-arid climate zones, the Loess Plateau soil erosion area, and grassland ecological fragile areas [24]. The stability of its WEFEC complex system and the sustainability of resource systems are inextricably linked to the overall risk level and economic development pattern of the Yellow River Basin and even the entire country.

Starting with “single-system endowment conditions, dual-system coordination status, and multi-system risk resistance capabilities,” this paper chooses reliability, synergy, and resilience as criterion layers and proposes a comprehensive risk-based analysis on WEFEC, specifically including resource shortage risks in water, energy, and food, ecological damage risks, and climate warming risks caused by excessive carbon emissions. By compiling and analyzing long-term serial data from 2004 to 2023 across 19 core cities in the Yellow River “Ji” Bay, and introducing a cloud model comprehensive evaluation method, risk levels were effectively characterized. Integration with a risk factor model enabled the precise identification of the system’s comprehensive risk determinants. This study not only fills the gap in the multi-dimensional collaborative assessment of the WEFEC system in the Yellow River “Ji” Bay but also provides a reproducible localized solution for the coordinated development of resources–ecology–economy in arid and semi-arid regions, offering important references for the sustainable management of similar ecologically fragile areas globally.

2. Study Area and Methods

2.1. WEFEC Research Framework

This study focuses on the interdependent relationships of the WEFEC complex system in the Yellow River “Ji” Bay. The first step entails disassembling the WEFEC complex system to analyze the interrelationships between the water, energy, food, ecology, and carbon sub-systems, and the reliability, synergy, and resilience criteria layers. The second step entails developing a risk evaluation index system for the “Ji” Bay WEFEC complex system, guided by the dimensions of reliability, synergy, and resilience. The third step is to use the cloud model to obtain cloud pictures, membership degrees, and risk level calculation results. The fourth step is to analyze the “Ji” Bay in temporal and spatial dimensions based on the cloud model calculation results, diagnose risk factors, and form a

technical path of “deconstruction–modeling–assessment–diagnosis.” The research technical route of this paper is shown in Figure 1.

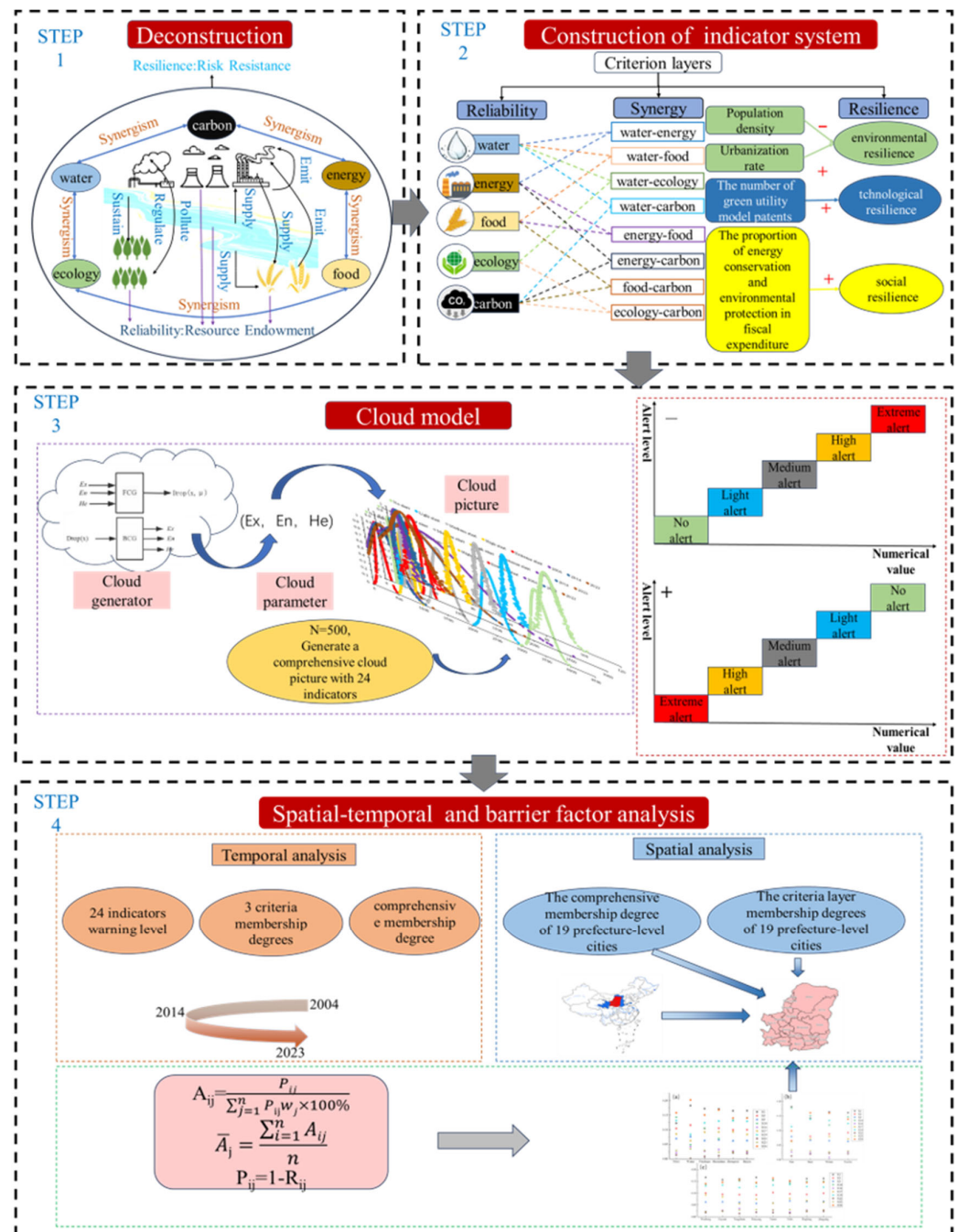


Figure 1. Technical approach.

2.2. WEFEC Comprehensive Evaluation Indicator System Construction

An evaluation index system of the WEFEC system was developed using scientific, rational, and feasible principles. Starting with three aspects—reliability, synergy, and resilience—24 secondary indicators reflecting the characteristics of the Yellow River “Ji” Bay were chosen. Among them, reliability refers to the ability of the five sub-systems (water, energy, food, ecology, and carbon emissions) to maintain the normal operation of the entire complex system, as measured by each sub-system’s resource quantity status such as water resource level, energy consumption level, and food production level. Reliability indicators can directly reflect the constraints of resource baseline conditions on the system;

the WEFEC sub-systems are interdependent. For example, agricultural production depletes water resources and emits carbon gases, and excessive groundwater extraction to ensure food production will exacerbate ecological degradation. Synergy is based on sub-systems' interconnection and dependency, which reflect the system's collaborative mechanism. Synergy indicators can quantify the degree of conflict and coordination between sub-systems. Resilience focuses not only on current risks but also on the system's recovery potential through policy and technical interventions.

Based on the previous studies [25–29], each indicator was divided into the following five levels: no alert, light alert, medium alert, high alert, and extreme alert. For indicators lacking a unified classification standard, the methods in the references [30,31] were used for classification. The coordination degree evaluation index system for the WEFEC system, including the meanings, attribute types, units, and alert thresholds of each indicator, are shown in Table 1.

Table 1. Risk evaluation index system for the complex system of WEFEC in the Yellow River “Ji” Bay.

Criterion Layers	Sub-System	Indicator Layer	Indicator No	Attribute	Indicator Meaning	Risk Levels				
						No Alert	Light Alert	Medium Alert	High Alert	Extreme Alert
Reliability	Water sub-system	Per capita water resources (m ³)	X ₁	+	Ratio of total water resources to population	3000–4000 [25]	2000–3000	1000–2000	500–1000	<500
	Water sub-system	Per capita water consumption (m ³)	X ₂	–	Ratio of water consumption to population	150–200 [25]	200–250	250–400	400–500	>500
	Water sub-system	Water yield modulus (10 ⁴ m ³ /km ²)	X ₃	+	Water resources per unit area	≥70 [26]	55–70	40–55	25–40	<25
	Water sub-system	Water consumption per 104 yuan GDP (m ³)	X ₄	–	Ratio of total water consumption to total GDP	<24 [27]	24–60	60–140	140–220	>220
	Food sub-system	Unit area yield (tons/hm ²)	X ₅	+	Yield per unit area	7–8 [28]	6–7	5–6	4–5	<4
	Food sub-system	Per capita grain production (tons)	X ₆	+	Ratio of grain production to population	500–600 [29]	400–500	300–400	200–300	<200
	Energy sub-system	Energy consumption elasticity coefficient	X ₇	–	Ratio of energy consumption growth rate to economic growth rate	–1.5––0.5 [30]	–0.5–0	0–0.5	0.5–1	1–1.5
	Energy sub-system	Per capita energy consumption (tons)	X ₈	–	Ratio of energy consumption to population	<1 [25]	1–2	2–3	3–4	>4
	Ecology sub-system	Vegetation cover (%)	X ₉	+	Ratio of vegetation area to total regional area	>18 [25]	15–18	12–15	9–12	<9
	Ecology sub-system	Water area ratio (%)	X ₁₀	+	Ratio of water area to total regional area	5–8 [25]	3.5–5	2–3.5	1–2	0.5–1
	Ecology sub-system	Industrial sulfur dioxide emissions (tons)	X ₁₁	–	Regional sulfur dioxide emissions	0–2 [25]	2–5	5–10	10–15	15–20
	Carbon sub-system	Per capita carbon emissions (10 ⁴ tons)	X ₁₂	–	Ratio of carbon emissions to population	2–8 [30]	8–12	12–14	14–16	16–20
	Carbon sub-system	Carbon emission density (tons/km ²)	X ₁₃	–	Ratio of carbon emissions to regional area	50–200 [30]	200–800	800–1500	1500–3000	3000–10,000
Synergy	Food–Energy	Total power of agricultural machinery (kw·h/hm ²)	X ₁₄	+	Ratio of the total power of all machinery and equipment directly applicable to agricultural operations to the regional area	7.5–8.5 [28]	7–7.5	5.5–7	3.5–5.5	1.5–3.5

Table 1. Cont.

Criterion Layers	Sub-System	Indicator Layer	Indicator No	Attribute	Indicator Meaning	Risk Levels				
						No Alert	Light Alert	Medium Alert	High Alert	Extreme Alert
Resilience	Food–Energy	Use of chemical fertilizers and pesticides (10 ⁴ tons)	X ₁₅	–	Regional fertilizer and pesticide usage	8–9 [28]	9–10.5	10.5–12	12–15	>15
	Water–Food	Water consumption per mu (m ³)	X ₁₆	–	Ratio of water usage to cultivated land area	100–125 [28]	125–150	150–175	175–200	>200
	Water–Food	Proportion of agricultural water use (%)	X ₁₇	–	Ratio of agricultural water use to total water use	20–40 [30]	40–55	55–73	73–90	90–100
	Food–Carbon	Agricultural carbon emissions (10 ⁴ tons)	X ₁₈	–	Carbon emissions generated by agriculture	11–17 [28]	17–23	23–28	28–34	34–50
	Water–Ecology	Ecological water use rate (%)	X ₁₉	+	Ratio of ecological water use to total water consumption	6–8 [25]	4–6	2–4	1–2	0–1
	Water–Energy	Proportion of industrial water use (%)	X ₂₀	+	Ratio of industrial water use to total water consumption	45–55 [30]	35–45	20–35	5–20	0–5
	Social resilience	Population density (person/km ²)	X ₂₁	–	Population per unit area of land	100–1000 [31]	1000–2000	2000–4000	4000–6000	6000–10,000
	Social resilience	Urbanization rate (%)	X ₂₂	+	Ratio of urban population to permanent resident population	<20 [30]	20–50	50–60	60–80	>80
Resilience	Environmental resilience	Proportion of fiscal expenditure allocated to energy conservation and environmental protection (%)	X ₂₃	+	Ratio of energy conservation and environmental protection expenditures to total fiscal expenditures	≥2.2 [26]	1.7–2.2	1.2–1.7	0.7–1.2	<0.7
	Technological resilience	Number of green utility model patents (item)	X ₂₄	+	Number of green utility model patents	500–15,000 [30]	200–500	50–200	10–50	0–10

“+” indicates that a higher value of this metric is more beneficial for the WEFEC complex system, while “–” indicates the opposite.

2.3. Weight Calculation

This paper summarizes common weighting calculation methods used in fields such as ecological risk assessment and water resource carrying capacity evaluation, along with their advantages, shortcomings, and application scenarios, as shown in Table 2.

Table 2. Summary of common weight calculation methods.

Method	Advantages	Shortcomings	Application Scenarios
Entropy Weight Method [32]	Objectively determines weights based on the variability of data itself, reducing the interference of subjective factors.	Relies on data itself; if data is biased, it will affect the accuracy of weights; insufficient consideration of the actual importance of indicators.	Suitable for evaluation problems requiring objective weighting with large data volume, such as comprehensive performance evaluation and resource evaluation.
AHP (Analytic Hierarchy Process) [33]	Combines qualitative and quantitative analysis, capable of handling complex decision-making problems, and easy to understand and operate.	Strong subjectivity; scores from different experts may vary greatly; consistency test of judgment matrix is sometimes difficult to pass.	Widely used in multi-objective and multi-criteria decision-making problems, such as scheme evaluation.

Table 2. Cont.

Method	Advantages	Shortcomings	Application Scenarios
AHP Based on Genetic Algorithm [34]	Utilizes the global search capability of genetic algorithms to improve the accuracy and efficiency of AHP and avoid falling into local optima.	The parameter setting of genetic algorithm is complex and may require multiple tests for adjustment; relatively large amount of calculation.	Used in complex hierarchical decision-making problems when it is necessary to improve decision-making accuracy and avoid local optima.
CRITIC [35]	Effectively solves multi-criteria decision-making problems, with simple calculation and consideration of interactions between indicators.	The assumption about the correlation between indicators may not fully conform to reality; result interpretation is somewhat difficult.	Multi-criteria decision analysis, especially when there are interactions between indicators, such as urban sustainable development evaluation.
PP—Projection Pursuit Dynamic Weighting Method [36]	Can mine uncertain information in data and dynamically adapt to different data characteristics.	The determination of projection direction may have subjectivity; the calculation process is relatively complex.	Evaluation problems dealing with data with uncertainty and dynamic changes, such as water resources carrying capacity evaluation and environmental quality evaluation.
ANP (Analytic Network Process) [37]	Breaks away from the limitation of hierarchical structure, can handle problems with interdependence and feedback effects, and considers indicator correlation.	The process of establishing network structure and supermatrix is complex, with large calculation amount.	Suitable for system evaluation with feedback and interdependence relationships, such as social and economic system evaluation.
EFAST (Extended Fourier Amplitude Sensitivity Test) [38]	Can calculate indicator sensitivity indices and fully consider the impact of coupling effects between indicators on weights.	Large calculation amount for indicator sensitivity index; high requirements for model assumptions.	Applied in sensitivity analysis that needs to consider coupling effects between indicators, such as ecosystem evaluation.
Coefficient of Variation Method [39]	An objective weighting method that obtains weights through indicator information and can reflect the gaps between evaluation indicators.	Only considers the dispersion degree of data, not the actual importance of indicators; sensitive to outliers.	Evaluation problems sensitive to data dispersion, such as market competitiveness evaluation.
Game Theory [40]	Integrates the advantages of multiple methods, balances the characteristics of different methods, and improves the rationality of evaluation.	The solution of the game process may be complex; weight determination of different methods is difficult.	Used when it is necessary to integrate the advantages of multiple methods for evaluation, such as comprehensive risk evaluation.
Least Squares Method [41]	Can make weight distribution more in line with the inherent laws of data and optimize combined weights.	Has certain requirements for data distribution and structure; may fall into local optima.	Applied in problems where weights need to be determined by fitting data, such as cost–benefit analysis.

This paper involves a large volume of data, and the indicators exhibit feedback and interdependent relationships. Therefore, the analytic network process (ANP) is employed

to calculate subjective weights, while the entropy weight method is used to determine objective weights. By combining these weights through game theory, the accuracy of weighting is enhanced.

2.3.1. Analytic Network Process (ANP)

In real-world decision-making problems, the “independence” of factors is often an idealized assumption, while “interdependence” is the norm. Compared to the traditional analytic hierarchy process (AHP), the analysis network process (ANP) achieves its greatest breakthrough by breaking away from AHP’s rigid assumptions of “hierarchical structure and element independence,” better aligning with the complex interdependent relationships among factors in practical scenarios. ANP constructs network relationships to characterize the associative properties among criteria, quantifies the ultimate impact levels across control layers, and generates a supermatrix for analysis. Weight calculations based on the ANP method can be implemented using Super Decision 3.2 software.

2.3.2. Entropy Weight Method

The basic idea behind the entropy weight method is to determine the weights of each indicator based on the degree of variation in each variable, then make adjustments to obtain relatively objective weights, the magnitude of which can reflect the extent to which the indicator plays a role in decision-making.

Suppose there are m survey objects and n evaluation indicators. The algorithm is as follows:

(1) Standardize the indicator values using the following formula:

Positive indicator:

$$u_{ij} = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \quad (1)$$

Reverse indicator:

$$u_{ij} = \frac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}} \quad (2)$$

In the formula, x_{ij} denotes the j -th raw value of the i -th evaluation unit, while $\max x_{ij}$ and $\min x_{ij}$ represent the maximum and minimum values of the indicator, respectively.

(2) Calculate the characteristic proportion of the i -th evaluated object under the j -th indicator.

$$P_{ij} = X_{ij} / \sum_{i=1}^n X_{ij} (i = 1, 2, \dots, n; j = 1, 2, \dots, m) \quad (3)$$

(3) Calculate the entropy value of the j -th indicator.

$$e_j = -k \sum_{i=1}^n p_{ij} \ln p_{ij} \quad (4)$$

where $k = 1/\ln(n)$, ensuring that $0 \leq e_j \leq 1$.

(4) Calculate the difference coefficient of the j -th indicator.

$$g_j = 1 - e_j \quad (5)$$

The significance of an indicator is reflected by its difference coefficient. The larger the coefficient, the more important the indicator, the more attention needs to be paid to its role, and the larger the corresponding weight of the indicator.

(5) Calculate the weight of the j -th indicator.

$$w_j = \frac{g_j}{\sum_{j=1}^m g_j} \quad j = 1, 2, \dots, m \quad (6)$$

2.3.3. Combination Weighting Method

To improve the accuracy of combined weights based on multiple single weights and balancing various aspects, the weights obtained by the AHP method and the weights determined by the entropy weight method are used as the basic weights for calculation, and the final indicator weights are obtained using the combined weight calculation method. The algorithm is as follows:

$$W = \frac{Wi \times Wj}{\sum_{i=1}^n Wi \times Wj} \quad (7)$$

where Wi is the weight calculated by the AHP method, Wj is the weight obtained by the entropy weight method, and n is the number of indicators.

2.4. Comprehensive Evaluation Method Based on Cloud Model

The cloud model transforms the description of uncertain linguistic values into quantitative expression while incorporating the fuzziness and randomness of uncertain linguistic values. The cloud model achieves this through the use of specific algorithms, the two major ones being the forward cloud generator (FCG) and backward cloud generator (BCG). The former quantifies the qualitative concepts, while the latter qualifies quantitative data, completing the evaluation of the evaluation target through these two algorithms. The overall quantitative expressions of the cloud model's qualitative concept are expected value Ex , entropy En , and hyperentropy He . The cloud model mainly generates cloud drops and produces different cloud models according to the characteristics of Ex , En , and He .

The qualitative concept of positive cloud generators is converted into quantitative values, mainly through Ex , En , and He , to produce quantitative values. The algorithm steps are as follows: (1) generate a normal random number $y_i = R_N(En, He)$ with En as the expected value and He^2 as the variance; (2) generate a normal random number $x_i = R_N(Ex, y_i)$ with Ex as the expected value and y_i^2 as the variance; (3) calculate $\mu(x_i) = \exp\left(-\frac{(x_i - Ex)^2}{2y_i^2}\right)$; (4) x_i with a certainty degree of $\mu(x_i)$ becoming a cloud drop in the universe of discourse; and (5) repeat steps (1)–(4) until the required number of cloud drops are generated. Contrary to the forward cloud generator, the backward cloud generator converts quantitative data into qualitative language, represented by the following three digital characteristics: En , Ex , and He [42]. The schematic diagram of the cloud generator is shown in Figure 2.

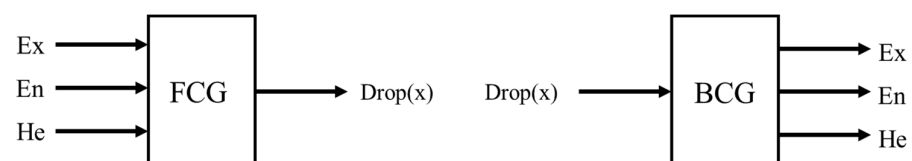


Figure 2. Cloud generator.

The membership matrix reflects the mapping relationship of the evaluation set V on the evaluation factor set U . Using the weight matrix W and the membership matrix Z for the fuzzy transformation, the fuzzy subset B on the evaluation set V is calculated.

$$B = W \cdot Z \quad (8)$$

where $B = (b_1, b_2, \dots, b_m)$, representing the membership degrees corresponding to each level of the evaluation set.

2.5. Risk Factor Model

The WEFEC is a complex system, and the influence degree of each sub-system on the total system varies slightly. A risk factor model is introduced to diagnose the risk factors of the WEFEC complex system. The method is as follows:

$$F_j = w_j w'_j \quad (9)$$

$$I_j = 1 - u_{ij} \quad (10)$$

$$H_j = \frac{F_j I_j \cdot 100\%}{\sum_{j=1}^n F_j I_j} \quad (11)$$

where w_j and w'_j are the weights of the j -th indicator layer and criterion layer indicators; I_j is the difference between the standardized value u_{ij} of each indicator and 100%; and H_j is the obstacle degree of the j -th indicator in the indicator layer.

2.6. Study Area

The “Ji” Bay in this study primarily refers to the inner area of the Yellow River “Ji” Bay. The Yellow River “Ji” Bay flows through four provinces: Shaanxi, Inner Mongolia, Ningxia, and Gansu, as well as 19 cities, including Xi’an, Ordos, Yinchuan, and Baiyin. The “Ji” Bay and the 19 cities from the study area are shown in Figure 3. The region covers approximately 380,000 km² and had a population of 52.495 million in 2023. The “Ji” Bay is an important ecological barrier in northern China and is located at the border of agricultural and pastoral areas. To meet water demand, extensive groundwater extraction and the appropriation of river–lake ecological water have taken place. After years of high-intensity development, the prospect for its sustainable use has deteriorated. The proportion of agricultural water use in the “Ji” Bay is 78.6%, significantly higher than the national level of 62.3%, while the proportion of industrial water use is only 12.2%, far lower than the national level of 21.1% [43]. For a long time “water scarcity” has been a significant barrier to ecological protection and high-quality development of the Yellow River “Ji” Bay. The Yellow River “Ji” Bay is rich in natural resources and is also a national fossil energy enrichment area, with a secondary industry making a significant contribution to the economy. In 2019, the secondary industry in the “Ji” Bay accounted for 48.01% of the regional GDP, and the leading industries had a strong homogeneity [44]. Mining activities such as coal mining in the “Ji” Bay have increased the exploitation of natural resources, resulting in issues such as declining groundwater levels, soil erosion, land desertification, and wastewater/sludge pollution [45]. At present, the contradiction between energy development and ecological protection is still very visible, and land degradation and environmental pollution are severe.

2.7. Data Sources

The study period for this paper is 2004–2023, and the spatial scale is 19 cities in the Yellow River “Ji” Bay. Data on population, economy, and food are derived from the Statistical Yearbooks of Inner Mongolia Autonomous Region, Shaanxi Province, Gansu Province, and the Ningxia Hui Autonomous Region from 2004 to 2023, as well as the Water Resources Bulletins of these regions, which include water resource quantity, agricultural water use, industrial water use, and other water resource data. The data presented above are authentic and reliable, as reported by the National Bureau of Statistics and the Ministry of Water Resources.

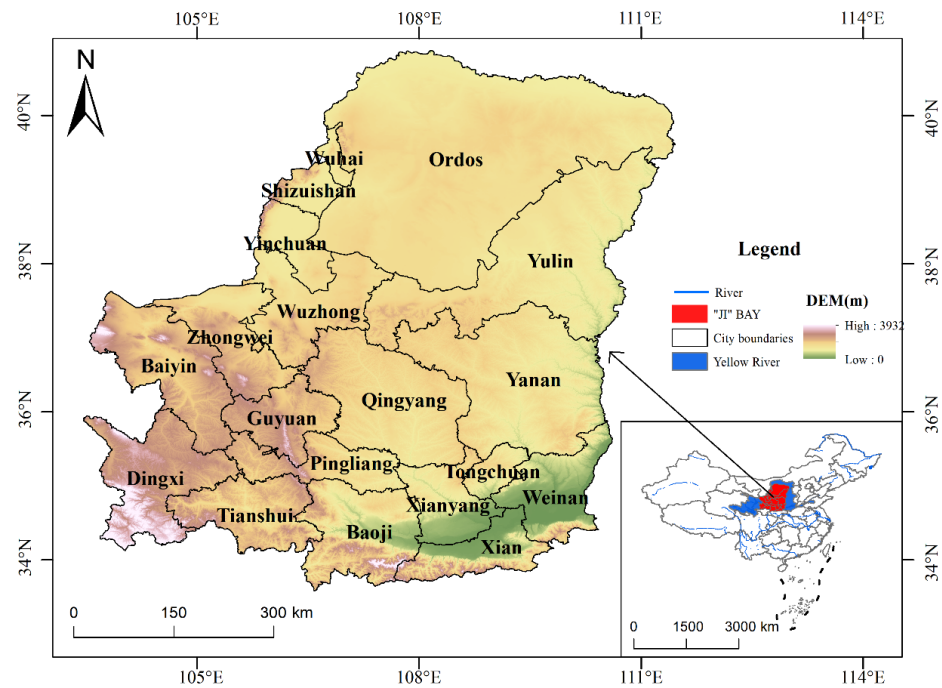


Figure 3. Study area map.

3. Results Analysis

3.1. Weight Analysis

In this study, the ANP-entropy weight combination weighting method is employed to calculate the indicator weights. Based on the DEMATEL (Decision-Making Trial and Evaluation Laboratory), the ANP network structure of the three criterion layers and their sub-systems for the risk assessment of the WEFEC complex system is constructed. Taking reliability as an example, Figure 4 illustrates its ANP network architecture. The judgment matrices are established in accordance with the 1–9 evaluation scale table, and all judgment matrices have passed the consistency test after calculation. With the aid of the Super Decisions software, the supermatrix and limit matrix are computed to obtain the subjective weights.

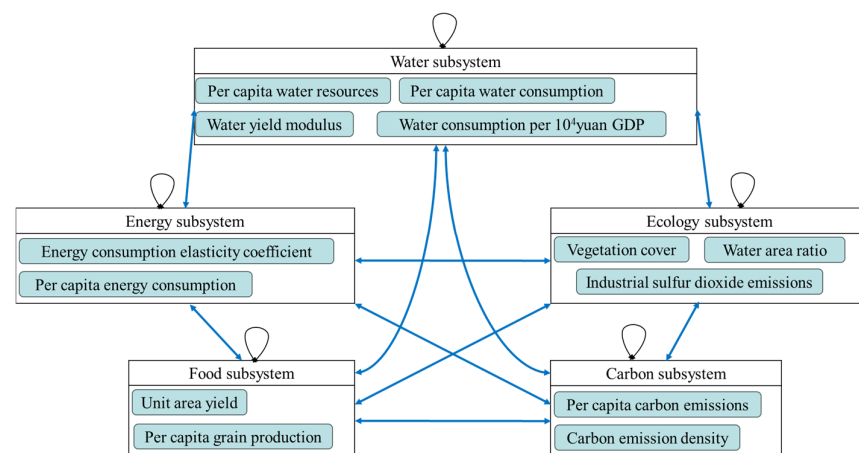


Figure 4. The ANP network structure of reliability. (Double arrows indicate mutual influence between node indicators in two clusters. Circular arrows indicate mutual influence between node indicators within the same cluster).

The objective weights calculated using the entropy weight method and the subjective weights obtained via ANP are combined using the combination weighting method, aiming to improve the accuracy of the weights. The findings show that indicators such as ecological water use rate (X_{19}), proportion of fiscal expenditure allocated to energy conservation and environmental protection (X_{23}), and number of green utility model patents (X_{24}) have higher comprehensive weights, reflecting the important impact of ecological water allocation, fiscal environmental protection investment, and low-carbon technological innovation on system risks. The weight analysis results are shown in Table 3.

Table 3. Weight of risk evaluation indicators for WEFEC in the Yellow River “Ji” Bay.

Indicator	ANP Weight	Entropy Weight	Combination Weight	Indicator	ANP Weight	Entropy Weight	Combination Weight
X_1	0.0541	0.0672	0.0987	X_{13}	0.0241	0.0046	0.0030
X_2	0.0362	0.0854	0.0839	X_{14}	0.0294	0.0271	0.0216
X_3	0.0304	0.0768	0.0633	X_{15}	0.0294	0.0053	0.0042
X_4	0.0331	0.0024	0.0021	X_{16}	0.0764	0.0054	0.0111
X_5	0.0241	0.0501	0.0328	X_{17}	0.0705	0.0340	0.0650
X_6	0.0483	0.0274	0.0359	X_{18}	0.0411	0.0109	0.0121
X_7	0.0121	0.0060	0.0020	X_{19}	0.0705	0.1039	0.1987
X_8	0.0483	0.0035	0.0046	X_{20}	0.0588	0.0033	0.0052
X_9	0.0273	0.0173	0.0128	X_{21}	0.0443	0.0125	0.0151
X_{10}	0.0273	0.1125	0.0832	X_{22}	0.0221	0.0226	0.0136
X_{11}	0.0393	0.0054	0.0057	X_{23}	0.0996	0.0532	0.1437
X_{12}	0.0425	0.0031	0.0035	X_{24}	0.0111	0.2604	0.0782

3.2. Analysis of Temporal Evolution Characteristics

3.2.1. Temporal Evolution Characteristics of the Target Layer and Criterion Layer

The comprehensive evaluation results of the WEFEC complex system target layer were calculated by taking the average values of each indicator from 2004 to 2023. According to the weights of the evaluation indicators obtained by the ANP-entropy weight method, the fuzzy subset B on the evaluation set V was obtained through fuzzy transformation using the weight set W and the membership matrix Z. The results are shown in Table 4 (risk statuses marked with special colors represent risk assessment results. The same applies below). According to the maximum membership principle, this indicates that the risk level of the WEFEC complex system in the Yellow River “Ji” Bay from 2004 to 2023 was on high alert.

Table 4. Risk assessment results.

Membership				
No Alert	Light Alert	Medium Alert	High Alert	Extreme Alert
0.6410	0.6238	0.7332	0.7902	0.7737

Figure 5 shows the changes in membership degrees across the target and criterion layers for the Yellow River’s complex system risk involving water, energy, food, and carbon. Taking 2023 as an example (Table 5), based on the maximum membership degree principle, the WEFEC complex system risk in 2023 exhibited the following states: no warning at the target layer, extreme warning at the reliability layer, moderate warning at the coordination layer, and moderate warning at the resilience layer.

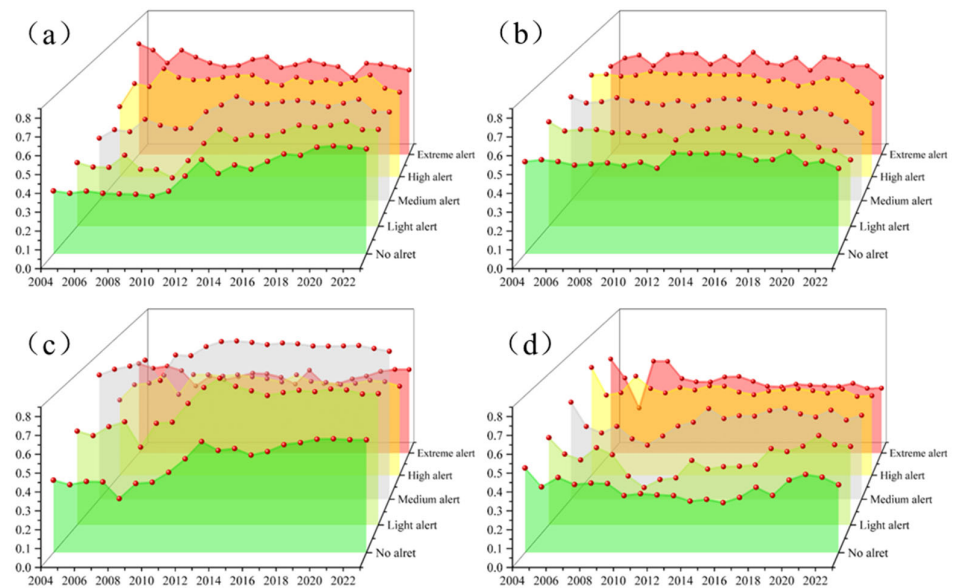


Figure 5. Changes in (a) comprehensive membership of each risk level from 2004 to 2023, (b) membership degrees of reliability risk levels from 2004 to 2023, (c) membership degrees of synergy risk levels from 2004 to 2023, and (d) membership degrees of resilience risk levels from 2004 to 2023.

Table 5. 2023 risk assessment results.

WEFEC Complex System	Membership				
	No Alert	Light Alert	Medium Alert	High Alert	Extreme Alert
Target Layer	0.56988	0.54538	0.51833	0.51223	0.53013
Reliability	0.46391	0.37418	0.39532	0.44504	0.48694
Synergy	0.61069	0.73857	0.86354	0.53840	0.52296
Resilience	0.36795	0.44136	0.48988	0.48133	0.40628

At the target layer, the risks of the WEFEC complex system in the Yellow River “Ji” Bay showed extreme alert or high alert from 2004 to 2020, and no alert or light alert from 2021 to 2023 (Figure 5a). From 2004 to 2023, the comprehensive membership degrees of extreme alert and no alert in the “Ji” Bay showed obvious downward and upward trends. The comprehensive membership degree of no alert increased from 0.3423 in 2004 to 0.5700 in 2023, while the comprehensive membership degree of extreme alert decreased from 0.6947 in 2004 to 0.5301 in 2023, indicating that the risks of the WEFEC complex system in the “Ji” Bay are continuously decreasing. Risk assessment results for the target layer from 2004 to 2023 are shown in Table 6.

From 2004 to 2023, the reliability risks of the “Ji” Bay only showed the following three states: extreme alert, extreme alert and high alert (Figure 5b). Among them, the membership degree of extreme alert showed a trend of first increasing and then decreasing, and after 2014, it was greater than the membership degrees of other warning states. The membership degree of no alert increased slightly, while the membership degree of high alert decreased significantly, from 0.6156 in 2004 to 0.4450 in 2023. This indicates that the membership degree of extreme alert for the reliability of the WEFEC complex system in the “Ji” Bay has always been high, with no obvious increase in the membership degree of light alert; the membership degree of light alert even decreased.

Table 6. 2004–2023 target layer risk assessment results.

Year	Target Layer Cloud Membership				
	No Alert	Light Alert	Medium Alert	High Alert	Extreme Alert
2004	0.34236	0.35874	0.36512	0.42498	0.69470
2005	0.32931	0.33377	0.41469	0.56461	0.65507
2006	0.34070	0.33198	0.40271	0.54584	0.57473
2007	0.32919	0.40036	0.47543	0.65474	0.65480
2008	0.32590	0.32060	0.43982	0.60150	0.61201
2009	0.32363	0.32038	0.42095	0.58711	0.57515
2010	0.31372	0.27276	0.42260	0.59022	0.55204
2011	0.34045	0.36962	0.51993	0.60287	0.55870
2012	0.42263	0.46691	0.55898	0.61293	0.59734
2013	0.51148	0.54507	0.60900	0.61611	0.61296
2014	0.43595	0.48939	0.57019	0.57413	0.54557
2015	0.48267	0.51317	0.56607	0.55392	0.56355
2016	0.45956	0.50961	0.57959	0.60283	0.59028
2017	0.50222	0.53422	0.58571	0.57308	0.56695
2018	0.54210	0.56944	0.57404	0.58658	0.55216
2019	0.53477	0.55917	0.54940	0.56208	0.48299
2020	0.57897	0.59845	0.56984	0.58402	0.57279
2021	0.58595	0.59660	0.58219	0.51643	0.56698
2022	0.58045	0.54403	0.52051	0.53607	0.51935
2023	0.56988	0.54538	0.51833	0.51223	0.51013

From 2004 to 2023, the synergy risks of the “Ji” Bay all showed a medium alert. The membership degrees of extreme alert and high alert remained relatively stable, while the membership degrees of no alert and light alert both showed an upward trend. Extreme alert first decreased and then increased, and high alert was basically flat (Figure 5c). The membership degree of medium alert was significantly higher than that of the other alert states. This suggests that the synergy between the two sub-systems of the WEFEC complex system in the “Ji” Bay was at a medium level during 2004–2023, with room for improvement.

From 2004 to 2023, the resilience risks of the “Ji” Bay showed high alert and extreme alert states for most of the time, and only showed a medium alert in 2023. The membership degrees of no alert and light alert began to decline in 2021, dropping from 0.4234 in 2021 to 0.3680 in 2023 (Figure 5d). This suggests that although the resilience of the WEFEC complex system in the “Ji” Bay is generally improving, there is a risk of shifting towards high alert.

3.2.2. Temporal Evolution Characteristics of the Indicator Layer

According to the established indicator system and alert thresholds for the Yellow River “Ji” Bay WEFEC, each indicator’s corresponding level was represented by cloud parameters using the formula. Assuming the number of cloud drops $N = 500$, based on the average values of each indicator in the Yellow River “Ji” Bay from 2004 to 2023, the membership matrix was calculated using the forward cloud generator, and the average membership degree of each indicator within different alert ranges is shown in Table 7. According to the maximum membership principle, during 2004–2023, the risk levels of X_1 (per capita water resources), X_2 (per capita water consumption), X_3 (water yield modulus), X^8 (per capita energy consumption), X_{10} (water area ratio), X_{16} (water consumption per mu), and X_{20} (proportion of industrial water use) were at the extreme alert level.

Table 7. Average assessment values for indicators of cloud models.

No.	No Alert	Light Alert	Medium Alert	High Alert	Extreme Alert
X ₁	0.0000	0.0000	0.0391	0.5849	0.8663
X ₂	0.7848	0.8725	0.9425	0.7507	0.9937
X ₃	0.0000	0.0000	0.0000	0.0000	0.7504
X ₄	0.5912	0.8253	0.7076	0.7169	0.6385
X ₅	0.7479	0.6683	0.5745	0.3898	0.7339
X ₆	0.7339	0.3275	0.2670	0.2070	0.1451
X ₇	0.3904	0.7653	0.9355	0.7501	0.4539
X ₈	0.4774	0.6219	0.7996	0.9490	0.9953
X ₉	0.8610	0.6278	0.5263	0.3035	0.5898
X ₁₀	0.0000	0.0000	0.9903	0.9960	0.9979
X ₁₁	0.6685	0.9225	0.8627	0.3552	0.0650
X ₁₂	0.6087	0.9128	0.9963	0.9673	0.8225
X ₁₃	0.4514	0.5765	0.7827	0.9678	0.6289
X ₁₄	0.6981	0.6902	0.7260	0.7247	0.6546
X ₁₅	0.0000	0.3727	0.7991	0.0105	0.0000
X ₁₆	0.9354	0.9593	0.9840	0.9951	0.9983
X ₁₇	0.6316	0.8513	0.8893	0.7154	0.5378
X ₁₈	0.9840	0.9338	0.7356	0.4925	0.2143
X ₁₉	0.9251	0.9830	0.9945	0.9673	0.8887
X ₂₀	0.0000	0.7776	0.8572	0.7237	0.9260
X ₂₁	0.7076	0.0000	0.0000	0.0000	0.0000
X ₂₂	0.4607	0.7200	0.9119	0.7195	0.3691
X ₂₃	0.9883	0.9926	0.9830	0.7880	0.0000
X ₂₄	0.4888	0.9592	0.8808	0.0000	0.0000

Figure 6 shows the comprehensive cloud picture of the 24 evaluation indicators of the “Ji” Bay WEFEC complex system. According to the maximum membership principle, the change situations of indicator risk levels are divided into three categories. The first category is indicators showing an improving state (cloud drops shifting toward no alert), with approximately 46% of indicator risk level changes belonging to this category, such as X₄ (water consumption per 10⁴ yuan GDP), X₅ (unit area yield), X₇ (energy consumption elasticity coefficient), X₁₁ (industrial sulfur dioxide emissions), X₁₆ (water consumption per mu), etc. Taking X₄ as an example, it showed extreme alert, medium alert, and light alert states in the three typical years of 2004, 2014, and 2023, respectively, demonstrating a trend of shifting from extreme alert to light alert, indicating that annual changes have reduced water consumption per 10⁴ yuan GDP, improved water resource utilization efficiency, and significantly improved water-saving policies and management.

The second category is indicators with enhanced risk levels (cloud drops shifting toward extreme alert), with 25% of indicator risk level changes belonging to this category. X₁₂ (per capita carbon emissions), X₁₃ (carbon emission density), and X₁₈ (agricultural carbon emissions) showed a gradual increase in risk levels during 2004–2023, and 25% of indicator risk level changes belonged to this category. For example, X₁₂ showed extreme light alert, medium alert, and high alert states in the three typical years of 2004, 2014, and 2023. Analysis shows that X₁₂, X₁₃, and X₁₈ are all related to carbon emissions, indicating that carbon emissions in the Yellow River “Ji” Bay have been severely excessive, restricting the sustainable development of the “Ji” Bay.

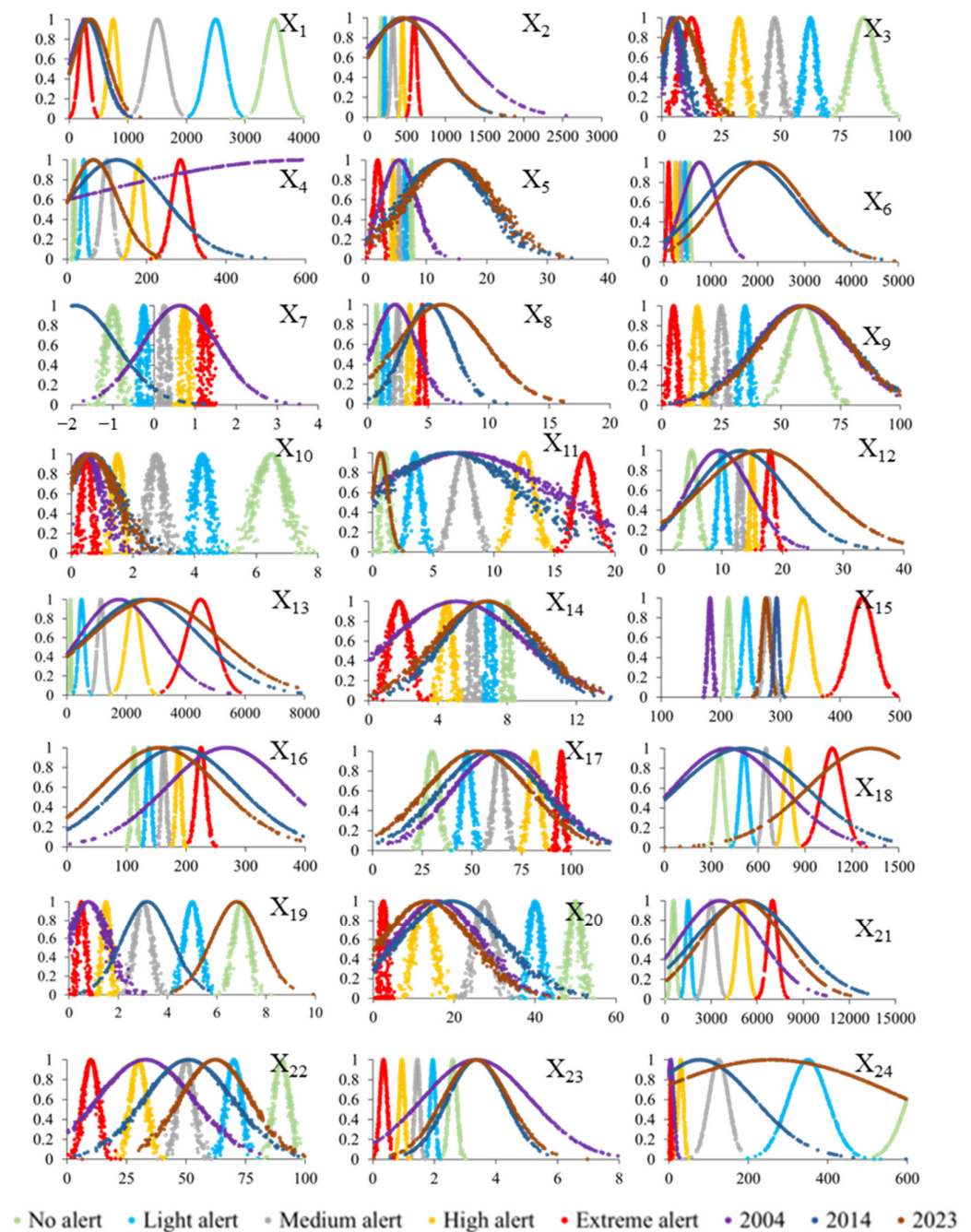


Figure 6. Comprehensive cloud picture for typical years for each indicator.

The third category is indicators with unchanged risk levels. During 2004–2023, 29% of indicator risk level changes belonged to this category. The cloud drops of X_1 (per capita water resources), X_2 (per capita water consumption), X_3 (water yield modulus), X_{10} (water area ratio), and X_{20} (proportion of industrial water use) showed no significant changes and always remained around the extreme alert and high alert standard cloud drops. Analysis shows that indicators around high alert and extreme alert are all related to water resources, indicating that water resource shortage and allocation have always been significant risks to resource–economy–ecology coordination in the Yellow River “Ji” Bay. X_{23} (proportion of fiscal expenditure allocated to energy conservation and environmental protection) was not on alert in the three typical years.

3.3. Spatial Differentiation Pattern

3.3.1. Spatial Differentiation Characteristics of the Target Layer

To better analyze the risk status of the WEFEC complex system in the Yellow River “Ji” Bay spatially, this paper divided 2004–2023 into three time periods on average (2004–2010, 2011–2016, and 2017–2023). Figure 6 shows the spatial changes in the Yellow River “Ji” Bay during the three time periods. Overall, in the three periods, red (extreme alert) was mostly located in the northwest of the “Ji” Bay, and dark green (no alert) showed a point-like distribution; according to the calculation results, the number of cities in extreme alert decreased from 8 in the first period (Figure 7a) to 3 in the second period (Figure 7b) and 1 in the third period (Figure 7c); the number of cities in no alert state also increased from 1 in the first period (Figure 7a) to 4 in the second period (Figure 7b) and 5 in the third period (Figure 7c). Among them, the number of cities in high alert and light alert states also decreased and increased accordingly. Wuzhong maintained an extreme alert status from 2004 to 2023. According to the analysis, this city has extremely limited water resources, with a per capita water resource amount of 82.54 m^3 , accounting for only $1/4$ of the per capita water resources in the “Ji” Bay. The agricultural water use is 93.6%, with a water consumption per mu of 389 m^3 , exceeding the average of 214 m^3 in the “Ji” Bay. The city has a high energy consumption coefficient, and its economic activities are heavily reliant on energy, which could be attributed to a large proportion of highly energy-consuming industries, and outdated technology and equipment. The spatial characteristics of the target layer are consistent with the findings of Tong Lei et al. [46]. Each city’s class for each period is shown in Table 8.

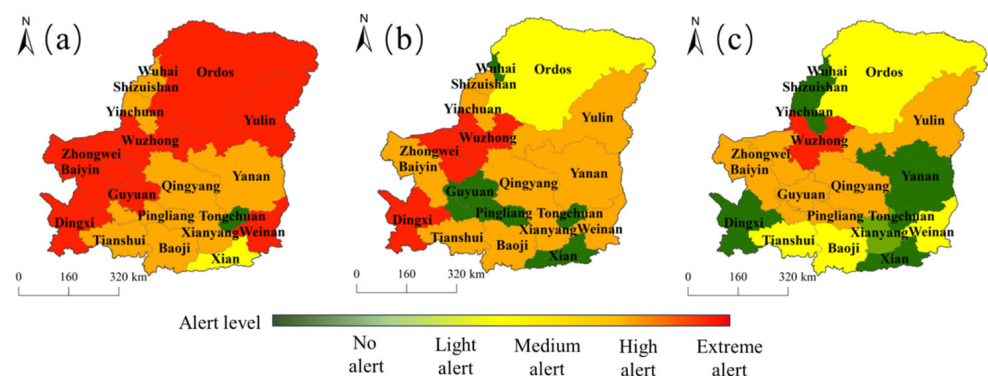


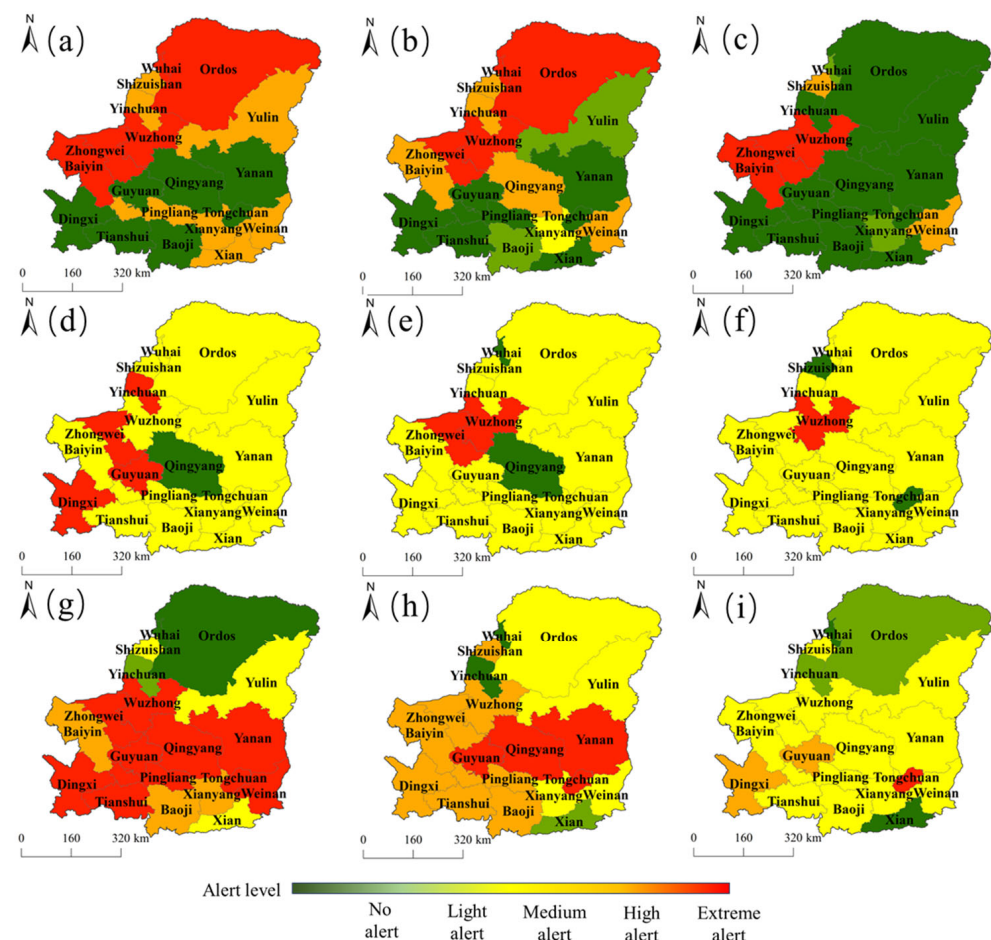
Figure 7. Spatial distribution of WEFEC complex system risk levels in “Ji” Bay from 2004 to 2023 (a–c).

3.3.2. Spatial Differentiation Pattern of the Criterion Layer

In terms of reliability, the WEFEC complex system in the “Ji” Bay has been relieved of extreme and high alert status in most cities, according to the different criterion layers. The number of cities in extreme alert status decreased from 4 in the first period (Figure 8a) to 3 in the third period (Figure 8c), while the number of cities in no alert status increased from 6 in the first to 12 in the third period. However, as evidenced by the temporal evolution characteristics of the criterion layer, the reliability of the “Ji” Bay has always been in a high alert or extreme alert state, implying that the reliability level of cities such as Baiyin, Shizuishan, Weinan, Wuzhong, and Zhongwei is relatively severe.

Table 8. City's class for each period.

City	2004–2010	2011–2016	2017–2023
Baiyin	Extreme alert	High alert	High alert
Baoji	High alert	High alert	Medium alert
Dingxi	Extreme alert	Extreme alert	No alert
Ordos	Extreme alert	Medium alert	Medium alert
Guyuan	Extreme alert	No alert	High alert
Pingliang	High alert	No alert	High alert
Qingyang	High alert	High alert	High alert
Shizuishan	High alert	High alert	No alert
Tianshui	High alert	High alert	Medium alert
Tongchuan	No alert	No alert	No alert
Weinan	Extreme alert	High alert	Medium alert
Wuhai	High alert	No alert	No alert
Wuzhong	Extreme alert	Extreme alert	Extreme alert
Xian	Medium alert	No alert	No alert
Xianyang	High alert	High alert	Light alert
Yanan	High alert	High alert	No alert
Yinchuan	High alert	High alert	No alert
Yulin	Extreme alert	High alert	High alert
Zhongwei	Extreme alert	Extreme alert	High alert

**Figure 8.** Spatial distribution of reliability risk levels in "Ji" Bay from 2004 to 2023 (a–c), spatial distribution of synergy risk levels in "Ji" Bay from 2004 to 2023 (d–f), and spatial distribution of resilience risk levels in "Ji" Bay from 2004 to 2023 (g–i).

In terms of synergy, most cities were on medium alert. During the first period, only Yinchuan, Zhongwei, Guyuan, and Dingxi were in extreme alert status (Figure 8d). They all progressed to medium alert status in the third period (Figure 8f). Wuzhong changed from medium to extreme alert in the second period, and Qingyang changed from no alert to medium alert in the third period. The synergy is deteriorating, and attention must be paid to the collaborative relationship between their sub-systems.

In terms of resilience, the majority of cities in extreme alert and high alert status in the first and second periods were mostly in the central region of the “Ji” Bay. In the third period, the number of extreme alert and high alert cities decreased to 3, namely Tongchuan, Guyuan, and Dingxi. Although most cities’ resilience levels have been reduced from extreme alert to high alert, only Ordos, Wuhai, and Xi’an are now in no alert or light alert status, and other cities continue to face resilience risks.

3.4. Diagnosis of Key Risk Factors

Based on the spatiotemporal analysis, the indicator weights were calculated using the entropy weight method described earlier. This paper used the risk factor model to calculate the obstacle degrees of the 24 indicators and diagnose the risk factors of the WEFEC complex system in the “Ji” Bay. Due to the large number of years and indicators involved, the average values of each risk factor were analyzed, and indicators with an obstacle degree greater than 0.05 were chosen as the primary risk factors. According to the spatial analysis results, the “Ji” Bay was divided into the northwest, central, and southern regions for analysis.

Specifically, as shown in Figure 9, the per capita water resources (X_1), water area ratio (X_{10}), and water yield modulus (X_3) are the main risk factors restricting the WEFEC complex system in the “Ji” Bay, indicating that the water resource endowment in the “Ji” Bay is poor, and water resources have become the most important factor affecting the regional economy and ecological development. The number of green utility model patents (X_{24}) also has a high obstacle degree. Since it can reflect the regional low-carbon technology R&D capability and sustainable development level, attention must be paid to innovation in green technology fields during urban development. Per capita carbon emissions (X_{12}) become a main risk factor, possibly because the “Ji” Bay is an important energy industry base, leading to excessive carbon emissions. The main reasons why the proportion of agricultural water use and the proportion of ecological water use become major risk factors could be due to uneven water resource allocation and excessively high proportion of agricultural water use.

Overall, the risk factors of each city are similar, but the magnitude of obstacle degrees varies by region. The obstacle degree of the number of green utility model patents (X_{24}) in Wuhai is relatively large, whereas the Ecological water use rate (X_{19}) is relatively low. The obstacle degrees of per capita water resources (X_1) and water area ratio (X_{10}) in Xi’an are relatively large. From the regional analysis, the obstacle degree of the number of green utility model patents (X_{24}) in the northwest region is relatively higher than that in the other two regions, indicating that the technological innovation level in the northwest region of the “Ji” Bay needs to be improved. The risk factors of per capita water resources and water production modulus in the northwest region are greater than those in the central and southern regions, indicating that water resource problems in the upstream region of the “Ji” Bay are more serious, which is consistent with the findings of [46].

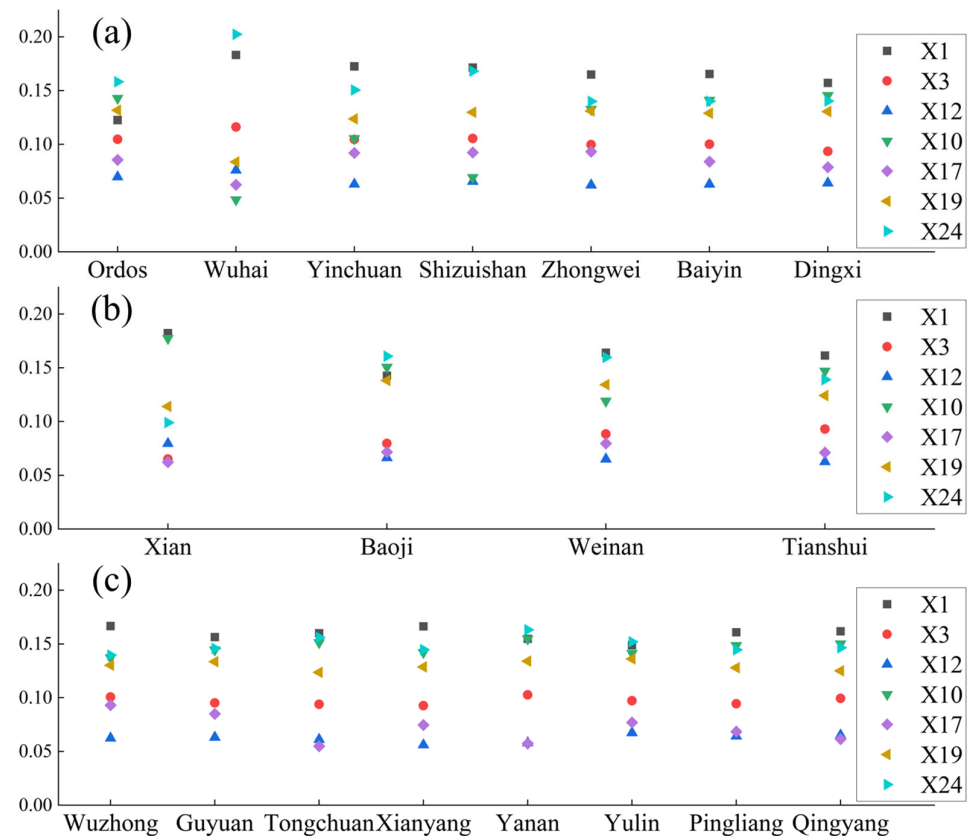


Figure 9. Risk factor analysis of cities in the (a) northwest region, (b) southern region, and (c) central region of the “Ji” Bay.

4. Discussion

4.1. Analysis of Evolution Mechanisms

From 2004 to 2023, the comprehensive risk of the WEFEC complex system in the Yellow River “Ji” Bay gradually shifted from extreme alert to high alert and then to medium alert. The number of cities in extreme alert and high alert states decreased, while the number of cities in no alert and light alert states increased. Extreme alert cities have shrunk from the northwest to a few areas, with the number of extreme alert cities in the northwest decreasing from 8 in the first period (2004–2010) to 1 in the third period (2017–2023), while the number of no alert cities increasing from 1 to 5. The risk in the central region (such as Wuzhong) remained high. The main reason is that policies, such as *Yellow River Basin Ecological Protection and High-Quality Development Plan Outline*, the *Yellow River Protection Law of the People’s Republic of China*, and the *Guiding Opinions of the Four Ministries and Commissions on Deeply Promoting the Green Development of Industries in the Yellow River Basin*, have significantly improved water, food, energy, ecology, and carbon emissions issues. Poor reliability is exemplified by a significant water resource shortage and excessive carbon emissions. The introduction of policies, such as the *Shaanxi Province Water Conservation Regulations* and *Inner Mongolia Autonomous Region Carbon Peaking Implementation Plan*, has improved reliability. For example, X_4 (water consumption per 10^4 yuan GDP) has decreased to 1/9 of its value in 2004 in 2023, and X_5 (unit area yield) has increased by nearly 2.5 times in 20 years. Synergy is at a medium level with significant room for improvement; due to the proposal of the *Science and Technology Innovation Implementation Plan for Ecological Protection and High-Quality Development of the Yellow River Basin* and the construction of major scientific and technological projects and platforms, the economy and technology in the “Ji” Bay have developed rapidly. The resilience indicators X_{22} (urbanization rate)

increased from 32% in 2004 to 62% in 2023, and X_{24} (number of green utility model patents) achieved explosive growth.

4.2. Policy Recommendations

From the perspective of different criterion layers, addressing water scarcity and high carbon emissions at the reliability level requires a dynamic, cross-regional water rights trading mechanism that allows for the conversion of agricultural water savings into industrial water indicators. Simultaneously, enforcing dual control measures on total energy consumption and intensity, and applying a carbon quota management for highly energy-consuming industries is required. To improve synergy, integrate water-saving irrigation and low-carbon fertilization techniques into agriculture, aiming to reduce water consumption per mu and agricultural carbon emissions. For stronger resilience, optimize the economic structure of ecologically fragile areas, foster scientific and technological innovation, and include fiscal spending on environmental protection as a key metric in evaluating local governments performance, ensuring the continuous advancement in sustainability investment.

From the perspective of risk factors, for water-related risk factors such as per capita water resources and water yield modulus, and rigid water resource management and control should be implemented; for carbon-related factors such as per capita carbon emissions and carbon emission density, carbon capture demonstration projects could be constructed in energy bases such as Ordos; and to improve ecological indicators such as water area ratio and ecological water use rate, red lines for river–lake ecological protection should be demarcated, and the project of returning farmland to lakes should be implemented in cities along the Yellow River.

From each region's perspective, the northwest region (such as Wuzhong and Zhongwei) must focus on resolving water resource issues and technical bottlenecks. It is important to construct cross-regional water diversion projects to supplement ecological water; the central energy-rich areas (such as Ordos and Yulin) should promote green industrial transformation and mandate a water cycle utilization transformation for coal chemical enterprises.

4.3. Limitations and Future Research Directions

This study conducted a comprehensive risk assessment of the WEFEC giant system, aiming to broaden the research perspective on the interconnections between the five sub-systems. However, this paper does have some limitations. This paper fails to verify whether the risks of the WEFEC complex system align with the EKC theory by integrating economic indicators such as regional per capita GDP growth and industrial structure upgrading. Additionally, due to data constraints, only carbon emission indicators were chosen for the “food–carbon” interconnection; however, in agricultural production, sowing food crops is also a carbon sink behavior, which may affect the synergy between “food and carbon.” Secondly, the existing risk factor analysis is based on historical data and does not combine the regional development transformation (such as new energy base construction and industrial upgrading) under policy guidance, such as the “double carbon” goal and the Yellow River Basin ecological protection plan, and, therefore, it lacks the dynamic prediction of future risk evolution. In the future, a scenario analysis model (such as the system dynamics model) will be constructed, fully considering other influencing factors, setting different scenarios, and quantitatively analyzing the risk mitigation effects of industrial structure adjustment and low-carbon technology popularization (such as carbon capture and utilization) on the WEFEC system to provide a scientific basis for medium- and long-term planning.

5. Conclusions

Based on the panel data of 19 cities in the Yellow River “Ji” Bay from 2004 to 2023, this study developed a risk assessment system for the WEFEC complex system and used the game theory–cloud model and risk factor model to analyze and determine the following: The multi-year average risk in this region is at a high alert level. Reliability is poor due to water resource shortage and excessive carbon emissions. Synergy is moderate, with considerable room for improvement. Resilience is generally improving, but there is a risk of shifting toward high alert in the later period; spatially, the number of cities in extreme alert decreased from eight in 2004–2010 to one in 2017–2023, while the number of cities in no alert increased from one in 2004–2010 to five in 2017–2023. Risks in the upstream region are more prominent, Wuzhong has always been in an extreme alert state, and per capita water resources, water production modulus, water area ratio, per capita carbon emissions, number of green utility model patents, etc., are the main risk factors. Based on this, the study proposes policy recommendations such as strengthening water rights management and trading, encouraging water-saving, energy-saving, and emission-reduction measures, optimizing economic structure, and improving ecological restoration capabilities.

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