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Spatial Evolution and Driving Factors of Ecological Well-Being Performance in the Yellow River Basin

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Abstract: Ecological well-being performance (EWP) is a key indicator of sustainable development and has garnered significant research attention. This study measures the overall and stage-by-stage efficiency of the urban agglomerations in the Yellow River Basin based on the ends–means framework of steady-state economics. This study then delves into the spatiotemporal transfer characteristics of EWP through Moran's I, and spatial Markov chains. Additionally, this research investigates the factors influencing EWP using a random forest model. The findings indicate a notable enhancement in EWP in the urban agglomerations in the YRB from 2006 to 2021, showing clear spatial agglomeration patterns. The shift in EWP types displays a "path dependence" effect, with distinct evolutionary paths influenced by spatial lag effects. Ecological input emerges as a key internal driver of EWP, while urbanization and technological advancements are highlighted as significant external factors. Industrial agglomeration and industrial structure also contribute to improving EWP. The findings of this study help to clarify the spatial and temporal characteristics of ecological welfare performance and its driving mechanisms in the urban agglomerations of the Yellow River Basin. This is conducive to the achievement of high-quality urban transformation and regional green development, and it provides a reference for the construction of an ecological civilization.

Keywords: ecological well-being performance; stage decomposition; random forest; driving factors; Yellow River Basin

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1. Introduction

With the evolution of society, scholars have observed a shift in the relationship between economic and ecological systems. There has been a transition from an "empty world" to a "full world" [1–4], where ecological capital is becoming increasingly scarce [5]. As demands for economic growth continue to escalate, the extensive exploitation of resources and energy has resulted in a significant depletion of natural capital and ecological services, imposing stricter constraints on economic and social development [6]. Human activities have exerted unprecedented pressure on ecosystems, prompting a reevaluation of the relationship between humans and nature [7]. In 2015, the United Nations General Assembly introduced 17 Sustainable Development Goals (comprising 169 targets) to guide global sustainable development progress by 2030, promoting the harmonious development of global society, the economy, and the environment [8]. Against this macro backdrop, the critical issue that governments worldwide need to reassess is how to balance natural resource consumption, economic growth, and welfare improvements within the limits of ecological carrying capacity. Consequently, the concept of EWP has garnered attention globally.

Despite China's impressive economic progress in recent decades, issues related to its natural resource consumption and environmental pollution remain prominent. Additionally, rapid economic growth in China has not necessarily translated into higher levels of well-being [9]. These challenges not only impact the high-quality development of the Chinese economy but also impede the establishment of a new model for coordinated regional

development in China. Consequently, the Chinese government has proposed accelerating reforms within the ecological civilization system, promoting green development and simultaneously advancing social equity to enhance people's well-being. Therefore, the primary concern facing the Chinese government is how to continually enhance human welfare while staying within the ecological carrying capacity [10]. EWP, a crucial indicator of the welfare derived from ecological resource consumption [11], can signify a country's or region's capacity for sustainable development. Hence, enhancing EWP has become a necessity for China's comprehensive green transformation of its economy and society [12].

The YRB comprises four major geomorphic units, the Qinghai–Tibet Plateau, the Inner Mongolia Plateau, the Loess Plateau, and the North China Plain, along with three major terraces in China's topography. This makes it a crucial ecological barrier and economic development zone in China. The basin plays a vital role in stabilizing national economic development and consolidating ecological security [13]. However, the YRB exhibits significant economic development disparities, severe ecological and water resource issues, and acute development contradictions [14], leading to a situation of severe imbalance and inadequacy in terms of development. As a result, the promotion of its sustainable economic development within the ecological carrying capacity, along with the improvement of its residents' well-being, has garnered high attention from various levels of Chinese government. In 2021, the Chinese government designated the ecological protection and high-quality development of the YRB as a major national strategy, emphasizing the improvement of the ecological environment in the basin and the enhancement of people's well-being. Faced with the important strategic goal of achieving ecological protection and high-quality development in the YRB in a new era, advancing sustainable development has become imperative. EWP, as an indicator of efficiency in transforming natural consumption into human well-being, will help with ecological security and achieving coordinated development between social development and residents' ecological well-being.

2. Literature Review

2.1. EWP Reported in the Selected Literature

The concept of EWP is rooted in the principles of sustainable development, which aim to maintain a balance between economic, social, and environmental systems to enhance human well-being [15]. Daly's theory of steady-state economics emphasizes the importance of controlling energy and material consumption within ecological limits for sustainable development [16,17]. While Daly's propositions are well known in the field of ecological economics, material flow measurements are too difficult to use in guiding policy makers' discussions of sustainable development [18]. The ecological footprint concept, introduced by Rees and Wackernagel [19], offers a more comprehensive assessment of natural resource consumption and environmental impact, advancing the understanding and adoption of EWP in the academic research. Zhu et al. [20] built upon Daly et al.'s ideas, defining EWP as the efficiency of converting ecological resource consumption into happiness. In his subsequent work, Zhu utilized the "purpose–means" framework of steady-state economics [21], incorporating economic output as an intermediate means. This allowed for the decomposition of ecological welfare performance into economic performance in terms of natural consumption and welfare performance in terms of economic growth [22]. EWP encompasses both ecological consumption and human well-being, two crucial indicators emphasized within sustainable development. It encourages countries to enhance human well-being in an eco-efficient manner [23]. EWP is a novel perspective on sustainable development research [24].

Scholars have made advancements in measuring ecological welfare performance by focusing on the indicator selection and calculation methods. There is debate among scholars regarding how to measure human well-being, with indicators such as Happy Life Years [25], Happy Plant Index [26], Happy Nation Index [27], and average life expectancy [28] commonly considered. The HDI index, proposed by the United Nations Development Program (UNDP), is widely used by scholars [29–31], although it is more suitable for global compar-

isons. In smaller-scale research, where acquiring HDI data is challenging, scholars often use comprehensive well-being as a proxy. For instance, Wang [32] assessed changes in Chinese provinces' ecological welfare performance by comparing comprehensive well-being with per capita ecological footprint. Wang suggested that the excessive growth rate of its per capita ecological footprint contributed to the decline in China's EWP.

In the assessment of EWP, two mainstream methods are commonly employed. The first method utilizes the ratio approach, with the HDI or the improved HDI as the numerator and ecological footprint as the denominator [33]. The other research method focuses on the input–output perspective of Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) to assess the sustainability of regions based on the welfare level of ecological input and output. These methods operate under the premise that EWP should achieve the maximum welfare output with a given level of ecological input, in line with the SFA and DEA models. For example, Dietz et al. [34] developed an SFA model using indicators such as life expectancy, per capita GDP, and education level as outputs and ecological footprint as the input to analyze the effective welfare of 135 countries. Their findings suggested that enhancing the efficiency of human and natural resource utilization can lead to simultaneous improvements in welfare and ecological protection. Dimaria [35] employed an enhanced DEA method utilizing ecological footprint to evaluate the EWP of different countries. Similarly, Bian et al. [36] utilized the Super-SBM model to determine the EWP of 30 provincial capital cities in China over a five-year period. However, traditional DEA methods often treat ecological welfare performance as a "black box," overlooking the intermediate stages of the inputs and outputs, which can hinder the identification of inefficiencies. In traditional DEA models, researchers often utilize per capita GDP as the final output, which may conflict with the concept of sustainable development in steady-state economics. Gómez-Calvet et al. [37] introduced a two-stage DEA model to assess the progression of environmental performance in EU countries between 1993 and 2010. Some researchers [38,39] have applied a two-stage network DEA model using Zhu's [22] decomposition formula to compute the ecological welfare performance, ecological–economic efficiency, and economic welfare efficiency of sub-stages, offering specific policy suggestions for analyzing input redundancy. Unlike the ratio method, which can be volatile due to changes in the numerator and denominator, and unlike SFA models, which necessitate assumptions about the production functions, DEA methods can account for undesirable outputs such as pollutants in the analysis. This method has gained traction among scholars as an effective approach to gauging EWP. Furthermore, coupling coordination models have been employed to evaluate EWP. For instance, Li [40] utilized a coupling coordination degree model to evaluate the EWP of Chinese cities based on the coordination of resource consumption, the ecological environment, and social welfare.

EWP is a multifaceted system influenced by ecological, economic, and social factors. Previous scholarly discussions on the influencing factors for EWP have yielded inconsistent results. Common [25] and Dietz [6] suggest a negative relationship between economic growth and EWP, whereas Jorgenson [28] argues against this notion. Zhang et al. [41] found an inverted U-shaped relationship and a U-shaped relationship between eco-consumption and income in developed and developing countries, respectively. Controversy also exists regarding the driving forces behind EWP. Feng [42] analyzed the impact of greening the industrial structure and green total factor productivity on EWP using spatial econometric models. His findings suggest that green total factor productivity has become the primary driving force of EWP over industrial greening transformation in various Chinese provinces. Similarly, Li [43] utilized geographically weighted regression methods to identify population urbanization and industrial urbanization as key factors influencing EWP. Zhu [44] asserts that technological progress, industrial structure, environmental regulations, and population density have varying degrees of impact on EWP.

2.2. The Research Gap and Aim

1. Existing research findings hold significant academic value for studying EWP and guiding sustainable development. However, further in-depth research is needed on a few key issues. Firstly, the current research mainly focuses on the national and provincial levels, and there is not yet a wealth of research on the Yellow River Basin, especially from the perspective of urban agglomerations. Urban agglomeration plays a crucial role in regional development and is becoming the primary spatial form of development [45]. Evaluating EWP in urban agglomeration involves identifying change patterns among cities of similar types or proximity, which differs from evaluations targeting individual cities. For instance, Hu et al. [46] discussed the spatial agglomeration patterns of the Yangtze River Delta urban agglomeration, while Xia and Li [39] used social network analysis to identify the spatial correlation among cities in the Beijing–Tianjin–Hebei urban agglomeration. Therefore, there is still room for expansion in spatial-scale studies. Secondly, while the existing research has analyzed the spatial differentiation of EWP from a geographical perspective [47,48], most studies have focused on distributional differences and characteristics in space. Limited attention has been given to the temporal and spatial dynamic transfer patterns of EWP. This study utilizes multiple methods such as Moran's I, LISA clustering, and Markov chain analysis to comprehensively examine the spatiotemporal distribution and evolution patterns of EWP in the YRB urban agglomeration. This can help identify the weaknesses and strengths of EWP in different regions, providing policy references for ecological protection and high-quality development in the basin. Finally, despite scholars discussing the factors influencing EWP, there is still no consensus on its key drivers. To explore the driving factors and mechanisms of EWP, this study uses a random forest model to quantify the relative importance of influencing factors and determine key factors. The analysis results from the random forest model, along with partial correlation plots, can reveal how EWP changes with driving factors.
2. Therefore, based on the framework of steady-state economics, this paper calculates and analyses the EWP of the Yellow River Basin urban agglomeration. The aim is to conduct a comprehensive analysis of the spatiotemporal evolution mechanisms and driving factors of ecological welfare performance. This analysis aims to effectively enhance the welfare levels of urban residents within ecological thresholds, promote high-quality transformation in ecologically sensitive areas, and advance ecological civilization construction. Additionally, this paper measures environmental well-being using ecosystem service value, considering the diverse services and functions provided by ecosystems to humans. Incorporating ecosystem services into decision making about ecological welfare performance can more effectively guide sustainable economic development patterns.

3. Methods and Materials

3.1. Study Area

The urban agglomeration in the YRB has played a significant role in fostering a harmonious relationship between humans and nature throughout history. It encompasses economically developed areas such as the Shandong Peninsula, as well as regions with lower economic levels such as Lanzhou–Xining and Guanzhong Plain. This area features vast plains suitable for agriculture and economic activities, along with important ecological zones such as Sanjiangyuan, the Qilian Mountains, and Ruoergai. In 2021, the Chinese government proposed developing the five urban agglomerations in the YRB into a "five-pole" development power pattern. These poles include the Shandong Peninsula (SP), Central Henan (CH), Guanzhong Plain (GP), Yellow River Bend (YB), and Lanzhou–Xining (LX) urban agglomerations (Figure 1). These urban areas are part of the 19 national-level urban agglomerations outlined in the "14th Five-Year Plan". The SP, CH, and GP urban agglomerations are classified under "development and growth," while the YB and LX urban agglomerations are categorized as "development and cultivation". Core cities in

these urban agglomerations include Xining, Lanzhou, Yinchuan, Hohhot, Xi'an, Taiyuan, Zhengzhou, Jinan, and Qingdao. Xi'an and Zhengzhou are designated as national central cities, with Jinan being a strong contender for this title.

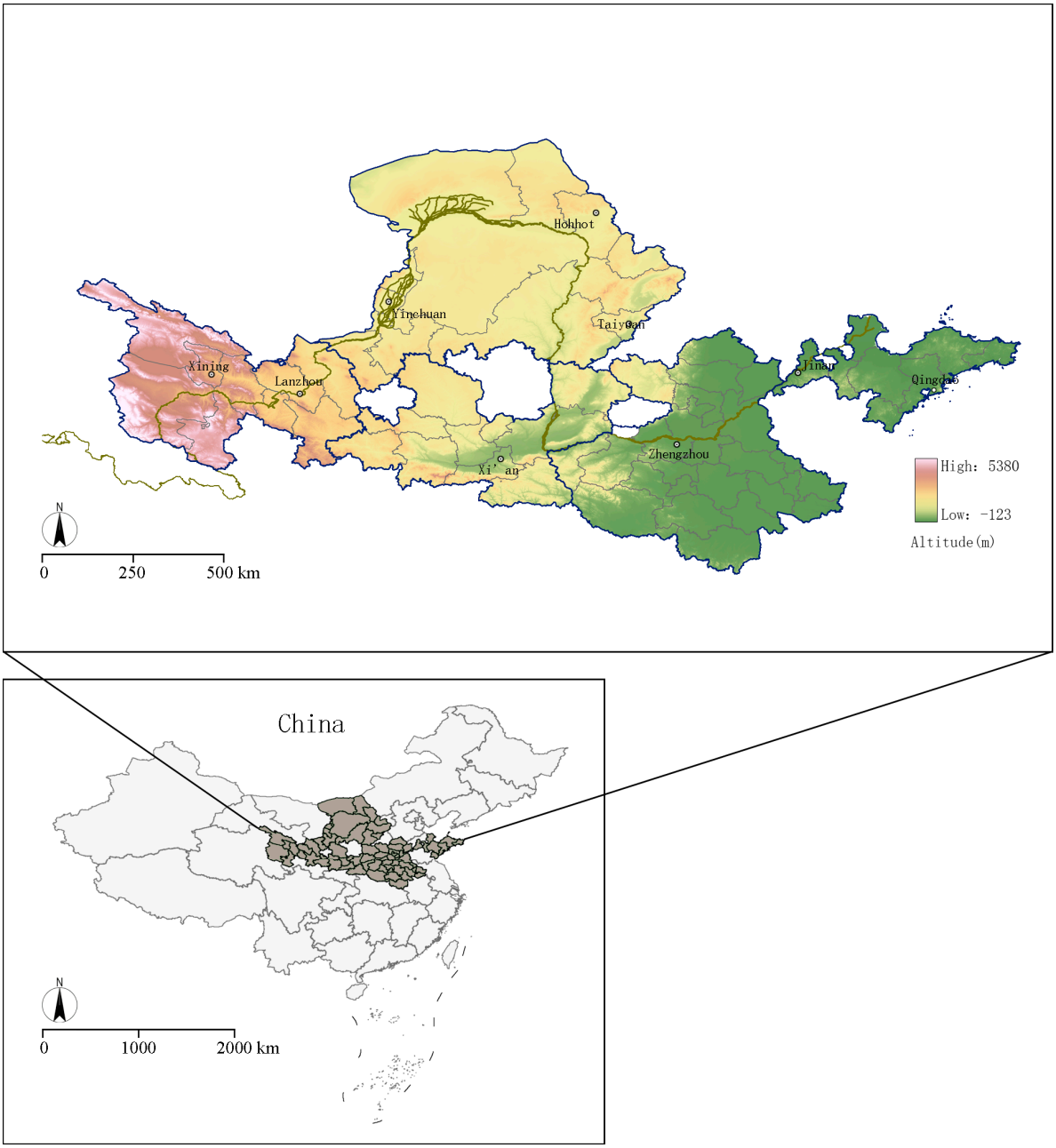


Figure 1. Geographical location of YRB (based on the Chinese Ministry of Natural Resources Standard Map Production (Survey Approval Number GS (2023) 2767); the base map boundaries remain unaltered).

3.2. Methods

Building on Zhu's research [22], this study breaks down the transformation process of EWP into two distinct stages, the conversion from ecological inputs into economic outputs and the subsequent conversion from economic outputs into welfare levels, as illustrated in Equation (1). This research categorizes EWP into ecological–economic efficiency (Stage 1) and economic welfare efficiency (Stage 2). During Stage 1, which functions as the production phase, a critical examination of the interplay between economic growth and

environmental resources is imperative to maximize economic value while minimizing resource consumption and environmental pollution. Moving on to Stage 2, which acts as the service phase, economic growth plays a vital role in providing material capital for societal development, ultimately aiming to enhance residents' welfare levels (Figure 2).

$$EWP = \frac{WB}{EI} = \frac{GDPPC}{EI} \times \frac{WB}{GDPPC} = EPNC \times WPEO, \quad (1)$$

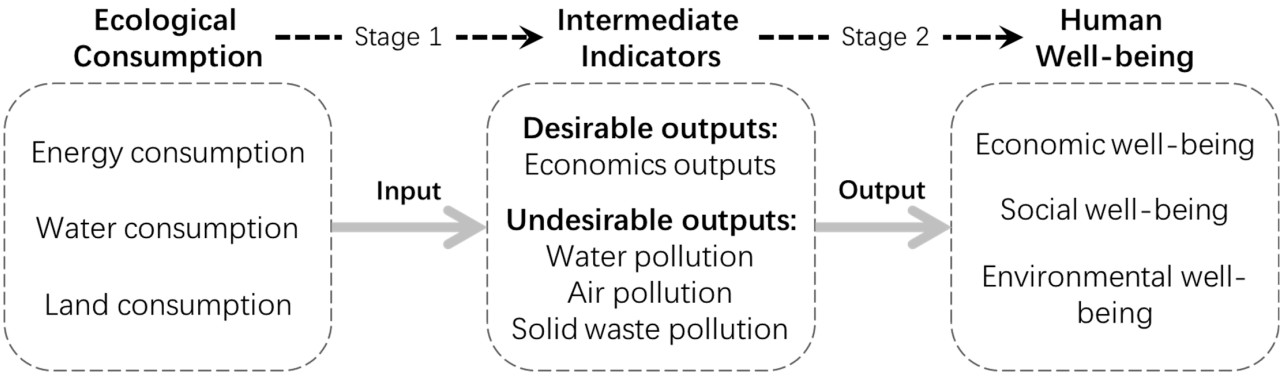


Figure 2. Stage decomposition of EWP.

In the above equation, *WB* is the level of human welfare, *EI* is the ecological input, *GDPPC* is the GDP per capita, *EPNC* is the economic performance of natural resource consumption, and *WPEO* reflects the welfare performance of economic output.

3.2.1. The US-NSBM Model

The DEA model is widely used to measure efficiency, as it can handle both desirable and undesirable outputs simultaneously without assuming a specific production function [49]. It is favored by scholars for its ability to fully consider ecological resource consumption and welfare improvement [50]. However, traditional DEA models are limited in evaluating system efficiency, as they treat the production process as a "black box" [51]. Tone [52] proposed a network DEA model with slack variables to assess sub-stage efficiency alongside overall efficiency. Building on this, Huang [53] introduced a two-stage network model with undesirable outputs and super-efficiency (US-NSBM), which can address ranking issues with undesirable outputs and the production frontier. This study employs the US-NSBM model to measure EWP using the formula provided.

$$\rho^*_{ewp} = min \frac{\sum_{k=1}^{K} \omega^k \left(1 + \frac{\frac{1}{m_k}\sum_{i=1}^{m_k} s_i^k}{x_i^k}\right)}{\sum_{k=1}^{K} \omega^k \left[1 - \frac{1}{v_{1k}+v_{2k}}\left(\sum_{r=1}^{v_{1k}} \frac{s_r^{gk}}{y_r^{gk}} + \sum_{r=1}^{v_{2k}} \frac{s_r^{bk}}{y_r^{bk}}\right)\right]} \quad (2)$$

$$s.t. \quad x^k - \sum_{j=1,\neq 0}^{n} \lambda_j^k x_j^k + s^{k-} \geq 0$$

$$\sum_{j=1,\neq 0}^{n} \lambda_j^k y_j^{gk} - y^{gk} + s^{gk} \geq 0$$

$$y^{bk} - \sum_{j=1,\neq 0}^{n} \lambda_j^b y_j^{bk} + s^{bk} \geq 0$$

$$1 - \frac{1}{v_{1k}+v_{2k}}\left(\sum_{r=1}^{v_{1k}} \frac{s_r^{gk}}{y_r^{gk}} + \sum_{r=1}^{v_{2k}} \frac{s_r^{bk}}{y_r^{bk}}\right) \geq \varepsilon$$

$$z^{(k,h)}\lambda^h = z^{(k,h)}\lambda^k$$
$$\sum_{i=1,\neq 0}^{N} \lambda_j^k = \sum_{k=1}^{K} w^k = 1$$
$$\lambda^k, s^{k-}, s^{gk}, s^{bk}, w^k \geq 0$$

In Equation (2), x, y^g, y^b, and z represent inputs, desirable outputs, undesirable outputs, and intermediate outputs, respectively. m_k and v_k denote the numbers of inputs and outputs in stage k, λ^k represents the model weight combination for stage k, and ω^k is the weight for stage k. Since this study divides ecological welfare into two stages, k takes the value of 2. Considering the significant role of ecological–economic efficiency and economic welfare efficiency in sustainable development, the weights for both stages are set to be the same, i.e., $\omega^1 = \omega^2 = 0.5$. s^{k-} and s^{k+} represent the slack variables for inputs and outputs, respectively, in stage k, while s^g and s^b denote the slack variables for desirable outputs and undesirable outputs, respectively.

The efficiency score calculation formula for each stage is shown in Equation (3):

$$\rho_{ewp}^{*1} = \frac{1 + (1/m_1)\left(\sum_{i=1}^{m_1}\left(s_i^{1-*}/x_i^k\right)\right)}{1 - (1/\zeta)\left(\sum_{r=1}^{\zeta}\left(s_r^{1+*}/z_r\right)\right)} \tag{3}$$

$$\rho_{ewp}^{*2} = \frac{1 + (1/\zeta)\left(\sum_{r=1}^{\zeta}\left(s_r^{1+*}/z_r\right)\right)}{1 - (1/(v_{12}+v_{22}))\left(\sum_{r=1}^{v_{12}}\left(s_r^{g*}/y_r^g\right) + \sum_{r=1}^{v_{22}}\left(s_r^{b*}/y_r^b\right)\right)}$$

In the above formula, ζ represents the number of intermediate variables. s_i^{1-*} and s_i^{1+*} are the optimal slack variables for inputs and outputs, respectively. s_r^{g*} and s_r^{b*} are the optimal slack variables for desirable and undesirable outputs, respectively. v_{12} and v_{22} represent the number of desirable and undesirable outputs, respectively. When the overall efficiency and the efficiencies of all sub-stages are greater than or equal to 1, it can be considered that the DMU is relatively effective.

3.2.2. Moran's I

Moran's I can be utilized to assess the presence of spatial autocorrelation in EWP [54]. The formula for calculation is as in Equation (4):

$$\text{Moran's } I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}\left(EWP_i - \overline{EWP}\right)\left(EWP_j - \overline{EWP}\right)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}} \tag{4}$$

In the equation, S^2 represents the variance of EWP; ω_{ij} denotes the spatial weight matrix, with this study using a spatial adjacency weight matrix to depict the spatial lag relationship among cities; and n represents the total number of cities. Moran's I ranges from -1 to 1, with values above 0, below 0, or equal to 0 indicating positive spatial autocorrelation, negative spatial autocorrelation, and random distribution, respectively. To analyze the spatial correlation between city i and its neighbors, the local Moran's I can be employed, with the calculation formula as in Equation (5):

$$\text{Moran's } I_i = \frac{\left(EWP_i - \overline{EWP}\right)}{S^2}\sum_{j=1}^{n} w_{ij}\left(EWP_j - \overline{EWP}\right) \tag{5}$$

A positive I_i value indicates that the city shares similar characteristics with its neighboring cities in space, manifested as "high–high" or "low–low" clustering on the LISA cluster map. Conversely, a negative I_i value suggests dissimilarity in the spatial characteristics between the city and its neighbors, observed as "high–low" or "low–high" clustering on the LISA cluster map.

3.2.3. Spatial Markov Chains

The Markov chain is a discrete process of both time and states, suitable for analyzing regional evolution processes without memory effects. A spatial Markov chain combines a traditional Markov chain with spatial lag, allowing for analysis of the transition patterns of the EWP types while considering spatial spillovers. If EWP is divided into K categories, it can form a $k \times k$ transition probability matrix, expressed as in Equation (6):

$$P = (P_{ij}) = \begin{bmatrix} p_{11} & p_{12} & p_{13} & \cdots \\ p_{21} & p_{22} & p_{23} & \cdots \\ p_{31} & p_{32} & p_{33} & \cdots \\ \cdots & \cdots & \cdots & \cdots \end{bmatrix}, P_{ij} = \frac{n_{ij}}{n_i} \quad (6)$$

P_{ij} represents the probability of EWP transitioning from type i to type j from year t to year $t + k$, where n_{ij} denotes the sum of cities transitioning from type i to type j during the study period, and n_i represents the number of cities initially belonging to type i.

The spatial Markov chain model considers spatial interactions by incorporating the spatial lag operator into the transition probability matrix. It decomposes the traditional Markov chain into multiple conditional transition probability matrices, providing a better understanding of the relationship between EWP type transfer and domain cities. The calculation formula is represented as $Lag_i = \sum_j W_{ij} EWP_j$. Here, W_{ij} denotes the spatial weight matrix, where adjacent areas are assigned a weight of 1 and non-adjacent areas are assigned a weight of 0.

3.2.4. The Random Forest Model

EWP is a multifaceted concept that encompasses ecological, economic, and social dimensions, influenced by various factors. Unlike traditional regression models, the random forest algorithm does not rely on strict assumptions, reducing issues such as multicollinearity and decreased degrees of freedom. This approach leads to more robust results [55]. The random forest model comprises multiple decision trees, with EWP as the continuous response variable. Each decision tree aims to minimize the sum of squared residuals between the predicted and actual EWP, selecting the optimal feature vectors. By conducting multiple random samplings, a collection of decision trees is generated, and their predicted results are averaged to produce the random forest model (Figure 3).

The formula for calculating the feature vectors of decision trees is as in Equation (7):

$$\min_{j,m} \left[\sum_{q_i \in R_1(j,m)} \left(q_i - \widehat{q_{R_1}}\right)^2 + \sum_{q_i \in R_2(j,m)} \left(q_i - \widehat{q_{R_2}}\right)^2 \right] \quad (7)$$

The symbols $\hat{q_{R_1}}$ and $\hat{q_{R_2}}$ represent the mean of the two groups of samples after partitioning, calculated by Equation (8):

$$\widehat{q_{R_1}} = \text{mean}[q_i | q_i \in R_1(j,m)] \quad (8)$$

$$\widehat{q_{R_2}} = \text{mean}[q_i | q_i \in R_2(j,m)]$$

R_1 and R_2 denote the different datasets after partitioning, and q_i represents the actual value of EWP. The objective of the calculation is to minimize the total residual sum of squares (RSS) between the predicted and actual values of EWP. This process is repeated 500 times to establish the random forest model.

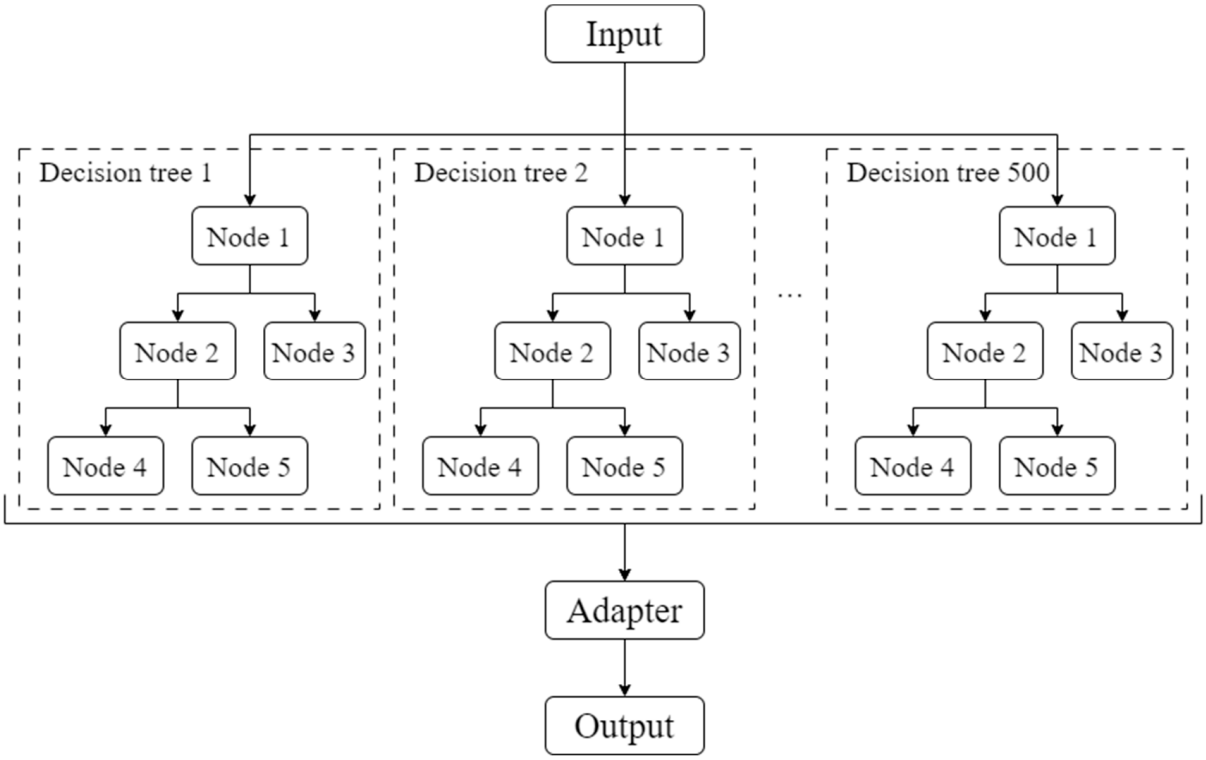


Figure 3. Schematic diagram of the random forest model.

The overall flow of this work is depicted in Figure 4.

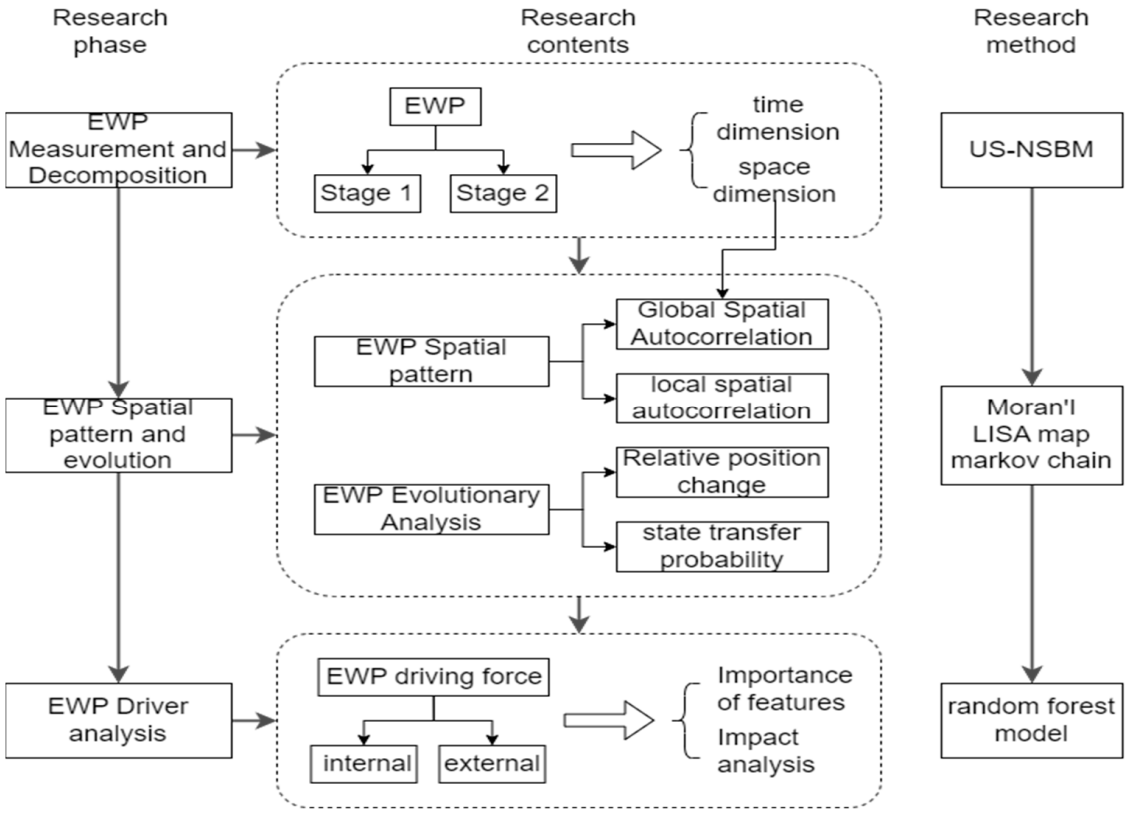


Figure 4. Research flowchart.

3.3. Indicator Selection and Data Sources

3.3.1. Indicator Selection

Based on Equation (1) and relevant studies by scholars, an evaluation index system for EWP was constructed, guided by the principles of scientificity, systematicity, and operationality (Table 1). In a "full world" context, natural capital is inherently scarce, necessitating human activities to operate within the carrying capacity of resources. Resource consumption plays foundational and binding roles in ecological civilization development. For instance, energy serves as a crucial engine driving economic and social development [56]. Land resources are essential for human survival and development [57]. Water resources are fundamental natural resources necessary for human survival, economic development, social stability, and ecosystem cycles [58]. The consumption of these resources inevitably impacts the goal of improving people's livelihoods and must be considered as a key input indicator in an ecological welfare performance assessment. Therefore, this study selects energy consumption, land consumption, and water resource consumption as the indicators of resource consumption in ecological welfare performance. Specifically, water resource consumption is measured by per capita industrial water use [11], land consumption by per capita built-up area [59], and energy consumption by per capita comprehensive energy consumption (standard coal) [60]. Welfare includes economic welfare, social welfare, and environmental welfare [39]. Economic welfare includes indicators such as the per capita disposable income of urban and rural residents, per capita social retail sales, Engel's coefficient, and price level, as referenced in the existing literature [11,39,46]. Social welfare includes indicators related to social security, healthcare, education, and public facilities. Environmental welfare is determined by the gas regulation value, climate regulation value, and cultural service value provided by the ecological environment [61,62]. Per capita GDP, representing economic output, serves as an intermediate variable [20]. Additionally, environmental pollution is considered an undesirable output at the production stage, characterized by indicators of water, air, and solid waste pollution [63]. Summary statistics for each indicator are provided in Appendix A.

Table 1. The evaluation index system of EWP.

Dimension	Category	Secondary Indicator	Indicator	Calculation Method
Stage 1	Inputs	Ecological resource inputs	Water consumption	Per capita industrial water consumption
			Land consumption	Per capita built-up area
			Energy consumption	Comprehensive energy consumption per capita (standard coal)
	Outputs	Desired outputs	GDP per capita	GDP per capita converted into 2006-based constant prices
		Undesired outputs	Environmental pollution	The entropy weighting method was used to determine the weights of PM2.5, wastewater emissions, industrial emissions, and solid waste generation indicators and to synthesize the pollution composite index.

Table 1. *Cont.*

Dimension	Category	Secondary Indicator	Indicator	Calculation Method
Stage 2	Inputs	Economic output	GDP per capita	
	Outputs	Well-being	Economic well-being	It is made up of a combination of the indicators of disposable income per capita for urban and rural residents, Engel's coefficient for residents, the consumer price index, and the total retail sales of consumer goods per capita.
			Social well-being	Composite of basic medical care participation rate, basic old-age pension participation rate, unemployment insurance participation rate, minimum wage, number of beds per 10,000 people, number of books per capita in public libraries, and teacher-to-student ratio indicators.
			Environmental well-being	The sum of the values of gas regulation per capita, the value of climate regulation per capita, and the value of cultural services per capita. Referring to the study results of Xie et al. [64], China's equivalence factors are adjusted to those of the Yellow River Basin by using net primary productivity for the calculation [65].

This study examines the key driving factors of EWP in the urban agglomeration of the YRB. Internal driving factors include ecological input, economic output, and well-being level, as well as first-stage and second-stage efficiency. Twelve factors have been selected as external influences on EWP, including per capita ecosystem service value (ESV), urbanization level (URB), population density (PD), urban administrative level (CL), road network density (RD), industrialization level (IL), energy use efficiency (EE), technological progress (TC), industrial structure (INS), industrial agglomeration (INA), economic openness (OPEN), and environmental regulations (ENR). These indicators cover ecological, economic, and social systems, offering a thorough evaluation of EWP's influencing factors. Descriptive statistical indicators for each influencing factor can be found in Appendix B.

3.3.2. Data Sources

Economic and social data related to each indicator from 2006 to 2021 were collected from various reputable sources, such as the China City Statistical Yearbook, the China Urban Construction Statistical Yearbook, and provincial statistical yearbooks, as well as the CSMAR and Wind databases. The land use data utilized for calculating the ecosystem service values were obtained from the CLCD dataset [66], with a spatial resolution of 30 m × 30 m. Each indicator was measured and compared on a per capita basis, with interpolation and extrapolation methods used to fill in a small number of missing data points. The influencing factors' relevant indicators were all processed using the min–max normalization method.

4. Results

4.1. Temporal Characteristics of EWP and Its Decomposition Stage

The US-NSBM model was utilized in this study to evaluate the EWP of the YRB urban agglomeration and its decomposed stage efficiency values (Figure 5). The EWP of the YRB urban agglomeration displayed an overall increasing trend from 2006 to 2021. Despite this, the overall level of EWP remained relatively low, with an average value of only 0.3649 over the study period, indicating a significant distance from the DEA production frontier.

The efficiency values in Stage 1 closely mirrored the trend in the EWP, showing a general increase, while Stage 2 efficiency exhibited more pronounced fluctuations. Between 2006 and 2015, there was a fluctuating upward trend, peaking in 2015 before declining until 2021, with a slight rebound occurring thereafter. This indicates that as ecological civilization construction advances in the YRB urban agglomeration, the government is increasingly prioritizing ecological governance and protection, resulting in a notable enhancement of ecological–economic efficiency. However, economic welfare efficiency has not kept pace with this improvement.



Figure 5. Temporal changes in EWP and decomposition stages.

From an urban agglomeration perspective within the basin, there is a clear east–high and west–low trend in EWP. The urban agglomeration with the highest EWP is the SP UA (0.4899). Within this agglomeration, the cities of Qingdao (0.6360), Weihai (0.5365), and Jinan (0.5348) rank in the top 10 among all cities in the study area, and the rest of the cities exceed the average EWP of the study area. This urban agglomeration is considered to be in the mature stage within the YRB, situated along the coast and serving as a frontier

for China's collaboration with Northeast Asia. With high economic development, well-established urban systems, sound infrastructure, and a comprehensive transportation network, residents enjoy a high level of welfare. Furthermore, the core cities of Jinan in the east and Qingdao in the west play significant roles in driving development in the surrounding areas.

The YB UA (0.4177) ranks second. This metropolitan area is an important energy and chemical industry base, including three urban agglomerations, Ningxia–Yellow River, Hubaoe, and Taiyuan, with major provincial capitals such as Taiyuan, Hohhot, and Yinchuan, as well as various energy and chemical industry bases. The region has made significant industrial advancements, benefiting from national strategies such as Western Development, West–East Power Transmission, and West–East Gas Transmission, due to its rich coal, oil, and gas resources. However, challenges such as a limited core city driving capacity, low coordination, an unbalanced industrial structure, and inadequate public services impede its sustainable economic growth. Furthermore, the region faces considerable ecological and environmental pressure, with many areas marked by characteristics such as being old revolutionary base areas, areas inhabited by ethnic minorities, remote areas, and impoverished areas and therefore lacking the necessary momentum for positive EWP trends.

The CH UA (0.3655), LX UA (0.2704), and GP UA (0.2568) rank in the bottom three. In the CH UA, with a higher proportion of low- and medium-level cities than in the SP and YB UAs as the reason for this lower ranking. The LX UA and GP UA have lower economic and welfare levels compared to the other urban agglomerations, placing them fourth and fifth in terms of EWP.

4.2. Characteristics of the Spatial Evolution of EWP

4.2.1. Characterization of Spatial Correlation

Moran's I values for EWP and its decomposition stages for the YRB urban agglomeration were computed from 2006 to 2021 and visualized using LISA cluster maps. Figure 6 illustrates that except for the second stage in 2021 where Moran's I was not significant, the Z-values of EWP and its sub-stage Moran's I exceeded the critical value of 2.58 at the 0.01 significance level for all four periods. This suggests that as the transportation infrastructure improved, the flow of factors between regions increased. Consequently, throughout the study period, the EWP of the YRB urban agglomeration displayed significant spatial autocorrelation, emphasizing notable spatial clustering characteristics.

The study area showed a variety of EWP clustering types that evolved over time. Initially, the most common type was L–L (low–low), with 18 occurrences, followed by H–H (high–high) with 3, H–L (high–low) with 1, and L–H (low–high) with 0. As time progressed, the distribution shifted to H–H (9), L–L (7), H–L (4), and L–H (2). The number of clustered areas decreased, particularly noticeable in the reduction in L–L type areas. By 2006, these areas were mainly located in a large strip south of the YRB which is gradually shrinking. By 2021, they were concentrated in the border area between the LX UA and GP UA, as well as some cities in the southwest of the CH UA, indicating a decrease in the spatial homogenization of low-level EWP clustering. The main reason for this is that this type of city is located in relatively economically underdeveloped regions in China. These cities mostly rely on the development of traditional resources and lack advanced technology empowerment. Consequently, the degree of industrial structure advancement and rationalization is low, resulting in a low level of EWP, forming low-value agglomeration areas of EWP. The H–H type areas were more spatially concentrated, primarily found in the Hetao Plain area of the YB UA, CH UA, and SP UA. This type of city can be divided into two categories. The first category includes coastal, economically developed regions with competitive advantages in terms of trade, capital, talent, and technology. These cities exhibit a high level of EWP due to the coordinated coupling of high-quality resources and industrial structure, forming high–high (H–H) agglomeration areas. The second category includes resource-rich cities that are actively undergoing transformation. For instance, Ordos

and Bayannur are significant energy resource bases in China. These cities experienced substantial growth by leveraging abundant natural resources in the early stages. Since 2012, they have actively sought to transform their economic development models to promote sustainable urban development. This includes advancing resource industries towards high-end, low-carbon development, promoting traditional industries towards green, low-carbon, and circular development, and building modern energy economic systems. Additionally, they have strengthened urban public service construction, enhanced ecological protection and restoration efforts, and improved residents' well-being. The number of H–L type areas increased by three, mainly in provincial capital cities such as Lanzhou and Taiyuan. These cities themselves have a high level of EWP, but the surrounding areas have low EWP levels. This may indicate a "siphon" effect, hindering the development of the surrounding regions and ultimately forming H–L types. The L–H clusters were dispersed and showed frequent changes throughout the study period, without a clear trend.

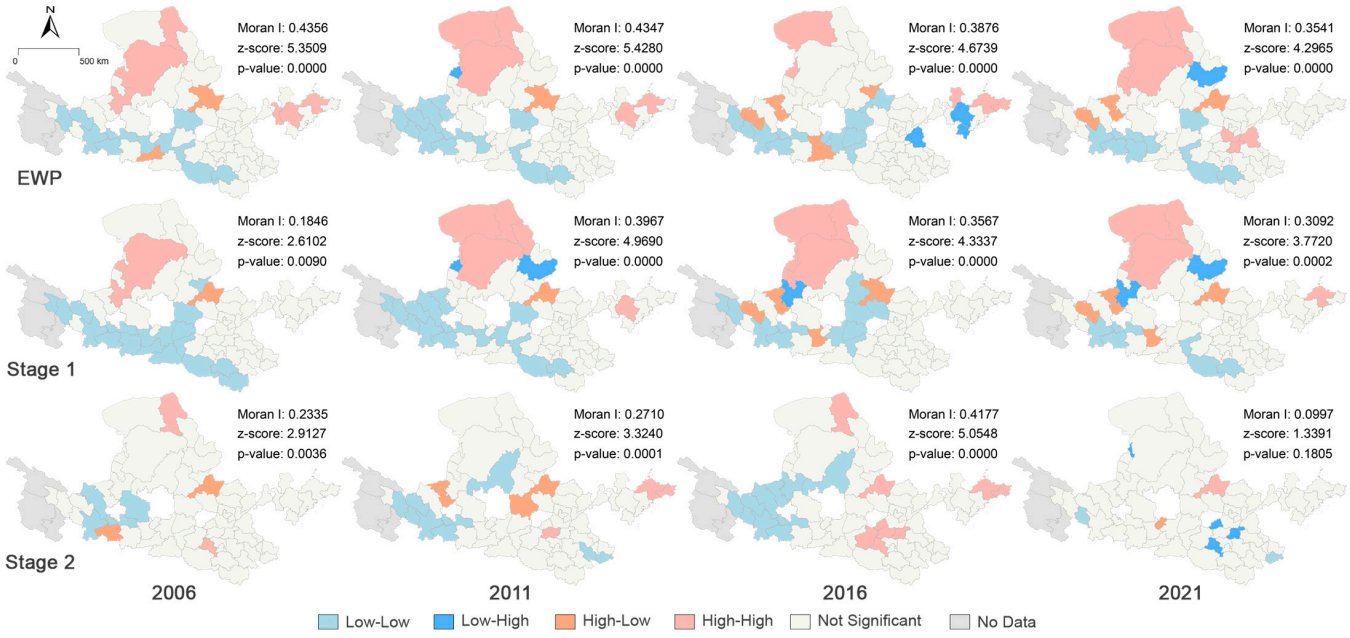


Figure 6. LISA clustering of EWP and decomposition stages.

In the context of the EWP Stage 1 clustering types, the progression shifted from L–L (12) > H–H (7) > H–L (3) > L–H (0) to H–H (6) = L–L (6) > H–L (4) > L–H (2), exhibiting a distribution pattern akin to that of EWP. This suggests that the alterations in Stage 1 served as the primary catalyst for changes in EWP. Moving on to EWP Stage 2, the clustering types transitioned from L–L (5) > H–H (2) > H–L (3) > L–H (0) to L–H (4) > L–L (2) > H–H (1) = H–L (1). Comparing this to Stage 1, the level of clustering decreased in Stage 2, with no discernible clustering trend evident by 2021, indicating a more noticeable shift towards spatial randomization.

4.2.2. Characteristics of EWP Type Transfer

To illustrate the changes in EWP concretely, this study employs a Markov transition matrix to analyze the dynamic transitions within the urban agglomeration of the YRB. EWP is categorized into four levels, I, II, III, and IV, which correspond to low, low–medium, medium–high, and high levels of EWP, respectively. By utilizing both traditional Markov chains and spatial Markov chains, the study computes the transition matrix of EWP in the YRB urban agglomeration to uncover the transition characteristics and evolutionary patterns of EWP. The findings are depicted in Figure 7.

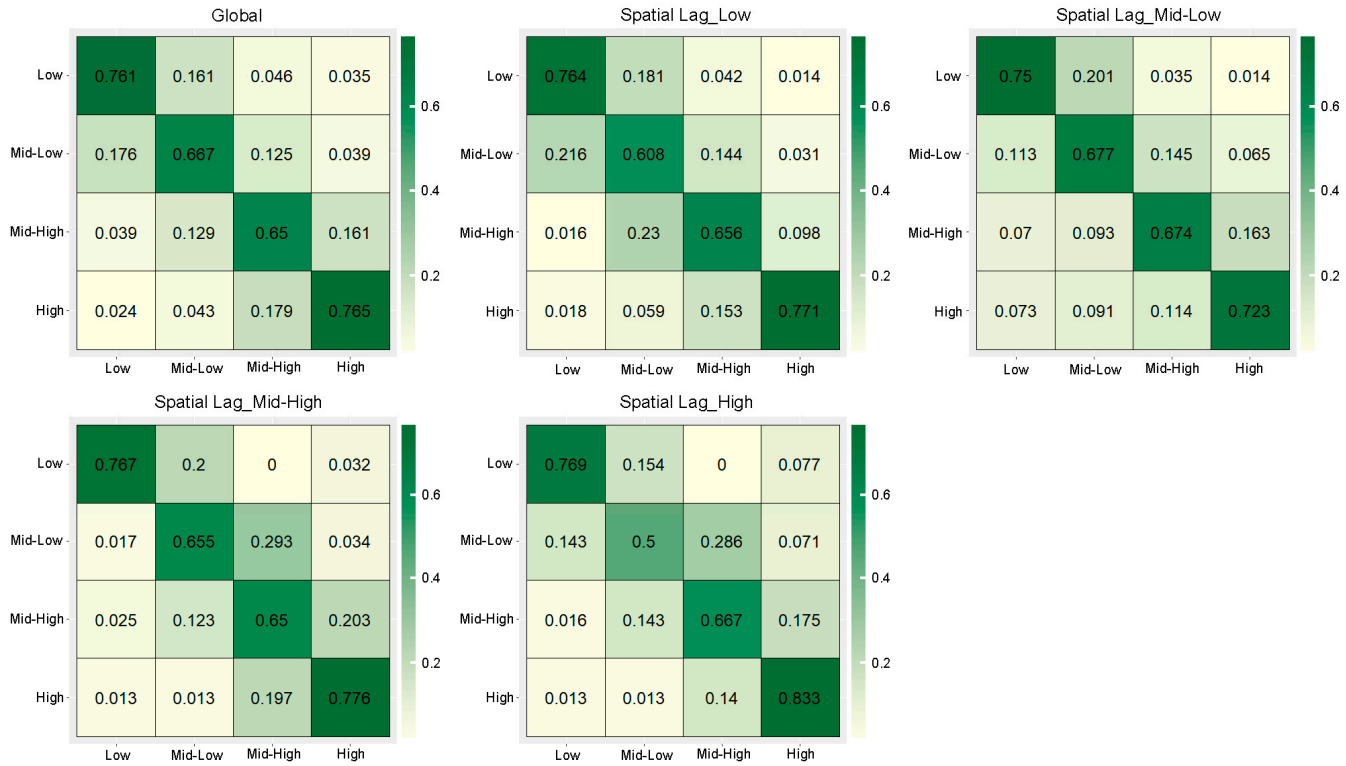


Figure 7. Markov transfer probability matrices for EWP.

The results of the traditional Markov chain transition matrix, not considering spatial lag effects, indicate that the probability values along the diagonal are significantly higher than those that are not on the diagonal. The smallest probability value on the diagonal is 0.65, suggesting a "solidification" characteristic of EWP status within the YRB urban agglomeration. Additionally, the probability values on either side of the diagonal decrease gradually, indicating a tendency for the four types of states to transition to adjacent types rather than across types. This is due to the need to address two key issues in elevating EWP: decoupling economic growth from natural resource consumption and decoupling the improvement of welfare levels from economic growth [67]. As a result, the probability of achieving significant growth in EWP in the short term is relatively low.

A traditional Markov chain typically overlooks the impact of spatial factors and only considers its own changes. To address this limitation, we enhanced the traditional Markov chain by incorporating a spatial spillover term that takes into account adjacency relationships. This allowed us to create a spatial Markov chain transition probability matrix, as illustrated in Figure 6.

During the study period, the probabilities of EWP type transitions varied significantly under different spatial lag contexts, leading to distinct evolutionary paths for EWP. Type I cities are less affected by spatial spillover effects; regardless of the type of spatial lag they face, their probabilities of upward transition are relatively similar, with probabilities of maintaining their own status consistently being above 0.75. Such cities are prone to serious path dependence, forming collapse zones for EWP. Type II and III cities exhibit similarities in their evolutionary paths. When facing type I spatial lag, the probability of downward transition is higher than that of upward transition, whereas when facing types II, III, and IV, the probability of upward transition is significantly higher than that of downward transition, indicating an overall positive trend for type II and III cities. Type IV cities have probabilities of maintaining their status above 0.72, reaching up to 0.833 when facing adjacent type IV, indicating a prominent "club convergence" effect in high-EWP cities. Incorporating spatial lag factors into the Markov transition probability matrix resulted in significant changes in the EWP state transition probabilities because high-EWP

cities and low-EWP cities have entirely different spatial spillover effects. Ecology and welfare exhibit typical public properties; higher EWP not only improves local ecological and welfare conditions, provides ecological products, and generates economic benefits but also enhances the environmental conditions of surrounding areas. On the one hand, they promote regional interaction and shared ecological achievements; on the other hand, they boost the green development level of surrounding areas through spillover effects [68]. Conversely, lower EWP levels may have an inhibitory effect on the ecology and social conditions of the surrounding areas, forming low-lying areas in terms of EWP.

4.3. EWP Driver Identification

This study utilizes the random forest model to analyze the driving factors for EWP, considering both internal and external sources. The paper uses China's "Five-Year Plans" as benchmarks and divides them into three time periods: 2006–2010, 2011–2015, and 2016–2021. Based on the annual averages, the feature importance for each of these time periods is calculated. The results, illustrated in Figure 8, reveal that Stage 1 consistently plays a more significant role in enhancing EWP compared to Stage 2. This suggests that ecological–economic efficiency is crucial for improving EWP in the YRB, supporting previous findings. The lower importance of Stage 2 may be attributed to China's policy of equalizing basic public services, which has led to notable advancements in income and consumption levels [69]. This has detached welfare levels somewhat from economic output capacity. Analysis of the input–output nodes shows that economic output was the most critical factor from 2006 to 2010, while ecological input took precedence in subsequent periods. The study indicates that, early on, maximizing economic growth drove improvements in EWP, whereas later on, the focus shifted towards enhancing ecological resource utilization efficiency. Optimizing the energy structure and improving ecological resource utilization efficiency are key strategies for enhancing EWP.

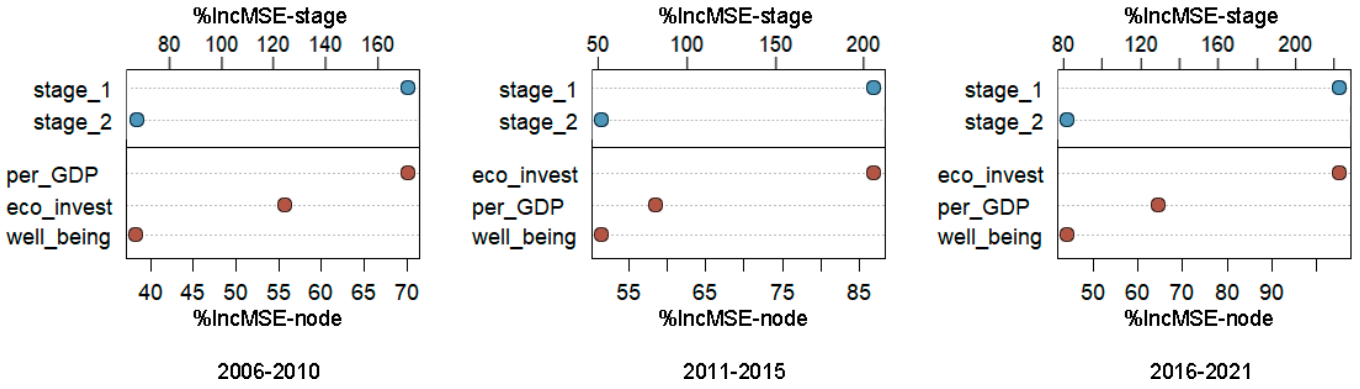


Figure 8. Feature importance of EWP internal factors.

This study delves deeper into the external factors influencing EWP. Figure 9 highlights that among the selected factors, urbanization (URB), technological progress (TC), industrial agglomeration (INA), and industrial structure (INS) have the most significant impact on EWP. Urbanization has a positive correlation with EWP. The driving force of urbanization for EWP is evident in two main aspects: (1) Urbanization facilitates the concentration of factors such as population, capital, and information, leading to improved resource utilization efficiency through economies of scale, agglomeration effects, and diffusion effects, ultimately driving economic growth; (2) urbanization encourages government investment in the livelihood sector, enhancing public services for residents and improving societal welfare levels. EWP's response to technological progress demonstrates a clear inflection point. Prior to this point, technological progress had a significant promoting effect on EWP. However, post-inflection, this effect becomes less pronounced, potentially due to the resource and environmental rebounds resulting from technological advancements [70]. Additionally, EWP's reaction to industrial agglomeration and structure shows positive

nonlinear characteristics. While these factors can enhance production efficiency, drive technological innovation, and support sustainable development, they also create challenges such as traffic congestion and air pollution. EWP also exhibits a positive nonlinear response to industrial agglomeration and industrial structure. Industrial structure and agglomeration are outcomes of resource integration, determining the operational efficiency of economic systems and serving as critical elements in coordinating economic development and environmental issues. For economic production systems, the industrial structure acts as a converter of natural resource inputs, while for ecosystems, it functions as a controller of environmental pollutants. Compared to secondary industry, tertiary industry can provide more job opportunities for residents, absorb more of the rural population, reduce energy and resource consumption, and decrease pollutant emissions, thereby improving the urban ecological environment. Additionally, tertiary industry requires less capital input but more labor input, effectively adjusting the income distribution and narrowing wealth gaps between urban and rural residents, promoting income equality, and indirectly enhancing social welfare. Therefore, expanding the scale of the tertiary industry and strategically adjusting and optimizing the industrial structure are crucial measures for enhancing ecological welfare performance.

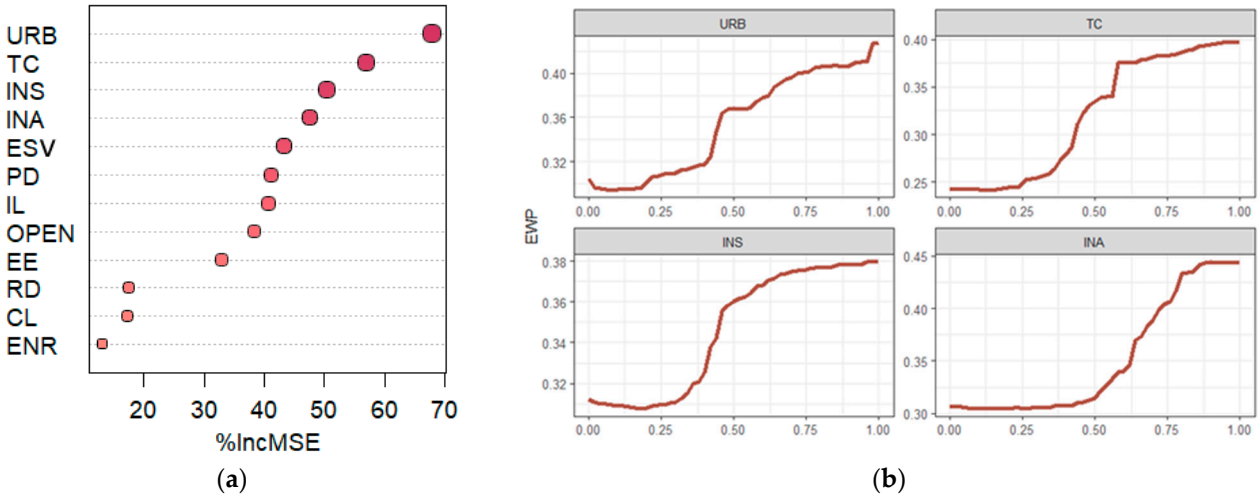


Figure 9. (**a**) Ranking of importance of EWP external features; (**b**) important feature partial dependence plot.

5. Discussion

EWP plays a critical role in guiding ecological environment protection and the high-quality development of the YRB. Wohlfart et al. [71] point out that structural contradictions between ecological protection and economic development in the basin are the primary reasons for its vulnerability and various issues, emphasizing the significant ecological constraints on sustainable development. Acting as a new research tool for evaluating the ability of ecological capital to sustainably and effectively enhance human well-being within limited boundaries, EWP is particularly relevant to the current challenges in the YRB, such as resource scarcity, environmental pollution, and ecological degradation. Therefore, this study has important implications for local governments in terms of implementing effective measures to reduce ecological resource consumption and improve the quality of life and well-being of residents.

Compared to previous studies [72,73], our research focuses on decomposing EWP to provide more targeted measures for sustainable development. We also examine the spatial distribution and agglomeration patterns of EWP and its decomposed stages, in addition to discussing the phase transition characteristics. Our findings show an uneven distribution of EWP in the YRB, with downstream areas performing better than upstream and midstream regions, consistent with Feng's results [74]. It is noteworthy that areas with low EWP

values are likely to remain unchanged, leading to the formation of EWP collapse zones and hindering sustainable development in surrounding regions. These low-value areas are predominantly found in economically underdeveloped regions known as old revolutionary base areas, areas inhabited by ethnic minorities, remote areas, and impoverished areas, thereby highlighting the challenges faced in balancing ecological protection and economic growth for sustainable development. This type of region should optimize its economic model, take "green, recycling, and low-carbon" as its guiding principles, vigorously develop an eco-economy based on a positive ecological environment, and aim towards new forms and modes of the eco-economy. These strategies will help create a harmonious living environment, provide high-quality eco-products, and transform ecological wealth into economic wealth, ultimately allowing for the harmonious development of man, nature, and society.

The identification of driving factors is crucial for enhancing EWP and achieving sustainable development. This study reveals that the primary internal factor influencing the current EWP of the YRB is the efficiency of converting ecological resources into economic growth. Wang [75] utilized the LMDI model to break down EWP and arrived at a similar conclusion. However, our study goes a step further: before 2011, the primary internal driving factor for EWP was an increase in economic output; after 2011, efficient utilization of ecological resources became the main internal driving factor for EWP. External factors such as urbanization, technological advancement, industrial concentration, and industrial structure play a significant role in influencing EWP. Following Chennery's industrialization stage theory, as urbanization progresses, leading industries undergo upgrades and optimizations, shifting towards technology- and knowledge-intensive sectors. Moreover, spatial agglomeration fosters industrial concentration and technology diffusion. Consequently, urbanization, technology diffusion, industrial concentration, and industrial structure optimization resulting from urbanization are pivotal external driving factors for enhancing EWP in urban agglomerations within the YRB. For policy makers, promoting the high-quality development of urbanization, adjusting the industrial structure, and developing a green economy are the main goals of the current EWP enhancement policy in the Yellow River Basin.

The quantitative research results of this study provide a relative assessment of EWP in urban clusters within the YRB. However, they do not offer precise values for EWP. Future research should consider a broader perspective to achieve more accurate findings. Additionally, the ecological input indicators used in this study, such as per capita built-up area, water consumption, and energy consumption, may not fully capture the human consumption of ecosystem resources. Future studies should focus on ecosystem services to better evaluate the human impact on ecosystem resources. Furthermore, due to data limitations, some potential factors influencing EWP may not have been included in the analysis. Despite these limitations, our study presents valuable insights that can guide sustainable development in the YRB.

6. Conclusions and Policy Implications

6.1. Conclusions

EWP is instrumental in steering the construction of an ecological civilization and promoting high-quality development in the YRB. This research, utilizing the US-NSBM model, constructs an evaluation index system for EWP and evaluates both the overall efficiency and stage decomposition efficiency of EWP in five urban clusters within the YRB. The study delves into the spatial distribution and agglomeration status of EWP and its decomposition stages while also investigating the evolutionary patterns and internal and external driving forces impacting EWP. The key findings of this study are as follows:

- From 2006 to 2021, the study area showed an increasing trend in EWP, with distinct variations among urban agglomerations indicating a pattern of high downstream values and lower values in the middle and upper reaches. In terms of spatial agglomeration, cities categorized as L–L clusters experienced a notable decrease, while H–H

type cities saw a significant increase, highlighting clear spatial agglomeration characteristics. The stage distribution of EWP revealed that Stage 1 aligns with the overall trends, whereas Stage 2 displays a growing trend towards spatial randomization over time.

- When examining the transfer trend of EWP, it became evident that the study area exhibits a degree of path dependence, making leapfrog development challenging. Introducing the concept of spatial lag revealed distinct evolution paths for different city types: where type I areas tend to experience EWP collapse, type II and III areas show steady to positive transfer trends, and type IV areas tend to form club convergence. To foster sustainable development in the YRB, local governments must prioritize the development of lagging EWP areas.
- An analysis of EWP's drivers indicated that the efficiency of converting ecological inputs into economic outputs serves as a crucial internal driver in the urban agglomeration of the YRB. Urbanization and technological advancements play significant roles as external drivers of EWP, while industrial agglomeration and structure also contribute positively to EWP.

6.2. Policy Recommendations

Taking into account the analyses and conclusions above, we propose the following policy recommendations. First, the development stages of ecological welfare performance must be balanced. Stage-specific balance should be emphasized in the development of ecological welfare performance, and improvement strategies based on the identified shortcomings should be implemented. To effectively enhance the ecological welfare performance level during the collaborative development of urban clusters in the Yellow River Basin, efforts should be made to improve economic welfare conversion efficiency while maintaining high efficiency in the ecological–economic conversion stage. This includes improving the income distribution, enhancing public services such as education and healthcare, and promoting cross-regional ecological environment cooperation in the context of high-quality economic development to achieve comprehensive improvements in economic, social, and environmental welfare. Second, regional development must be coordinated and tailored strategies implemented. Weak regional polarization trends should be addressed by implementing development strategies tailored to local conditions. Guided by the disparities in the ecological welfare performance levels between cities, support should be provided to lower-performing cities. This includes facilitating the rational flow of elements between cities and optimizing the capacity of low-performing cities to accommodate functional transfers from higher-performing cities, thereby forming a well-coordinated development mechanism that gradually reduces the ecological welfare performance gap between cities. Efforts should also be made to prevent the downward transfer of high-performing cities, achieving an overall improvement in the ecological welfare performance of urban clusters in the Yellow River Basin. Third, we look to strengthening transportation infrastructure and expanding the core city influence. The construction of transportation infrastructure should be further strengthened, particularly highways and high-speed rail, to enhance the connectivity within and between urban clusters. By leveraging the driving role of core cities in the Yellow River Basin, industrial coordination can be effectively achieved across different regions, forming a comprehensive development pattern that will promote multi-level and all-encompassing cooperative relationships in the basin.

Author Contributions: N.L.: conceptualization, methodology, formal analysis, investigation, and writing—original draft; S.L.: methodology, visualization, and writing—review and editing; Y.W.: project administration, supervision, conceptualization, and writing—review and editing. All authors have read and agreed to the published version of the manuscript.

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

Appendix A. Summary Statistics for Each Indicator

Indicator	Max	Min	Mean	SD	CV
Comprehensive energy consumption per capita (standard coal)	5.3250	0.0017	0.3955	0.6175	1.5611
GDP per capita (10,000 CNY)	28.5818	0.2757	4.6075	4.1374	0.8980
PM2.5 ($\mu g/m^3$)	108.9549	19.7800	52.2461	17.0745	0.3268
Per capita built-up area (10,000 persons/km^2)	1.7810	0.0240	0.3126	0.2872	0.9185
Per capita industrial water consumption (m^3)	268.7213	1.1205	51.9955	40.4166	0.7773
Per capita value of environmental cleanup (CNY)	69.2721	0.1529	8.2642	11.5558	1.3983
Per capita industrial SO_2 emissions (ton)	0.2750	0.0000	0.0200	0.0321	1.6032
Per capita industrial wastewater emissions (ton)	1403.5576	0.1716	20.8779	64.0377	3.0672
Per capita industrial dust emissions (ton)	0.1716	0.0000	0.0110	0.0173	1.5712
Per capita value of cultural services (CNY)	34.8730	0.0811	3.7106	5.2950	1.4270
Per capita value of gas regulation (CNY)	74.8596	0.3139	5.7422	9.6279	1.6767
Per capita value climate regulation (CNY)	184.1628	0.3715	12.5036	23.6683	1.8929
Per capita total consumer goods (CNY)	70,631.6135	413.9378	15,839.8783	13,621.6181	0.8600
Per capita disposable income of rural residents (CNY)	26,790.2996	1609.0000	9744.0243	5070.7649	0.5204
Per capita disposable income of urban residents (CNY)	60,239.0000	6690.0000	24,276.7023	10,372.2386	0.4273
Basic pension participation rate	1.3883	0.0044	0.1550	0.1505	0.9708
Basic health insurance participation rate	0.9140	0.0193	0.1706	0.1350	0.7910
Unemployment insurance participation rate	0.3328	0.0070	0.0884	0.0592	0.6690
CPI	110.1000	98.0000	102.5319	1.7522	0.0171
Teacher–student ratio	0.6996	0.0361	0.0657	0.0228	0.3474
Minimum wage (CNY)	2100.0000	320.0000	1068.1058	454.9126	0.4259
Doctors per 10,000 people	81.9295	4.5161	22.1974	10.4473	0.4707
University students per 10,000 people	1398.2876	1.8905	194.9924	266.8614	1.3686
Hospital beds per 10,000 people	128.6784	9.5665	42.5703	17.1320	0.4024

Appendix B. Summary Statistics of Influencing Factors

Variable	Max.	Min.	Mean	SD	CV
CL	1.0000	0.0000	0.1077	0.3101	2.8799
EE	6.1768	0.0077	0.1620	0.2579	1.5922
ENR	0.0119	0.0002	0.0034	0.0014	0.4288
ESV	730.9041	3.4162	69.8845	98.1175	1.4040
IL	80.6800	15.8800	50.9349	11.0286	0.2165
INA	9.6406	2.9531	6.5378	1.2341	0.1888
INS	68.6700	14.7900	37.1785	9.2311	0.2483
OPEN	13.7080	3.1355	9.5221	1.9511	0.2049
PD	7.2727	2.7658	5.8578	0.9084	0.1551
RD	5.9473	0.4807	3.4798	0.9819	0.2822
TC	13.4126	5.0499	9.5802	1.4844	0.1549
URB	0.9648	0.1257	0.5066	0.1577	0.3113

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