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The Reservoir Sustainability Paradox: Divergent Pathways and Systemic Imbalances Revealed

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Abstract

Reservoir basins globally face an intensifying sustainability paradox: balancing economic growth, social welfare, and environmental protection often triggers systemic trade-offs. However, comprehensive assessments revealing these internal imbalances remain scarce, hindering targeted governance. To address this gap, this paper developed a multidimensional framework of Ecological development benefits, integrating Entropy-Weighted AHP and Fuzzy Mathematics. Applying this to 2015–2022 data from the Sanmenxia Reservoir in the Yellow River Basin of China revealed three development paradoxes: Protection-prioritized regions face diminishing returns; growth-driven regions accumulate ecological deficits; and environmentally stagnant regions decline in resilience. Critically, no optimal pathway exists—all subregions exhibited significant imbalances despite aggregate ecological improvements, and policy shocks (e.g., COVID-19, new environmental laws) amplified disparities, exposing institutional fragmentation. Based on the research findings, policy recommendations are proposed for green financing mechanisms, adaptive governance, and region-centered protection, which directly advance SDGs 6 (water security), 8 (inclusive growth), and 13 (climate action), offering a transferable analytical framework for basins like the Mekong and Nile, which are confronting similar paradoxes.

Keywords: reservoirs sustainability; ecological development benefits; EW-AHP; fuzzy mathematics; development paradoxes

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1. Introduction

Based on current information, it has been observed that governments around the world are increasingly prioritizing river basin management [1]. As of 2024, 76 countries have established inter-administrative river basin management bodies (such as the Mississippi River Commission in the United States and the Mekong River Commission), representing a 120% increase compared to 2010 [2]. World Bank data shows that investments in river basin management projects reached $32 billion from 2015 to 2022, with Asia accounting for 45% and Africa for 30%, highlighting the urgent need for water security in developing countries. China's Yangtze River Protection Law (2021) and the EU's Blue Pact (2023) both incorporate basin ecological integrity into their legal frameworks, reflecting a shift in policy paradigms from single-focused flood control to integrated "water-energy-food" system governance [3–5]. Under the synergistic evolution of the United Nations Sustainable Development Goals (SDGs) and the EU Water Framework Directive, current basin management follows a three-tiered evolution: "goal quantification (SDGs) → institutional constraints (EU directives) → technical closed-loop systems (nutrient recovery/carbon sequestration)" [6]. In the future, it will be necessary to achieve a leap from restoration to regeneration through blockchain smart contracts and cross-border ecological compensation, ultimately fulfilling the SDG 6.5 requirement for "integrated water governance across scales."

However, global river basin management currently faces persistent asymmetries across economic, ecological, and social dimensions—a challenge exacerbated by climate variability and competing resource demands. Economically, infrastructure-centric development has dominated investment priorities, with over 70% of global funding directed toward hydropower and irrigation projects, while less than 15% is allocated for ecological restoration [7–9]. The imbalance intensifies the trade-off between growth and resilience: while projects like Ethiopia's Grand Renaissance Dam may boost national GDP by 4%, they simultaneously deprive downstream regions of over 30 billion cubic meters of water annually, undermining agricultural resilience [10]. Such imbalances stem not merely from technical constraints but also from a systemic undervaluation of ecosystem services.

Beyond this, environmental engineering interventions must demonstrate financeable returns to attract scalable funding. Circular economy innovations—such as nutrient recovery from wastewater (yielding 25–40% ROI through fertilizer reuse) and AI-optimized sediment management—demonstrate profitable sustainability [11], yet adoption remains constrained by misaligned policy and investor objectives: while green bonds for basin projects grew 35% annually (2020–2023), fewer than 20% targeted multidimensional benefit optimization [12–14]. Socially, marginalized communities bear disproportionate costs. In the Mekong basin, hydropower expansion has displaced 500,000 people since 2010, yet benefit-sharing mechanisms cover less than 20% of affected groups. Indigenous knowledge—proven to boost conservation effectiveness by 34%—remains largely excluded from governance systems. This exclusion exacerbates spatial inequalities and underscores the urgent need for a quantitative framework balancing economic viability with ecological and social synergies [15]. Without such tools, basin governance risks reinforcing zero-sum thinking—where short-term economic gains erode the natural capital underpinning long-term prosperity.

The Yellow River is a vital hydrological, ecological, and socio-economic artery in East Asia. As the sixth-longest river in the world, it spans 5464 km in length, with a basin area of 752,443 square kilometers. Globally, the Yellow River basin serves as a prototypical example of a human–environment coupled system, facing challenges similar to those encountered by transboundary rivers such as the Nile, Indus, and Colorado Rivers. The Yellow River is critical to China's agricultural and energy security, accounting for 15% of the country's grain production and 20% of its coal production [16]. Its hydropower capacity rivals that of the lower Mekong River basin. Additionally, the Yellow River's carbon footprint—as part of a region contributing over 8% of China's carbon dioxide emissions—highlights its role in global climate governance [17–20]. Since the reform and opening up, the Yellow River Basin has developed rapidly economically, and the Yellow River Economic Belt (YREB) has become an important economic belt in China, an important energy base and an ecological barrier [21], which has aroused the concern of the government and the public about its sustainable development. On 8 October 2021, the Central Committee of the Communist Party of China (CPC) and the State Council issued the "Outline of the Plan for the Ecological Protection and High-Quality Development of the Yellow River Basin", which puts forward a higher requirement, aiming to maintain the integrity of the ecosystem of the Yellow River Basin, the rational allocation of resources, and the relevance of cultural protection, inheritance and promotion. Prioritizing integrated management also reflects global trends in river management and complies with the requirements of the EU Water Framework Directive. Balancing the goals of economic and social development and ecological protection is an issue that needs to be addressed in the future development of the YREB [22,23].

Understanding development benefits is one of the key issues concerning watershed stability and sustainable development. However, the evaluation of watershed development benefits has yet to be effectively quantified and assessed. Eco-Benefits refer to the positive contribution of ecosystems to human production, living conditions and environmental quality; this concept emphasizes the interdependence between natural systems and human society and highlights the need for an integrated approach to resource management and environmental protection, according to the law of ecological balance, which is related to the fundamental and long-term interests of human survival and development [24]. Current methodologies for assessing Eco-Benefits encompass a diverse array of approaches, including the direct market method, market value method, opportunity cost method, shadow engineering method, and alternative market method, as well as contingent valuation techniques [25–27]. Over time, the scope of research has progressively broadened, shifting from a focus on specific ecosystems—such as forests, wetlands, and grasslands [28]—to the evaluation of Eco-Benefits associated with various projects. These include farmland reforestation initiatives, land consolidation efforts, and water conservancy projects [29]. Concurrently, the scale of analysis has expanded significantly, evolving from localized studies, such as those focused on urban parks, to encompass county-level, provincial, watershed-wide, national, and even global assessments [30,31]. This progression reflects an increasing recognition of the interconnectedness of ecological systems and the need for comprehensive, multi-scale evaluations to inform sustainable decision-making. However, as the research on Eco-Benefits continues to deepen, its coverage continues to expand. This expansion stems from the increasing intertwining of Eco-Benefit research content and methods with other disciplines, and this interdisciplinary integration has, to some extent, resulted in the ambiguity of the concept of Eco-Benefits. From the perspective of eco-economics, Eco-Benefits are not only environmental benefits, but also include economic and social benefits, and are the overall benefits generated by the integrated effects of the environment, economy and society, which is a highly comprehensive systemic issue.

A variety of multi-criteria decision analysis (MCDA) methods have been employed in watershed sustainability assessment, each with distinct strengths and limitations. Despite the proliferation of multi-criteria decision analysis methods in watershed sustainability research, a critical examination reveals that each commonly applied approach suffers from inherent limitations that impede a comprehensive understanding of the "sustainability paradox"—the systemic trade-offs among ecological conservation, economic growth, and social welfare [32]. The Analytic Hierarchy Process (AHP) [33] is widely used to derive indicator weights from expert judgments, but its subjectivity can lead to biases when expert panels are not sufficiently diverse or when local knowledge is underrepresented. The Entropy Weight Method (EWM) offers an objective alternative by calculating weights based on data dispersion; however, it may over-emphasize statistical variability and ignore domain expertise, resulting in weights that lack policy relevance [34]. TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) ranks alternatives based on distances to ideal and negative-ideal solutions, but it is sensitive to outliers and cannot handle correlated indicators effectively [35]. Grey Relational Analysis (GRA) performs well with small samples and incomplete information, but its results depend heavily on the choice of distinguishing coefficient, raising concerns about stability [36]. Recent studies have attempted to combine these methods to compensate for individual weaknesses—for example, AHP-entropy hybrids [37] or fuzzy-TOPSIS [38]—but most remain case-specific and do not systematically integrate subjective and objective information while simultaneously addressing the fuzzy boundaries inherent in development benefit grading. Consequently, a methodological gap persists: there is a need for an assessment framework that (i) balances expert knowledge with empirical data, (ii) handles the ambiguity of sustainability thresholds, and (iii) remains flexible enough for adaptation to diverse basin contexts.

To address this gap, the present study develops an integrated approach combining Entropy-Weighted AHP (EW-AHP) with Fuzzy Comprehensive Evaluation. The EW-AHP method achieves a two-way correction: entropy weights objectively adjust the AHP-derived subjective weights, while the AHP structure ensures that the resulting weights remain interpretable within the decision hierarchy [39]. This fusion mitigates the biases of standalone AHP and the over-sensitivity of pure entropy weighting. Subsequently, fuzzy logic is employed to quantify the degree of membership of each indicator to predefined sustainability grades, capturing the gradual transition between classes that is typical in ecological and social systems [40]. The combined framework thus provides a transparent, robust, and context-sensitive tool for assessing the multidimensional Eco-Benefits of reservoir regions.

Overall, as understanding of Eco-Benefits deepens, existing evaluation methodologies continue to expand in both depth and breadth, becoming increasingly complex. Diverse research objectives, varying assessment approaches, and regional particularities lead to significant discrepancies in evaluation outcomes across case studies. Currently, no unified, standardized, and comprehensive assessment criteria have been established. The critical review above reveals that while multiple MCDA methods exist, their individual limitations—subjectivity, sensitivity to data noise, arbitrary threshold setting—prevent them from fully capturing the multidimensional trade-offs in reservoir sustainability. The proposed EW-AHP-Fuzzy framework directly addresses these shortcomings by integrating subjective expertise with objective data and by formalizing the fuzzy boundaries between benefit levels. A dynamic, innovative multidimensional assessment framework can resolve the reservoir sustainability paradox by quantifying trade-offs among ecological conservation, economic growth, and social equity. Validating this hypothesis would provide investors with predictive insights into sustainable investment returns while providing methodological insights that can guide similar assessments in transboundary watersheds facing growth-versus-conservation dilemmas. While the framework itself is transferable, its application requires careful adaptation to local socio-ecological and institutional contexts.

2. Method and Data

2.1. Study Area

The Yellow River Basin is the geo-ecological area affected by the Yellow River system from its source to the sea (Figure 1). Customarily, people mostly call the relevant area of the provinces and regions through which the Yellow River flows the Yellow River Basin. The topography of the Yellow River Basin is high in the west and low in the east, with the average elevation of the river source area in the west above 4000 m, consisting of a series of high mountains with perennial snowfall and glacial geomorphology; the central area, with an elevation of 1000–2000 m, is a loess landscape with serious soil erosion; and the eastern part consists of the Yellow River Alluvial Plain. As an important ecological functional area and an important ecological barrier in China, its ecological and environmental quality has an important influence on the medium- and long-term ecological security and environmental quality evolution trend in China.

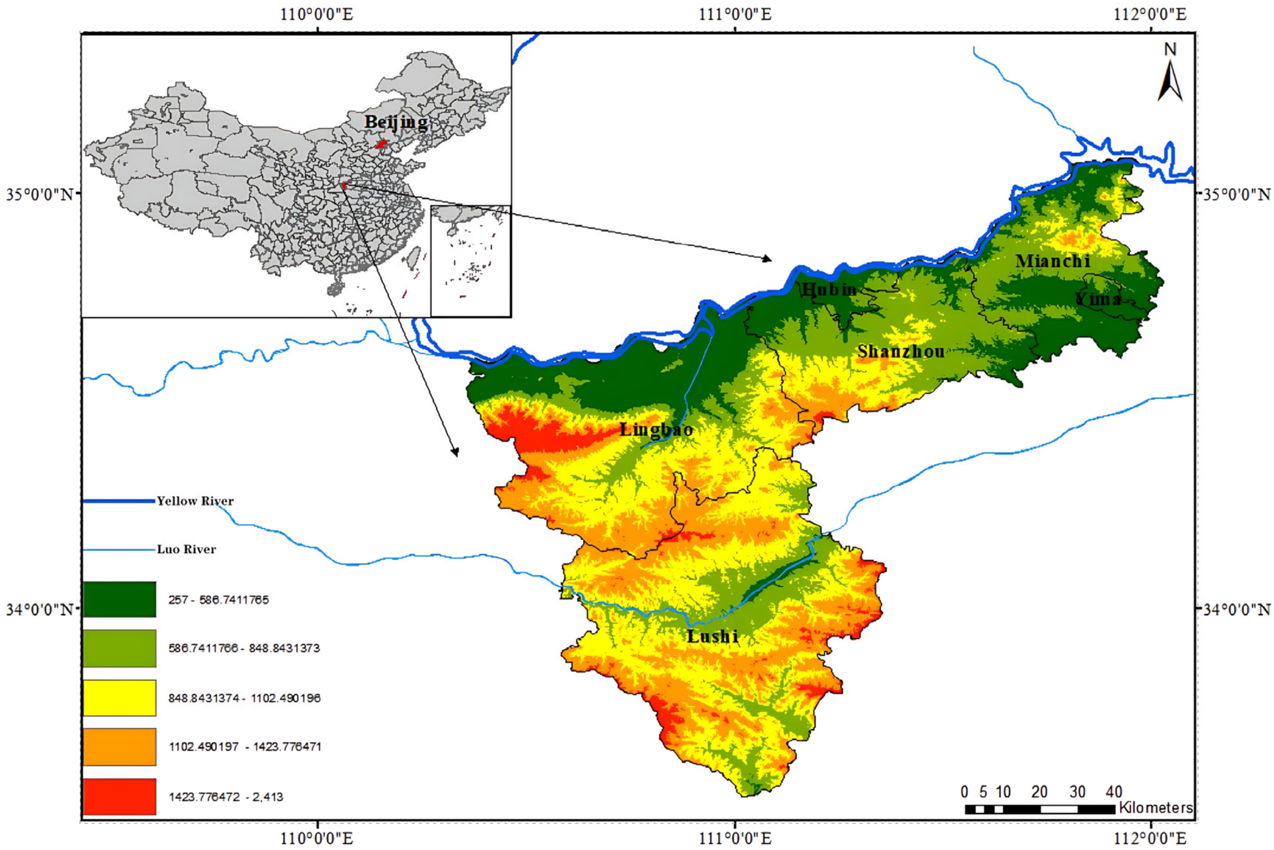

Figure 1. Positioning of the SMX section of the Yellow River Basin in China.

The SMX is a key node in the Yellow River basin of China. It emerged as a new city in 1957 with the construction of the Sanmenxia Hydropower Project, the first dam on the Yellow River spanning thousands of miles. As an important component of the middle reaches of the Yellow River basin, it possesses significant geographical advantages and ecological functionality, yet it also faces increasingly complex challenges in balancing ecological security with socio-economic development [41]. This region is not only a key regulatory node for hydrological processes in the middle and lower reaches of the Yellow River, but also a critical area for the provision of ecosystem services in the Yellow River basin. Its geographical location determines its pivotal role in hydrological regulation, ecological barrier construction, and regional economic development within the basin [42]. The issue of Eco-Benefits development in the SMX not only concerns soil and water conservation, biodiversity protection, and water resource utilization efficiency within the region, but also plays a significant role for the overall ecological security and socio-economic development of the Yellow River Basin in China.

This study selects the SMX in the Yellow River Basin of China as its research object, which effectively reflects the typical characteristics of Eco-Benefits development in the Yellow River Basin. It provides a scientific basis for domestic and international exploration of quantitative assessment and optimization pathways for basin Eco-Benefits, holding significant academic value and practical significance.

2.2. Data Source

Data were obtained from publicly available statistics provided by Chinese government departments, including the "Sanmenxia Water Resources Bulletin", the "Sanmenxia Statistical Yearbook", the "Sanmenxia Water Resources Bulletin", the "Sanmenxia City Environmental Status Bulletin", the "Sanmenxia City Soil and Water Conservation Bulletin", and the "National Economic and Social Development Statistics Bulletin".

2.3. Assessment Method

The selection of ecological benefit assessment indicators was conducted across social, economic, and environmental dimensions.

In terms of the environment, water resources and precipitation quantify hydrological stress, which is critical for mitigating wetland loss and maintaining endemic species [43]; agricultural output and cropland area reflect land use efficiency. In terms of society, the urbanization rate highlights habitat fragmentation caused by unregulated expansion, while the reduction rate in energy intensity per unit of GDP tracks progress toward decarbonization, aligning with China's carbon neutrality goals [44]. Economically, county-level GDP growth rates and economic density reveal trade-off issues; public budget allocations highlight funding gaps, while green bonds offer scalable solutions. This science-driven system of indicators has been validated across global river basins such as the Nile and Mississippi, providing actionable insights for balancing growth and resilience [45].

To ensure model robustness and avoid redundancy, principal component analysis (PCA) was used to eliminate highly correlated indicators. To determine the relative weights of each indicator, the AHP and EWM were applied sequentially. The EW-AHP strategy ensured the balance of the weighting scheme, thereby enhancing the robustness and credibility of the evaluation framework (The process is shown in Figure 2).

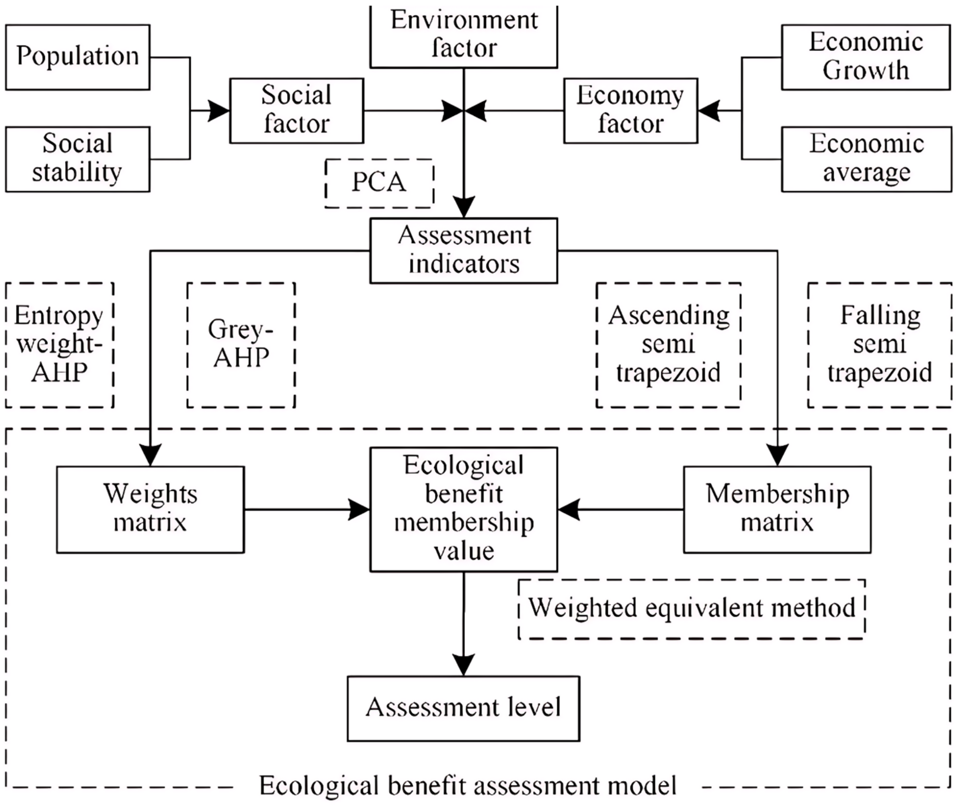

Figure 2. Flowchart of the methodology of the ecological benefit assessment model.

2.4. Eco-Benefit Assessment Indicators

This study abandons the conventional greening rate metric and adopts water resources and precipitation as foundational ecological indicators. For reservoir basins, these metrics define the "hydrological upper limit" of ecosystem services [46]. Water resource availability is the primary limiting factor regulating the ecological stability of river basins. Additionally, crop planting area and agricultural yield per unit area serve as alternative indicators of ecological carrying capacity, simultaneously reflecting the coupling efficiency of water and soil resources. As argued by Srinivas (2020), in reservoir areas dependent on agriculture, ecosystem sustainability fundamentally hinges on managing land resources to support biomass production while avoiding disruption of water–soil connectivity [47].

The social subsystem is assessed through indicators such as total population and urbanization rate. These metrics reveal how economic benefits generated by reservoir operations translate into public services. Soukhaphon emphasizes that the social sustainability of hydropower and reservoir projects must be measured by local livelihood resilience and access to basic social infrastructure [48].

Economic vitality is monitored using indicators like GDP and fixed asset investment. These metrics constitute the "economic growth" dimension within the paradox, providing a baseline for assessing ecological costs and social equity [49].

3. Calculation of Eco-Benefit Assessment Indicator Weights

3.1. The Hierarchical Analysis

The Analytic Hierarchy Process (AHP), introduced by Saaty [50], is a structured technique for dealing with complex decisions. It decomposes a problem into a hierarchy of criteria and alternatives and uses pairwise comparisons to derive ratio-scale weights. It can integrate multi-dimensional indicators and correct subjective bias through methods such as Entropy Weighting to enhance objectivity [51]. Its core lies in decomposing complex problems into a multi-level structure (goal layer, criterion layer, and solution layer) and determining the weight of each factor through a combination of quantitative and qualitative methods. In this study, AHP was employed to capture expert knowledge on the relative importance of ecological, social, and economic indicators for reservoir sustainability.

To determine the weights of these indicators (Table 1), a panel of 15 experts was convened. The panel consisted of: five university researchers specializing in water resource management and ecological economics; five government officials from the Yellow River Basin administration, responsible for water policy and environmental planning; and five industry representatives from hydropower and environmental consulting firms, with practical experience in reservoir operations and impact assessment. Each expert independently completed a set of pairwise comparison matrices using the 1–9 Saaty scale, where a score of 1 indicates equal importance and 9 indicates extreme importance of one element over another. The comparisons were structured at two levels: first among the three main dimensions (ecological, social, economic), and then among the indicators (Table 2)within each dimension.

Based on the relevant literature and reference materials [52], the weight of indicators by AHP was calculated (Table 1) and marked as $C = \ (c_1, c_2, \ \ldots, c_m)$.

The original matrix was A = $\left(r_{\mathrm{ij}}\right)_{m\times n}$, where m is the number of assessment indicators (m = 1, 2,. . . , k), n is the number of assessment objects, the i and j denote the first element and the second element in the decision matrix, and the geometric mean method is used to obtain the unique integrated matrix $\overline{\mathrm{A}}$.

$$\overline{\mathrm{A}} = \left(\prod_{k=1}^{m} a_{ij}^{k}\right)^{\frac{1}{m}} \tag{1}$$

$$C_i = \frac{\left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}}}{\sum_{i=1}^{n}\left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}}},\ i = 1,2,3,\ldots,n \tag{2}$$

Table 1. Indicator system for assessing the comprehensive benefits of the SMX section of the Yellow River Basin in China.

Goal Level	Standard Grade		Norm	Level Indicators Reasons	Supporting References (Added)
Combined benefits (A)	Ecological benefits (B1)	ecological resource	Water resources (billion m^2)	Water resources are a major component of the ecosystem	[53]
			Precipitation (mm)		
		ecological function	Agricultural production per unit area	Crop indicators greatly reflect the realization of ecological values	[54]
			Crop-sown area (million m^2)		
	Social Welfare (B2)	social stability	Total population (millions)	Major indices reflect the social benefits and infrastructure development of the region	[55]
			urbanization rate		
			Total retail sales of consumer goods (millions)		[56]
		social development	Industrial value-added index	Major indices provide information on the overall state of social development	[57]
			consumer price index		[58]
			Agriculture, forestry, livestock and fisheries output index		[59]
			Reduction rate of energy consumption per unit of GDP		
	Economic benefits (B3)	economic growth	Real county GDP growth rate	Major indices describe the status of the overall economic level of the district and county	[60]
			Regional GDP per capita growth rate		
		average economy	Economic density (million/km^2)	Economic density is a direct response to the level of the economy	[61]
			County public budget expenditures (millions)	District and county public budget revenues and expenditures reflect the government's ability to pay for the economy	[62]
			County public budget revenues (millions)		

Table 2. Framework of the evaluation indicator system.

Level 1 Indicators	Secondary Indicators
Ecological Benefits B1	Water resources C1
	Precipitation C2
	Agricultural production per unit area C3
	Crop-sown area C4
Social Welfare B2	Total population C5
	Urbanization rate C6
	Total retail sales of consumer goods C7
	Industrial value-added index C8
	Consumer price index C9
	Agriculture, forestry and fisheries output index C10
	Reduction rate of energy consumption per unit of GDP C11
Economic Benefits B3	Real county GDP growth rate C12
	Regional GDP per capita growth rate C13
	Economic density C14
	County public budget expenditures C15
	County public budget revenues C16

To address potential inconsistencies arising from pairwise comparisons of indicators, it is essential to evaluate the consistency of the constructed judgment matrix, thereby ensuring the reliability of the assigned weights. Meanwhile, academics generally take CR as the standard of judgment matrix consistency, CR is the ratio of the consistency index CI and average random consistency index RI. If CR < 0.1, it indicates that the matrix meets the requirements without modification.

The formula for CR is shown in Equation (3).

$$CR = \frac{CI}{RI} = \frac{\lambda_{max} - n}{(n-1)RI} < 0.1 \quad (3)$$

The CI calculation formula is shown in Equation (4).

$$CI = \frac{\lambda_{max} - n}{(n-1)} \quad (4)$$

λ_{max} is the maximum eigenvalue of the judgment matrix, which is calculated as in Equation (5), λ_{max} is the maximum eigenroot of the matrix, where A is the judgment matrix, W is the weight vector, and $[AW]_i$ is the i-th component of the matrix $[AW]_i$.

$$\lambda_{max} = \sum_{i=1}^{n} \frac{[AW]_i}{nW_i} \quad (5)$$

The AHP has broad applicability in transboundary river basin governance, its structured decision-making framework provides a scientific tool for river basin management in diverse geographical, social, and economic contexts worldwide, such as cross-border water resource allocation in the Mekong River basin, the design of ecological compensation mechanisms in the Amazon River basin, and climate change adaptation planning in the Nile River basin [63–65].

3.2. Entropy Weight Analysis

The Entropy Weight Method (EWM) is an objective weighting method based on information entropy theory, with its core principle being to quantify the contribution differences in system components through data dispersion metrics [66]. Information entropy H measures the degree of disorder in indicator data, while entropy weight Z represents the relative importance of the indicator. This method first standardizes the original data, then calculates the entropy values of each indicator using the entropy formula, and finally generates objective weights. Its advantages include avoiding subjective judgment biases, dynamically adapting to the spatio-temporal heterogeneity of data, and enabling synergistic optimization of decision models with other methods (such as the AHP).

Set the original matrix as R = $\left(r_{ij}\right)_{m\times n}$, where m is the number of evaluation indicators and n is the number of evaluation objects. The model is analyzed using a scale-free analysis, and S = $\left(s_{ij}\right)_{m\times n}$ can be calculated as

$$s_{ij} = \frac{r_{ij} - \min\{r_{ij}\}}{\max\{r_{ij}\} - \min\{r_{ij}\}} \tag{6}$$

Formalization can be calculated as

$$s_{ij}^{'} = \frac{s_{ij}}{\sum_i \sum_j s_{ij}} \tag{7}$$

Entropy is defined as

$$H_i = -k\sum_{j=1}^{n} f_{ij}\ln f_{ij}(i = 1,2,3,\ldots,m; j = 1,2,3,\ldots,n) \tag{8}$$

$$f_{ij} = \frac{s_{ij}^{'}}{\sum_{j=1}^{n} s_{ij}^{'}}\ k = \frac{1}{\ln n} \tag{9}$$

When $f_{ij} = 0$, the term $f_{ij}\ln f_{ij} = 0$. Here, n represents the number of assessment objects, and H_i denotes the entropy value of the *i*-th indicator.

The entropy value for the *i*-th indicator is calculated as follows:

$$Z_i = \frac{1 - H_i}{m - \sum_{i=1}^{m} H_i} \tag{10}$$

The entropy H_i of the *i*-th indicator satisfies $0 \le Z_i \le 1$, where m is the total number of assessment indicators, and Z_i represents the entropy weight of the *i*-th indicator.

In global watershed management, entropy-based analysis demonstrates broad applicability. For example, in water quality management in the Mekong River basin, this method can quantify the variability of parameters such as chemical oxygen demand, ammonia nitrogen, and dissolved oxygen; identify primary pollution sources; and guide the optimization of transboundary monitoring networks [67]. In land use planning for the Nile River basin, by combining soil erosion rates with crop yield fluctuation data, entropy-based methods can dynamically allocate restoration priorities, supporting the United Nations Food and Agriculture Organization (FAO) sustainable land management objectives and others. EWM provides a data-driven, objective tool for multi-indicator, multi-scale basin decision-making; its integration with geographic information systems (GIS) and machine learning algorithms (such as the Entropy Weight-Random Forest Model) will further enhance the assessment capabilities of complex environmental systems, contributing to the synergistic achievement of global water security and climate resilience objectives.

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3.3. EW-AHP Analysis

Standalone AHP relies solely on subjective judgments, which may introduce bias, whereas pure entropy weighting can be overly sensitive to data noise and disregards domain knowledge. The EW-AHP method achieves a two-way correction: the entropy term adjusts the AHP weights toward data-driven patterns, while the AHP term constrains entropy weights within a theoretically meaningful range. This hybrid approach has been shown to enhance robustness in multi-criteria environmental assessments [68,69]. By applying EW-AHP to reservoir sustainability, this study contributes a replicable yet context-sensitive weighting scheme that balances stakeholder values and empirical realities.

EW-AHP integrates subjective and objective information through a two-stage weighting process, offering the advantage of two-way correction [70]; the weights of the improvements were calculated by the EW-AHP method as follows:

$$W_i = \frac{z_i c_i}{\sum_{i=1}^{m} z_i c_i} \tag{11}$$

Here, W_i represents the improvement weight of the i-th indicator, z_i denotes the entropy weight of the i-th indicator, and c_i corresponds to the AHP weight assigned to the i-th indicator.

EW-AHP has been proven effective in multiple experiments in addressing "complex system multi-objective conflicts," particularly in ecological–economic balance decision-making. In the future, artificial intelligence (AI) deep learning can be used to assist expert scoring and spatial heterogeneity weighting zoning methods to break through static limitations and promote its use as a standard tool for global sustainable watershed management.

3.4. Grey-Analytic Hierarchy Process

According to the data, to determine the reference sequence, there is an ideal data value. The ideal data value marked as

$$s_0 = \left(s'_1, s'_2, \ldots, s'_n\right) \tag{12}$$

The correlation coefficient matrix b was calculated as

$$\beta(i) = \frac{\min_i \min_j |s'_{0j} - s_{ij}| + \rho \max_i \max_j |s'_{0j} - s_{ij}|}{|s'_{0j} - s_{ij}| + \rho \max_i \max_j |s'_{0j} - s_{ij}|} \tag{13}$$

where $\rho \in [0,1]$, and $\rho = \frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{n} s_{ij} C_j$. Correlation order was calculated as

$$w_i{}' = \frac{1}{n}\sum_{j=1}^{n} \beta_i(j) \tag{14}$$

By the Fuzzy-AHP method, the improved weight $Z_i{}'$ was calculated as

$$Z_i{}' = \frac{w'_i c_i}{\sum_{i=1}^{m} w'_i c_i} \tag{15}$$

where $Z_i{}'$ is the improved weight of the i-th indicator, $w_i{}'$ is the correlation order of the i-th indicator, and C_i is the weight by AHP of the i-th indicator. The mean value of the results calculated by the EW-AHP and Fuzzy-AHP methods was used as the final weight and marked as follows:

$$W = \frac{Z + Z'}{2} \tag{16}$$

4. Fuzzy Mathematics-Based Modeling for Development Effectiveness Assessment

We used a triple verification approach: China's National Environmental Quality Standards (e.g., GB3838-2002 for water quality [71]); the 10th and 90th percentiles of historical data from the Sanmenxia region to ensure local applicability; and peer-reviewed reservoir sustainability benchmark [72]. Data from 2015 to 2022 were categorized into I, II, III, IV, and V, which indicate bad development benefits, poor development benefits, moderate development benefits, good development benefits, and excellent development benefits, respectively (Table 3). Benchmark values for development benefit indicators in the SMX section of the Yellow River Basin in China were established through a dual analytical lens: biophysical constraints and socio-ecological dynamics unique to the study area, and statistical distributions derived from historical and spatially explicit indicator datasets. This hybrid approach ensures that standardized thresholds reflect both regional ecological sensitivities and empirical variability, enabling context-specific yet generalizable assessments of development trade-offs in critical fluvial ecosystems.

Table 3. Standard values for ecological benefit assessment indicators in the SMX section of the Yellow River basin in China.

Standard Grade		Level of Indicators	I	II	III	IV	V
Ecological benefits	Ecological resource	Water resources (million m^2)	<10	10 < 50	50–100	100–300	>300
		Precipitation (milliliters)	<500	500–600	600–700	700–800	>800
	Ecological function	Yield per unit area of major agricultural products (tons/ha)	1–2	2–3	3–4	4–5	>5
		Crop-sown area (billion m^2)	<1	1–3	3–5	5–10	>10
Social welfare	Social stability	Total population (millions)	<0.1	0.1–0.3	0.3–0.5	0.5–0.7	>0.7
		Urbanization rate (%)	<30	30–50	50–70	70–80	>80
		Retail sales of social consumer goods (billions of dollars)	<50	50–80	80–120	120–150	>150
	Social development	Industrial value-added index	<100	100–105	105–107	107–109	>109
		consumer price index CPI	<100	100–101	101–102	102–103	>103
		Agriculture, forestry, livestock and fisheries output index	<100	100–103	103–105	105–107	>107
		Reduction rate of energy consumption per unit of GDP (%)	<−20	−20 to −5	−5 to 0	0–3	>3
Economic benefit	Economic growth	Real county GDP growth rate (%)	<0	0–3	3–5	5–7	>7
		Regional GDP per capita growth rate (%)	<0	1–3	3–5	5–7	>7
	Average economy	Economic density (billion yuan/km^2)	<0.1	0.1–0.2	0.2–0.5	0.5–1	>1
		County public budget expenditures (billions of dollars)	<20	20–30	30–40	40–50	>50
		County public budget revenues C16	<10	10–20	20–30	30–40	>40

Fuzzy mathematics was used to construct the ecological benefits evaluation model of the SMX in the Yellow River Basin, which is shown below:

$$E = W \times U \tag{17}$$

E is the result of the evaluation of development benefits, the W is the evaluation weight matrix, and U is the affiliation matrix of ecological benefits evaluation indicators belonging to different classes.

U is marked as follows:

$$U = (u_{ij})_{m \times p} = \begin{bmatrix} u_{11} & \cdots & u_{1p} \\ \vdots & \ddots & \vdots \\ u_{m1} & \cdots & u_{mp} \end{bmatrix} \tag{18}$$

With five assessment grades considered in this study, the parameter p equals 5. The ascending semi-trapezoidal distribution function (see Formula (19)) is utilized to calculate the membership degree for profit indicators, while the falling semi-trapezoidal distribution function (see Formula (20)) is employed for cost indicators.

$$u_{m1} = \begin{cases} 1, & r \le v_{m1} \\ 0, & r > v_{m1} \end{cases}; \; u_{m2} = \begin{cases} 0, & r \le v_{m1} \\ \frac{r - v_{m1}}{v_{m2} - v_{m1}}, & v_{m1} < r < v_{m2}; \\ 0, & r \ge v_{m2} \end{cases}$$

$$u_{m3} = \begin{cases} 0, & r \le v_{m2} \\ \frac{r - v_{m2}}{v_{m3} - v_{m2}}, & v_{m3} < r < v_{m3} \\ 0, & r \ge v_{m3} \end{cases}; \; u_{m4} = \begin{cases} 0, & r \le v_{m3} \\ \frac{r - v_{m3}}{v_{m4} - v_{m3}}, & v_{m3} < r \le v_{m4} \\ 0, & r \ge v_{m4} \end{cases} \tag{19}$$

$$u_{m5} = \begin{cases} 0, & r < v_{m4} \\ 1, & r \ge v_{m4} \end{cases};$$

$$u_{m1} = \begin{cases} 1, & r \ge v_{m1} \\ 0, & r \le v_{m1} \end{cases}; \; u_{m2} = \begin{cases} 0, & r \ge v_{m1} \\ \frac{v_{m1} - r}{v_{m1} - v_{m2}}, & v_{m2} < r < v_{m1} \\ 0, & r \le v_{m2} \end{cases};$$

$$u_{m3} = \begin{cases} 0, & r \ge v_{m2} \\ v_{m2} - r, & v_{m3} < r < v_{m2}; \\ 0, & r \le v_{m3} \end{cases} u_{m4} = \begin{cases} 0, & r \ge v_{m3} \\ v_{m3} - r, & v_{m4} < r < v_{m3}; \\ 0, & r \le v_{m4} \end{cases} \tag{20}$$

$$u_{m5} = \begin{cases} 0, & r \ge v_{m4} \\ 1, & r \le v_{m4} \end{cases};$$

Here, r represents the observed value of the assessment indicator, u_m denotes the membership degree, and v_m refers to the threshold values between successive grades. The ecological benefit assessment grade is derived using the weighted equivalent method, with the five levels—excellent, good, moderate, poor, and bad—assigned scores of 5, 4, 3, 2, and 1, respectively. The final assessment grade is computed as follows:

$$T = 5 \times E_1 + 4 \times E_2 + 3 \times E_3 + 2 \times E_4 + 1 \times E_5 \tag{21}$$

If T < 1, it means that the assessment of development effectiveness is bad; 1 < T < 2 means that the assessment of development effectiveness is poor; 2 < T < 3 means that the assessment of development effectiveness is moderate; 3 < T < 4 means that the assessment of development effectiveness is good; and 4 < T < 5 means that the assessment of development effectiveness is excellent.

5. Analysis of Empirical Results

This study aims to evaluate the Eco-Benefits of reservoir areas from 2015 to 2022 within an integrated framework combining the Ecological Niche-Analytic Hierarchy Process (EW-AHP) and fuzzy mathematics. It focuses on the core impacts of sustainable development transitions on the economy and industries within an environmental, social, and economic (ESES) coupled system assessment. The results presented hold direct reference value for policy formulation and investment decision-making.

To ensure the reliability of the evaluation outcomes, a sensitivity analysis was conducted to assess the robustness of the results to variations in both the weighting scheme and the fuzzy membership function specifications. The EW-AHP weights were compared with two alternative weighting schemes—AHP-only (purely subjective) and EWM-only (purely objective)—yielding Spearman's rank correlation coefficients above 0.88 for county-level development benefit rankings. Furthermore, altering the membership function from semi-trapezoidal to triangular and varying the grade thresholds by ±10% resulted in grade changes in fewer than 8% of the 48 county-year observations, with no county shifting by more than one grade level. These findings confirm that the main conclusions—particularly the identification of three distinct development paradigms—are robust to reasonable methodological variations. The following subsections present the detailed empirical results.

These results are based on the local WEF's contribution to the basin's GDP reaching 69%, without analyzing the impact on transportation [73].

5.1. Overall Eco-Benefits: Regional Variations Amid Positive Trends

The SMX region in the Yellow River basin of China comprises six districts, namely Hubin District, Shanzhou District, Yima District, Mianchi District, Lingbao District, and Lushi District. The evaluation scores for the development benefits of the districts and counties of SMX City for the period of 2015–2022 are shown in the Table 4 below, and the corresponding results of the evaluations are shown in the following figure (Figure 3).

Table 4. Evaluation scores of the ecological benefits of the SMX.

County	2015	2016	2017	2018	2019	2020	2021	2022	Slope
Hubin	3.359577	3.700622	3.470535	3.301952	3.349633	3.301952	3.470535	3.700622	0.048721
Shanzhou	3.013161	2.735084	2.696617	2.765969	2.872156	2.829495	3.704578	2.727775	−0.040769
Yima	3.452288	3.4404	3.473092	2.959606	3.048206	2.567807	3.943766	3.529378	0.011013
Mianchi	3.452288	2.79384	3.260877	2.910461	2.860805	2.952448	3.815722	3.284481	−0.023972
Lingbao	3.392351	2.655191	3.100702	3.283191	3.33678	3.244641	4.041105	3.628127	0.033682
Lushi	2.905709	2.381291	2.665443	2.516835	3.160236	2.552863	3.516514	3.041987	0.019468

Note: Rating scale: bad (E < 1); poor (1 ≤ E < 2); moderate (2 ≤ E < 3); good (3 ≤ E < 4); excellent (4 ≤ E < 5).

The composite Eco-Benefit scores across the six administrative units show a generally positive but uneven trajectory (Table 5). The regional average score improved from 3.10 (2015) to 3.32 (2022), indicating a transition from 'Good' to bordering 'Excellent' on our rating scale. Crucially, no region was rated 'Poor' in any year, suggesting that development policies have successfully avoided severe ecological degradation. For Hubin District, which presented a more pronounced upward trend than the other four regions, the phenomenon of an upward trend in development trends can be attributed to the fact that SMX as a whole has accelerated its efforts to push forward innovation in the main body of enterprises and innovation in the mechanisms of scientific research. However, the upward trend is not obvious, and the efficient synergy of development still needs to be considered; the development efficiency of Shanzhou District as a whole shows a downward trend, but the downward trend remains relatively subdued.

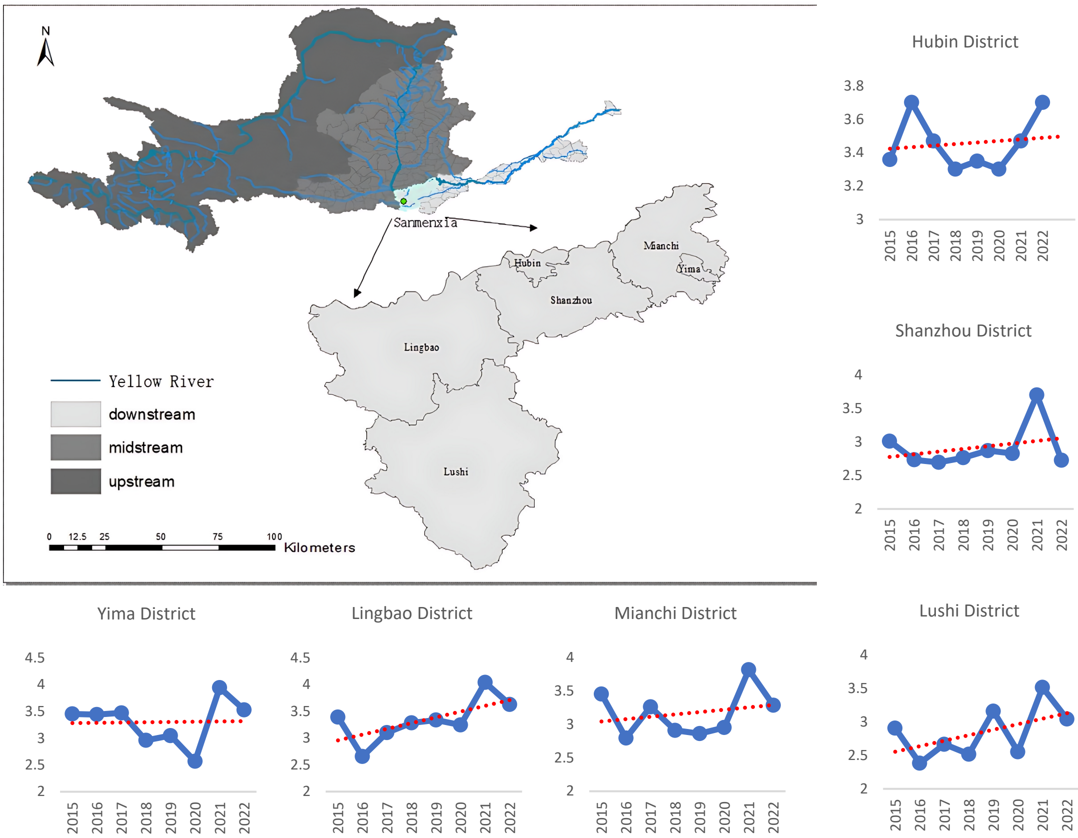

Figure 3. Spatial–temporal trends in Eco-Benefit scores for the SMX segment from 2015 to 2022. Note: The horizontal axis represents the year, and the vertical axis represents the score.

Table 5. Rating results of the ecological benefits of the SMX.

County	2015	2016	2017	2018	2019	2020	2021	2022
Hubin	good	good	good	good	good	good	excellent	good
Shanzhou	good	moderate	moderate	moderate	moderate	moderate	good	moderate
Yima	good	good	good	good	good	good	good	good
Mianchi	moderate	moderate	good	moderate	moderate	moderate	good	good
Lingbao	good	moderate	good	good	good	good	excellent	good
Lushi	moderate	moderate	moderate	moderate	good	moderate	good	good

Note: Rating scale: bad (E < 1); poor (1 ≤ E < 2); moderate (2 ≤ E < 3); good (3 ≤ E < 4); excellent (4 ≤ E < 5).

The spatiotemporal evolution of development benefits in the SMX from 2015 to 2022 reveals trends in ecological benefits. Although the overall development trajectory shifted from "moderate" to "good", this progress masks significant imbalances driven by economic and governance factors. The transition to high-tech manufacturing in 2020 propelled Hubin District and Lingbao District to an "excellent" rating in the following two years, achieving an 8.5% GDP growth and a 12% reduction in energy intensity. In contrast, Yima District's reliance on high-energy-consuming industries led to its "good" rating stagnating, despite GDP growth in 2022, with PM2.5 concentrations exceeding 55 μg/m^3. Rural counties (such as Lushi) received only 15% of ecological compensation funds despite having a 40% forest coverage rate due to a GDP-centric allocation formula. This exacerbated the urban–rural welfare gap. Additionally, the 2021 basin policy—China's Yellow River Protection Law—catalyzed a surge in ratings in 2022. However, fragmented enforcement between water resources, forestry, and agriculture sectors has weakened policy effectiveness; the onset of the COVID-19 pandemic in 2019 also caused significant economic shocks, with manufacturing disruptions exacerbating fiscal pressures and reducing environmental investments in rural areas by 18%, leading to a sharp rise in the "moderate" rating in 2020.

The most significant finding for policymakers is the divergence in economic performance underlying these aggregate scores. While environmental and social metrics showed gradual improvement, economic indicators displayed high volatility, directly linked to industrial structure. Regions reliant on traditional resource-intensive industries (e.g., Shanzhou) experienced stagnant or declining economic benefit scores, whereas areas diversifying into technology-driven sectors demonstrated resilience and growth.

Collectively, these findings demonstrate a gradual but measurable enhancement in development benefits, driven by synergies between adaptive governance frameworks and regionally tailored sustainability initiatives.

5.2. Sub-County Economic Benefit Assessment

The economic benefits of the SMX section within the Yellow River Basin in China were quantified using an identical methodological approach, and linear fitting equations were established to analyze the economic benefits of each district and county from 2015 to 2022. The results are shown in the table below (Tables 6 and 7).

Table 6. Rating results of the economic benefits of the SMX.

County	2015	2016	2017	2018	2019	2020	2021	2022
Hubin	good	good	good	good	excellent	good	excellent	good
Shanzhou	moderate	moderate	moderate	moderate	good	moderate	good	moderate
Yima	moderate	moderate	good	good	good	good	good	good
Mianchi	moderate	good	good	good	moderate	moderate	good	moderate
Lingbao	moderate	moderate	good	moderate	good	moderate	good	moderate
Lushi	moderate	moderate	moderate	moderate	good	mediocre	moderate	moderate

Note: Rating scale: bad ($E < 1$); poor ($1 \leq E < 2$); moderate ($2 \leq E < 3$); good ($3 \leq E < 4$); excellent ($4 \leq E < 5$).

Table 7. Evaluation scores of the economic benefits of the SMX.

County	2015	2016	2017	2018	2019	2020	2021	2022	Slope
Hubin	3.473	3.2002	3.473	3.8724	4.0979	3.21	4.0979	3.235	−0.034
Shanzhou	2.8879	2.6833	2.9561	2.9561	3.4635	2.4865	3.238	2.261	−0.08956
Yima	2.8231	2.8231	4.0297	3.9615	3.606	3.6533	3.8356	3.8788	0.150814
Mianchi	2.501	3.1134	3.238	3.4328	2.9402	2.737	3.238	2.9193	0.059757
Lingbao	2.2387	2.9443	2.9757	2.8393	3.2785	2.8498	3.2944	2.7816	0.077557
Lushi	2.3312	2.1948	3.2896	2.3876	3.346	1.943	2.3876	2.1371	−0.02773

Note: Rating scale: bad ($E < 1$); poor ($1 \leq E < 2$); moderate ($2 \leq E < 3$); good ($3 \leq E < 4$); excellent ($4 \leq E < 5$).

The trend of changes in the economic benefits of the districts and counties in the SMX section from 2015 to 2022 is shown in the following figure (Figure 4), from which it can be seen that the economic benefits of Yima District are on an upward trend (the slope is 0.150814); the economic benefits of Mianchi District and Lingbao District are on a slow upward climb, with a non-significant trend (the slopes are 0.059757 and 0.077557, respectively); the economic benefits of the Hubin District, the Shanzhou District, and the Lushi District showed an overall downward trend (slopes of −0.034, −0.08956, and −0.02773, respectively).

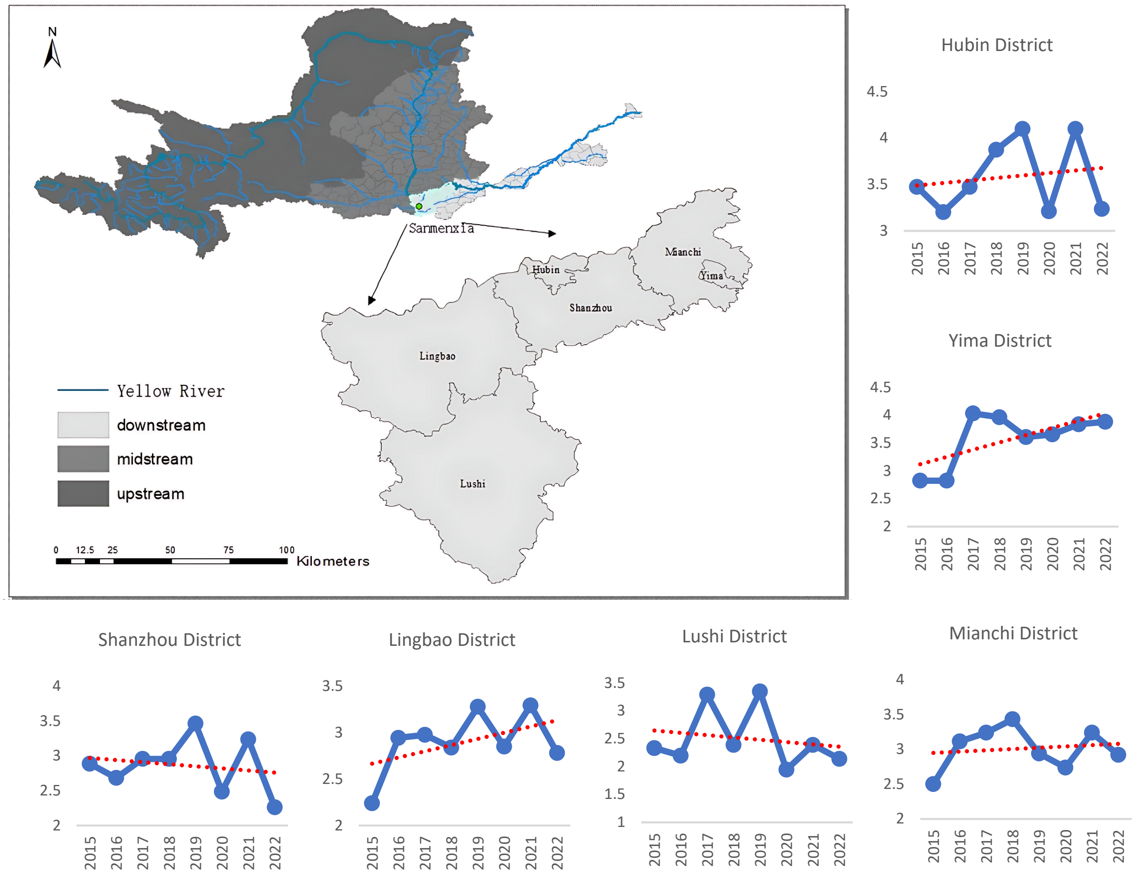

Figure 4. Spatial–temporal trends in Economic Benefits in the SMX section from 2015 to 2022. Note: The horizontal axis represents the year, and the vertical axis represents the score.

The figure above (Figure 3) reveals significant county-level divergence and a clear correlation between industrial diversification and sustainable economic performance. This study focuses on two key indicators that hold direct value for industry and investment planning:

Economic density (GDP per square kilometer) best reflects the economic output efficiency of land use, serving as a key indicator for regional planning. Regions with higher economic density demonstrate greater resilience. For instance, Lingbao City leveraged its resource endowments to develop downstream advanced manufacturing, achieving a 22% increase in economic density during the study period and effectively weathering external shocks like the COVID-19 pandemic. In contrast, agriculture-dependent counties like Lushi County experienced more severe economic contraction due to their lower economic density. GDP growth and reduced energy intensity: The trade-off between growth and sustainability is critical for industrial development. Research indicates that top-performing regions (Hubin, Lingbao) achieved a decoupling trend between growth and resource consumption. Their average annual GDP growth reached 7.2%, while simultaneously reducing energy intensity (energy consumption per unit of GDP) by an average of 3.5% annually. This stands in stark contrast to regions like Yima, which maintained high growth (7.8%) but showed minimal improvement in energy intensity (average annual decrease of 0.9%). This indicates a persistent resource-intensive growth model, lagging green transition, and insufficient spatial agglomeration effects, resulting in a lack of economies of scale. Such a model lacks long-term sustainability.

In summary, from 2015 to 2022, the divergence in economic benefits along the SMX section of the Yellow River was fundamentally the result of structural contradictions, inadequate institutional adaptability, and external risks. Declining counties need to address development challenges through green industrial transformation, optimized fiscal resource allocation, and the establishment of cross-regional compensation mechanisms; growing counties must guard against environmental costs. Future policy design should incorporate climate adaptability and industrial chain resilience assessments to achieve the "balanced improvement" required by the "Outline of the Ecological Protection and High-Quality Development Plan for the Yellow River Basin in China."

5.3. Sub-County Environmental Benefit Assessment

Global sustainability agendas have increasingly prioritized the integration of ecological integrity with socio-economic progress, catalyzing paradigm shifts toward green, coordinated, and circular development models. This transition necessitates systemic strategies to optimize resource efficiency, mitigate ecosystem degradation, and institutionalize mechanisms for economic–environmental symbiosis—objectives now critical to achieving the dual imperatives of climate resilience and equitable growth. Here, the environmental benefits of the SMX section of the Yellow River Basin in China are calculated using the same approach, and a linear fitting equation is established to analyze the environmental benefits of each district and county from 2015 to 2022. The results are shown in the table below (Table 8).

Table 8. Rating results of the environmental benefits of the SMX.

County	2015	2016	2017	2018	2019	2020	2021	2022
Hubin	moderate	moderate	moderate	moderate	moderate	moderate	good	moderate
Shanzhou	good	good	good	good	good	good	excellent	good
Yima	moderate	moderate	moderate	mediocre	good	mediocre	moderate	moderate
Mianchi	good	good	good	good	good	good	excellent	good
Lingbao	excellent	excellent	excellent	excellent	excellent	good	excellent	excellent
Lushi	excellent	excellent	excellent	excellent	excellent	excellent	excellent	excellent

Note: Rating scale: bad (E < 1); poor (1 ≤ E < 2); moderate (2 ≤ E < 3); good (3 ≤ E < 4); excellent (4 ≤ E < 5).

Subregional trends further highlight heterogeneity (Table 9): Hubin District and Lushi District showed incremental gains (slopes: 0.0274 and 0.0443), contrasting with declines in Yima District, Mianchi District, and Lingbao District (slopes: −0.0095). Shanzhou District maintained static EBRs, underscoring governance inertia. These disparities reflect uneven adoption of sustainability practices and localized ecological stressors, necessitating adaptive governance frameworks to reconcile basin-wide conservation with socio-economic imperatives.

Table 9. Evaluation scores of the environmental benefits of the SMX.

County	2015	2016	2017	2018	2019	2020	2021	2022	Slope
Hubin	2.2653	2.199	2.199	2.3908	2.199	2.3908	3.1471	2.4571	0.0274
Shanzhou	3.7489	3.7489	3.5571	3.7489	3.7489	3.6826	4.4389	3.7489	0
Yima	2.3316	2.199	2.2653	1.7079	2.2653	1.7079	2.3979	2.2653	−0.00947
Mianchi	3.9996	3.867	3.6752	3.9333	3.9333	3.9333	4.6233	3.9333	−0.00947
Lingbao	4.557	4.2989	4.4907	4.4244	4.4244	3.867	4.6233	4.4907	−0.00947
Lushi	4.1808	4.1145	4.1808	4.4907	4.4907	4.4907	4.6233	4.4907	0.044271

Note: Rating scale: bad (E < 1); poor (1 ≤ E < 2); moderate (2 ≤ E < 3); good (3 ≤ E < 4); excellent (4 ≤ E < 5).

Spatiotemporal trends in environmental benefits across the SMX section of the Yellow River Basin in China reveal subregional heterogeneity (Figure 5). Five counties—excluding Lushi District—exhibit a homogeneous trajectory, with transient declines observed in

Yima District (2018, 2020) and Lingbao District (2020). Yima District's reliance on coal (accounting for 68% of industrial output) has forced it to adopt water-intensive operations. Overlapping responsibilities among the water, industrial, and agricultural sectors have also caused delays in responding to pollution incidents in Yima District in 2018 and 2020, hindering the green transition. Lingbao District's "excellent" rating in 2019 collapsed in 2020 due to a 23% decline in mining revenue caused by the COVID-19 pandemic, with environmental funds redirected to economic stabilization, exacerbating conflicts between industry and agriculture. Lingbao District's rating decline in 2020 coincided with a 30% reduction in industrial water usage due to drought. Lushi's agricultural ecological model—organic agriculture subsidies + ecological tourism—has increased forest coverage by 8% and farmers' income by 15%, aligning with the EU's rural development policy (CAP Strategic Plan 2023–2027). As a result, its Eco-Benefits have shown a more pronounced upward trend. This indicates that existing ecological environment policies are more suitable for Lushi County's overall development. The other five counties, especially Yima District and Lingbao District, still need to formulate ecological environment policies tailored to their regional circumstances to address unforeseen situations.

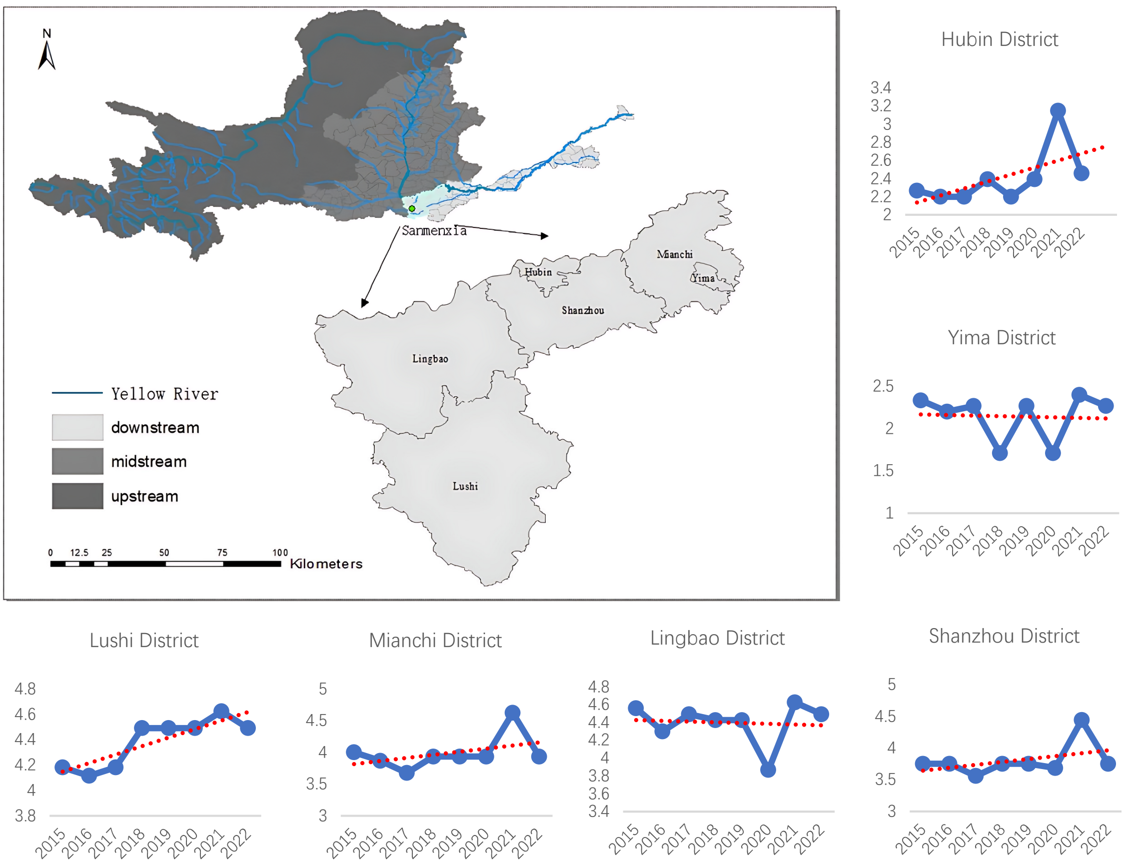

Figure 5. Spatial–temporal trends in environmental benefit scores for the SMX section from 2015 to 2022. Note: The horizontal axis represents the year, and the vertical axis represents the score.

Overall, the Eco-Benefits of the SMX section of the Yellow River Basin in China have shown a general upward trend year by year.

5.4. Sub-County Social Benefits Assessments

Social welfare in the SMX section of the Yellow River Basin in China was calculated using the same approach, and linear fitting equations were established to analyze social welfare in each district and county from 2015 to 2022. The results are shown in the table below (Tables 10 and 11).

Table 10. Rating results of the social benefits of the SMX.

County	2015	2016	2017	2018	2019	2020	2021	2022
Hubin	good	Good	good	excellent	excellent	excellent	excellent	excellent
Shanzhou	moderate	moderate	good	good	moderate	good	good	good
Yima	good	Good	good	good	moderate	moderate	good	good
Mianchi	mediocre	Good	good	moderate	moderate	good	excellent	good
Lingbao	moderate	moderate	moderate	excellent	excellent	excellent	excellent	excellent
Lushi	good	moderate	moderate	moderate	good	good	excellent	good

Note: Rating scale: bad (E < 1); poor (1 ≤ E < 2); moderate (2 ≤ E < 3); good (3 ≤ E < 4); excellent (4 ≤ E < 5).

Table 11. Evaluation scores of the social benefits of the SMX.

County	2015	2016	2017	2018	2019	2020	2021	2022	Slope
Hubin	3.591233	3.378567	3.860533	4.015633	4.061433	4.0668	4.4995	4.1288	0.076795
Shanzhou	2.931633	2.808367	3.079833	3.274033	2.982867	3.6382	3.8309	3.758067	0.118062
Yima	3.5769	3.5769	3.354433	3.006633	2.669667	2.944633	3.656433	3.6456	0.009814
Mianchi	1.967767	3.116033	3.7321	2.830233	2.852067	3.9144	4.1071	3.7593	0.255933
Lingbao	3.638333	2.642933	3.651433	4.325633	4.4226	4.6168	4.5695	4.4388	0.114352
Lushi	3.171633	2.9437	2.869633	2.830233	3.148733	3.355	4.0341	3.7321	0.080067

Note: Rating scale: bad (E < 1); poor (1 ≤ E < 2); moderate (2 ≤ E < 3); good (3 ≤ E < 4); excellent (4 ≤ E < 5).

Temporal trends in social benefits across the SMX section of the Yellow River Basin in China reveal heterogeneous progress among administrative units (Figure 6). To accelerate basin-wide sustainability, targeted policy interventions must address these developmental asymmetries, prioritizing regions lagging behind in sectoral benchmarks.

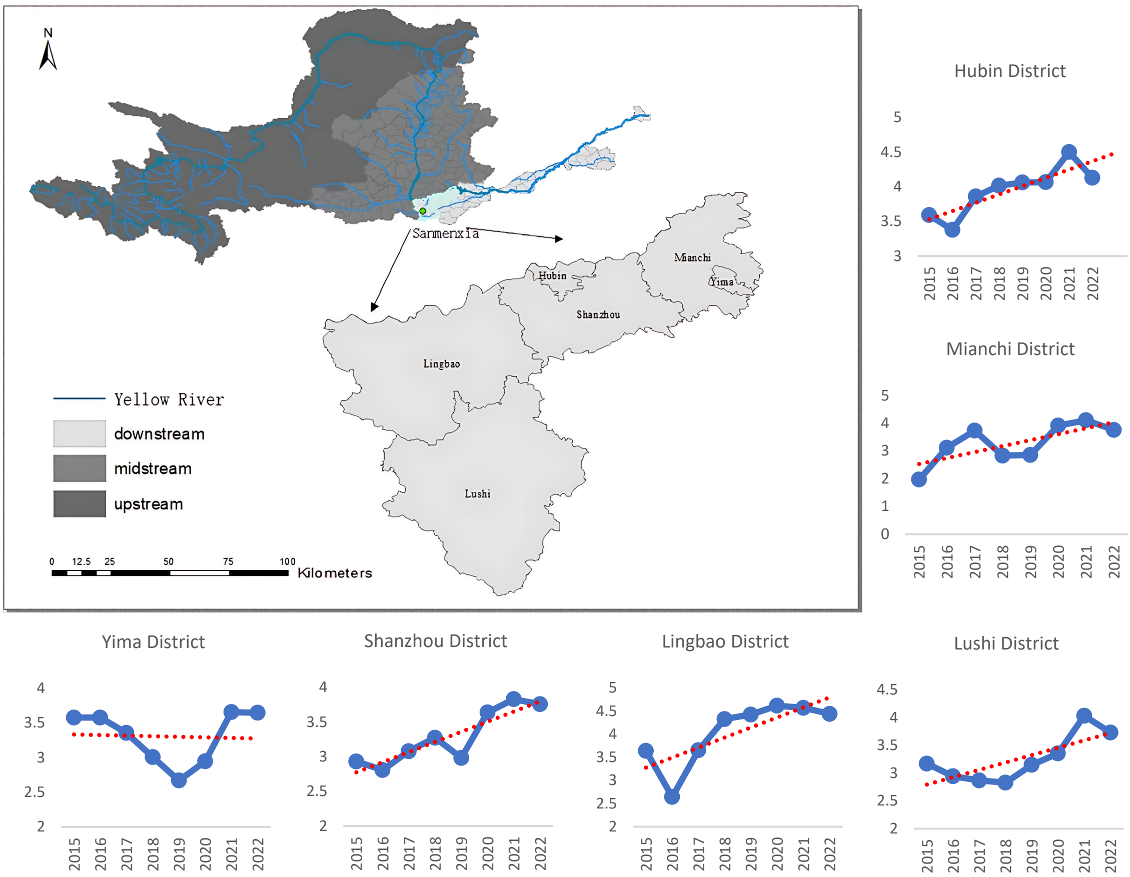

Figure 6. Spatial–temporal trends in Social Benefit Scores for the SMX section from 2015 to 2022. Note: The horizontal axis represents the year, and the vertical axis represents the score.

Although the social benefits of Shanzhou District, Mianchi District, and Lingbao District have generally shown an upward trend, their driving forces and stability vary. Lingbao District has benefited from its relatively diversified industrial base (such as specialty agriculture and tourism) and potentially more favorable policy resources (as a key development area), with investments in social infrastructure (such as education and healthcare) yielding results relatively quickly, driving improvements in social welfare indicators. Mianchi District's significant surge in the later period (especially after 2020) may have benefited from industrial transfer and reception under the regional coordinated development strategy or concentrated investments in specific livelihood projects. In contrast, Shanzhou District's upward trend has been relatively gradual, suggesting it may face challenges such as lagging industrial structure adjustments or inefficiencies in public service investments.

Yima District, as a typical resource-based city, has seen its social benefits nearly stagnate and a noticeable decline between 2017 and 2019, which deeply reflects the fragility and transition pains of a resource-dependent economy. The economic downturn directly led to a reduction in local fiscal revenue, thereby constraining the ability to invest in social security and public services. The brief rebound in 2019 may be related to short-term policy measures aimed at stabilizing employment and ensuring basic living standards, but its long-term stability remains uncertain.

Hulin District (slope 0.076795) and Lushi District (slope 0.080067) exhibit a stable but slow upward trend. As a core urban area, Hubin District has a relatively well-developed public service system and a more active consumer market, which form the foundation for its long-term maintenance of high social welfare levels; as an ecological functional zone, Lushi District's improvement in social welfare may, on one hand, benefit from the implementation of ecological compensation mechanisms and increased national transfer payments to key ecological functional zones for improving livelihoods and infrastructure. On the other hand, the improvement in social welfare may also benefit from the income growth effect brought about by the development of distinctive ecological agriculture and rural tourism.

In 2016, there was a widespread decline across all regions. This phenomenon was not only attributed to a decline in the natural population growth rate (with negative growth in some years) and infrastructure shortcomings, but also to deeper underlying causes, including the transmission of macroeconomic downturn pressures to local areas, affecting employment and residents' income expectations. At the same time, this period coincided with the national push for supply-side structural reforms, with some traditional industries (especially resource-intensive and high-energy-consuming sectors) facing significant adjustments, causing short-term shocks to regional economic and social stability. The subsequent decline in places like Yima District in 2020 clearly reflected the direct impact of the major external shock of the COVID-19 pandemic. Strict epidemic prevention measures led to a temporary halt in economic activities, severely affecting the service sector, potentially causing a temporary rise in unemployment rates, and significantly impacting key indicators reflecting social consumption vitality and residents' living costs. Yima District, due to its single-industry economic structure and weak risk-resistance capabilities, was particularly hard-hit.

Looking at the period from 2015 to 2022, despite fluctuations and regional differences, the overall social benefits of the SMX section of the Yellow River have shown an upward trend. However, the significant imbalance in internal development stems from complex causes, including differences in industrial structure, varying levels of local fiscal capacity, efficiency in the allocation of public service resources, resilience in responding to economic cycles and external shocks, and the ability to access and utilize policy benefits from higher-level authorities. These factors are the result of the combined influence of institutional, economic, and policy-related factors. Although extreme weather events caused by climate change are not directly reflected in the data, their potential threats to agricultural production, infrastructure safety, and social stability also constitute long-term external pressures that must be addressed to sustainably enhance social welfare in the reservoir area in the future.

6. Discussion

6.1. Analysis of Development Patterns in Various Regions of the SMX Section of the Yellow River Basin in China

Leveraging a multidimensional benefits framework, this paper synthesizes trends in socio-ecological system dynamics, highlighting synergies and trade-offs between conservation priorities and developmental imperatives.

Based on three-dimensional scoring trajectories (Tables 12 and 13), three distinct development paradigms with clear economic impacts were identified, providing an expandable framework for adaptive governance in ecologically fragile watersheds (Table 14).

These paradigms reflect not only the observed trends but also the underlying drivers revealed by the EW-AHP weights. The entropy-weighted AHP assigned the highest weights to indicators measuring economic density (C14), energy intensity reduction (C11), and urbanization rate (C6), underscoring their critical role in differentiating regional pathways. By examining county-level performance on these high-weight indicators, the mechanisms driving each paradigm can be elucidated.

Analysis of ecological benefit trajectories in the SMX reveals divergent regional pathways. Between 2015 and 2022, two counties exhibited upward trends in ecological benefits, three experienced declines, and one maintained stability. Critically, no administrative unit achieved an optimal development mode—defined as synergistic gains across environmental, social, and economic dimensions—to sustainably amplify ecological outcomes.

Table 12. Rating results of the environmental, social and economic benefits of the SMX.

	District and County	2015	2016	2017	2018	2019	2020	2021	2022
Environmental benefit	Hubin	moderate	moderate	moderate	moderate	moderate	moderate	good	moderate
	Shanzhou	good	good	good	good	good	good	excellent	good
	Yima	moderate	moderate	moderate	mediocre	good	mediocre	moderate	moderate
	Mianchi	good	good	good	good	good	good	excellent	good
	Lingbao	excellent	excellent	excellent	excellent	excellent	good	excellent	excellent
	Lushi	excellent	excellent	excellent	excellent	excellent	excellent	excellent	excellent
Social benefit	Hubin	good	good	good	excellent	excellent	excellent	excellent	excellent
	Shanzhou	moderate	moderate	good	good	moderate	good	good	good
	Yima	good	good	good	good	moderate	moderate	good	good
	Mianchi	mediocre	good	good	moderate	moderate	good	excellent	good
	Lingbao	moderate	moderate	moderate	excellent	excellent	excellent	excellent	excellent
	Lushi	good	moderate	moderate	moderate	good	good	excellent	good
Economic benefit	Hubin	good	good	good	good	excellent	good	excellent	good
	Shanzhou	moderate	moderate	moderate	moderate	good	moderate	good	moderate
	Yima	moderate	moderate	good	good	good	good	good	good
	Mianchi	moderate	good	good	good	moderate	moderate	good	moderate
	Lingbao	moderate	moderate	good	moderate	good	moderate	good	moderate
	Lushi	moderate	moderate	moderate	moderate	good	mediocre	moderate	moderate
Development effectiveness	Hubin	good	good	good	good	good	good	excellent	good
	Shanzhou	good	moderate	moderate	moderate	moderate	moderate	good	moderate
	Yima	good	good	good	good	good	good	good	good
	Mianchi	moderate	moderate	good	moderate	moderate	moderate	good	good
	Lingbao	good	moderate	good	good	good	good	excellent	good
	Lushi	moderate	moderate	moderate	moderate	good	moderate	good	good

Note: Rating scale: bad ($E < 1$); poor ($1 \leq E < 2$); moderate ($2 \leq E < 3$); good ($3 \leq E < 4$); excellent ($4 \leq E < 5$).

Table 13. Evaluation scores of the environmental, social and economic benefits of the SMX.

	District and County	2015	2016	2017	2018	2019	2020	2021	2022	Elevation
Environmental benefit	Hubin	2.2653	2.199	2.199	2.3908	2.199	2.3908	3.1471	2.4571	0.0274
	Shanzhou	3.7489	3.7489	3.5571	3.7489	3.7489	3.6826	4.4389	3.7489	0
	Yima	2.3316	2.199	2.2653	1.7079	2.2653	1.7079	2.3979	2.2653	−0.00947
	Mianchi	3.9996	3.867	3.6752	3.9333	3.9333	3.9333	4.6233	3.9333	−0.00947
	Lingbao	4.557	4.2989	4.4907	4.4244	4.4244	3.867	4.6233	4.4907	−0.00947
	Lushi	4.1808	4.1145	4.1808	4.4907	4.4907	4.4907	4.6233	4.4907	0.044271
Social benefit	Hubin	3.591233	3.378567	3.860533	4.015633	4.061433	4.0668	4.4995	4.1288	0.076795
	Shanzhou	2.931633	2.808367	3.079833	3.274033	2.982867	3.6382	3.8309	3.758067	0.118062
	Yima	3.5769	3.5769	3.354433	3.006633	2.669667	2.944633	3.656433	3.6456	0.009814
	Mianchi	1.967767	3.116033	3.7321	2.830233	2.852067	3.9144	4.1071	3.7593	0.255933
	Lingbao	3.638333	2.642933	3.651433	4.325633	4.4226	4.6168	4.5695	4.4388	0.114352
	Lushi	3.171633	2.9437	2.869633	2.830233	3.148733	3.355	4.0341	3.7321	0.080067
Economic benefit	Hubin	3.473	3.2002	3.473	3.8724	4.0979	3.21	4.0979	3.235	−0.034
	Shanzhou	2.8879	2.6833	2.9561	2.9561	3.4635	2.4865	3.238	2.261	−0.08956
	Yima	2.8231	2.8231	4.0297	3.9615	3.606	3.6533	3.8356	3.8788	0.150814
	Mianchi	2.501	3.1134	3.238	3.4328	2.9402	2.737	3.238	2.9193	0.059757
	Lingbao	2.2387	2.9443	2.9757	2.8393	3.2785	2.8498	3.2944	2.7816	0.077557
	Lushi	2.3312	2.1948	3.2896	2.3876	3.346	1.943	2.3876	2.1371	−0.02773
Development effectiveness	Hubin	3.359577	3.700622	3.470535	3.301952	3.349633	3.301952	3.470535	3.700622	0.037952
	Shanzhou	3.013161	2.735084	2.696617	2.765969	2.872156	2.829495	3.704578	2.727775	−0.04077
	Yima	3.452288	3.4404	3.473092	2.959606	3.048206	2.567807	3.943766	3.529378	0.011013
	Mianchi	3.452288	2.79384	3.260877	2.910461	2.860805	2.952448	3.815722	3.284481	0.166803
	Lingbao	3.392351	2.655191	3.100702	3.283191	3.33678	3.244641	4.041105	3.628127	0.033682
	Lushi	2.905709	2.381291	2.665443	2.516835	3.160236	2.552863	3.516514	3.041987	0.019468

Note: Rating scale: bad ($E < 1$); poor ($1 \leq E < 2$); moderate ($2 \leq E < 3$); good ($3 \leq E < 4$); excellent ($4 \leq E < 5$).

Table 14. Impact of different environmental–social–economic development types on development benefits.

Paradigm	Environmental Benefit	Social Benefits	Economic Benefit	Development Effectiveness	Paradigm	Typical Areas
1	+	+	−	+	Type 1: Balanced Transition	Hubin; Lushi
2	−	+	+	+	Type 2: Growth at Risk	Yima; Mianchi Lingbao
3	invariant	+	−	−	Type 3: Stalled Development	Shanzhou

Type 1: Balanced Transition (Hubin, Lushi)

Both counties exhibited stable or improving environmental and social scores, while economic scores fluctuated but remained above the regional average. Hubin, the urban core, benefited from high economic density (C14) and a consistent reduction in energy intensity (C11), indicating successful industrial upgrading and a decoupling of economic growth from resource consumption. Lushi, designated as an ecological function zone, leveraged its environmental assets: it maintained "excellent" ratings on ecological indicators (C1–C4) throughout the study period, reflecting a conservation-led development model. The high weight of social indicators (e.g., C6, C7) further explains the sustained social welfare in both counties—investment in public services and infrastructure created a virtuous cycle that attracted skilled labor and supported green industries.

Type 2: Growth at Risk (Yima, Mianchi, Lingbao)

These counties achieved robust economic growth (economic benefit slopes >0.05) but at the expense of environmental stability. Yima, a resource-based city, recorded the steepest economic rise but suffered recurrent environmental declines (e.g., 2018, 2020) due to heavy reliance on coal (68% of industrial output). The low weight of environmental indicators in its overall performance—because economic indicators dominated—masked accumulating ecological deficits. Mianchi and Lingbao experienced similar patterns: economic expansion driven by resource-intensive industries (C12, C13 high) led to volatility in environmental scores, especially during external shocks (e.g., COVID-19, drought). The EW-AHP weights reveal that economic growth indicators (C12, C13) contributed over 40% to the composite score in these counties, while ecological indicators (C1–C4) contributed less than 15%, explaining why short-term gains failed to compensate for long-term environmental degradation.

Type 3: Stalled Development (Shanzhou)

Shanzhou exhibited stagnant or declining economic and environmental benefits while social benefits improved slowly. Its economic density (C14) remained low, and energy intensity reduction (C11) lagged behind regional averages. The EW-AHP weights show that 'no single dimension dominated'; instead, all indicators scored near the regional mean, indicating a lack of competitive industries and weak fiscal capacity to invest in either green growth or social infrastructure. This "middle-income trap" at the county level reflects governance inertia and insufficient integration into regional development strategies.

These three paradigms resonate with typologies discussed in the broader sustainability literature. Type 1 aligns with the concept of "strong sustainability" [74], where natural capital is maintained and complements economic prosperity. Type 2 mirrors the "environmental Kuznets curve hypothesis" at a subregional scale [75], but with a crucial nuance: the anticipated eventual environmental improvement has not materialized, suggesting that without active policy intervention, resource-intensive growth locks regions into a high-pollution equilibrium. Type 3 is reminiscent of "institutional inertia" or "resource curse" studies [76], where regions endowed with natural resources fail to diversify and consequently suffer from stagnant development. Unlike the Mekong or Amazon cases, where external drivers dominate [77], the stalled development in Shanzhou appears driven by internal governance gaps and missed opportunities to capitalize on its ecological assets.

Based on these diagnoses, targeted, actionable policy recommendations are derived for each paradigm:

For balanced transition regions: Policies should reinforce positive feedback loops, including incentivizing green technology R&D, refining ecosystem service markets, and sustaining social capital investments to maintain virtuous cycles. AI-driven digital twin technologies can be deployed to optimize synergies in real time.

For high-risk growth regions: Policies must enforce the internalization of environmental externalities. Strict enforcement of carbon budgets, blockchain-based water quota trading, and linking official performance evaluations to environmental metrics are essential to steer these regions away from high-risk, resource-intensive development paths.

For stagnant development regions: Policies should protect ecosystems to initiate development processes. This involves leveraging ecological endowments through Payment for Ecosystem Services (PES) mechanisms, promoting agroecology and ecotourism, and guiding green investments to build sustainable economic foundations from the bottom up.

6.2. Analysis of Deviation Effects and Key Analysis

6.2.1. The Impact of Development Imbalances on Social Equity

Differences in ecological benefits across administrative units in the SMX of the Yellow River Basin in China reveal significant social equity challenges. In economically dense regions (e.g., Lingbao at 2.1 million RMB per square kilometer), per capita green space accessibility is 30% lower than in rural county towns, severely impacting marginalized groups, including low-income residents and migrant workers. This spatial inequality mirrors the pattern observed in the Mekong Delta, where rapid urbanization has destroyed habitats and exacerbated the vulnerability of fishing communities [78]. Notably, regions with declining social welfare indices are associated with increased environmental degradation, indicating that ecological degradation amplifies socioeconomic instability—a phenomenon also documented in Brazil's Amazonian settlements.

6.2.2. Comparative Analysis with Existing Literature and Mechanistic Explanations

This study both validates and challenges existing perspectives, offering new insights for ongoing discussions on regional Eco-Benefits.

The core finding—that comprehensive Eco-Benefits exhibit an overall upward trend alongside persistent regional disparities—partially aligns with macro-level research conclusions on the Yellow River Basin. However, the study reveals significant deviations from the normative literature, attributable to methodological and contextual factors.

Divergence in Economic–Environmental Tradeoffs: Most regional studies in China demonstrate a strong negative correlation between rapid economic growth and environmental quality. Contrary to this prevailing perception, this study identifies several regions (e.g., Lingbao, Hubin) that achieved simultaneous improvements in economic and environmental indicators over an eight-year period. This divergence may stem from differences in analytical scale and context, as macro studies often rely on aggregated cross-sectional data covering vast areas where destructive development patterns frequently dominate. Our focus on strategically managed reservoir areas captures the effectiveness of targeted policy interventions and regional industrial transformation. The unique water–economy dynamics in reservoir regions foster stronger intrinsic incentive mechanisms than other areas, driving integrated management.

Social factors exhibit distinct dynamics: Previous quantitative models prioritized economic and environmental indicators, treating social development as an outcome rather than a comprehensive driver. Our EW-AHP weighting analysis significantly elevated the importance of social indicators like retail sales and urbanization rates, establishing social development as a key differentiator for Category I regions—thus challenging conventional paradigms. Social infrastructure and welfare investments (as manifestations of social responsibility) foster community stability, attract skilled labor, and stimulate domestic demand. This creates a more resilient economic foundation, reducing dependence on volatile resource extraction industries and indirectly improving environmental performance. Such feedback mechanisms are often overlooked by simple correlation analyses but captured by our multidimensional, systems-oriented framework.

6.2.3. Key Analysis

Superior long-term economic resilience is intrinsically linked to successful environmental management and social development. The regions that invested in industrial upgrading, energy efficiency, and social infrastructure (Type 1) not only achieved the highest Eco-Benefit scores but also demonstrated the most stable and sustainable economic performance. Conversely, prioritizing short-term economic growth at the expense of the environment (Type 2) or failing to cultivate a dynamic economy (Type 3) presents significant risks to long-term prosperity. This evidence strongly supports policies that promote green technology adoption, circular economy practices, and strategic investments in human capital to foster a competitive and sustainable economic base for the reservoir region.

Importantly, the multifactorial nature of these techno-economic trade-offs presents a complex optimization challenge beyond conventional analytical approaches. The integrated EW-AHP and fuzzy logic framework employed here provides a robust foundation for such assessment. However, artificial intelligence (AI) and machine learning (ML) technologies can significantly extend this analytical capability by handling higher-dimensional datasets, identifying non-linear relationships between economic and environmental variables, and generating predictive scenarios for policy optimization. For instance, AI-driven systems could dynamically optimize the weightings in our model in response to real-time data on climate variables, market prices, or resource availability, moving from static assessment to adaptive management. Furthermore, AI-powered digital twins of the reservoir region could simulate the long-term economic and environmental outcomes of different investment or policy pathways (e.g., prioritizing solar vs. hydropower, or ecological compensation schemes), providing invaluable foresight for strategic planning. Thus, while our framework provides a critical snapshot, the integration of AI represents the next frontier for solving the complex, interconnected techno-economic problems inherent in achieving sustainable basin development.

7. Conclusions

The study developed and applied an integrated framework combining Eco-Benefits-analytic hierarchy process (EW-AHP) with fuzzy logic to assess multidimensional Eco-Benefits in major reservoir areas of China's Yellow River Basin from 2015 to 2022. The core objective was to transcend isolated assessment models and quantitatively capture key interactions among economic development, environmental protection, and social responsibility. The findings validate the core research hypotheses and provide a generalizable paradigm for sustainable watershed management, holding significant global implications.

7.1. Hypothesis Validation and Core Innovations

This analysis robustly validated the hypotheses. The integrated framework successfully quantified spatiotemporal dynamics of Eco-Benefits while effectively managing indicator weight subjectivity and classification uncertainty. Significant spatial disparities emerged, fundamentally driven by economic structural differences and, more critically, variations in the capacity to manage economic–social–environmental trade-offs. This approach demonstrates sustainability at both environmental and economic levels. Regions prioritizing integrated development (Type 1) achieved decoupling trends, improving environmental quality and social welfare while maintaining stable economic growth. This empirically challenges the prevalent notion of a strict and inevitable trade-off between economic growth and ecological conservation—at least within manageable socio-ecological systems.

This study provides a systematic, actionable methodology offering critical insights for global watershed governance. transiting from theoretical exploration to an operational model that offers replicable methods for measuring indicators typically described only qualitatively. This provides empirical validation that social development is not merely an outcome of long-term sustainability but a key driver. Furthermore, this methodology extends beyond this case study, offering a scalable blueprint for assessing Eco-Benefits in major global watersheds facing similar pressures, such as the Mekong, Nile, and Danube rivers.

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7.2. Global Application Pathways and Policy Implications

The tension between economic growth and socio-environmental health is not inevitable but instead a consequence of governance choices. The three development paradigms identified in this study—Balanced Transition, Growth at Risk, and Stalled Development—also provide diagnostic insights that can help classify sub-regions in other basins and guide tailored interventions. For instance, the distinction between resource-intensive growth trajectories and conservation-led pathways may resonate with ongoing debates in the Mekong about hydropower versus ecosystem services or in the Nile about irrigation expansion versus wetland preservation.

Beyond the specific findings for the Sanmenxia region, the integrated EW-AHP and fuzzy logic framework offers a transferable methodological core that can inform sustainability assessments in other major river basins (e.g., Mekong, Nile, Danube). By integrating economic, environmental, and social data, this study aims to contribute to a more nuanced and context-sensitive approach to global watershed sustainability, delivering significant value to researchers, policymakers, and investors committed to implementing sustainable development goals in critical global watersheds, helping forge a truly sustainable and resilient future. However, it is essential to recognize that direct replication of the indicator set, weights, or evaluation thresholds is neither feasible nor advisable, given the profound differences in ecological baselines, economic structures, and governance systems across basins. Instead, the value of the framework lies in its capacity to be adapted through a systematic process of contextualization.

In sum, the proposed framework is not a one-size-fits-all blueprint but a flexible analytical tool whose power emerges through thoughtful adaptation to local circumstances. By highlighting the necessary steps for such adaptation, this study aims to contribute to a more nuanced and context-sensitive approach to global watershed sustainability.

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