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Abstract: Ecological welfare performance (EWP) serves as a crucial measure for assessing the green development of a region. Exploring the spatial characteristics, network structure, and transfer paths of its specific stages is crucial for grasping an internal space’s EWP and optimizing urban ecological planning. This research employed a two-stage DEA model to assess the EWP of 284 Chinese cities from 2007 to 2022 and decompose it into an ecological–economic transition stage (L1) and an economic welfare transition stage (L2). Second, a social network analysis (SNA) was conducted to describe the EWP sub-stages’ network structure and construction mechanism. Finally, the transmission path process of EWP was revealed through Markov chains. It is found that (1) the overall trend of EWP is rising and then falling, with L2 as the critical constraint; (2) the network structure of the two stages is complex, dominated by industrial structure, urbanization, and healthcare level; and (3) ‘club integration’ constrains the transfer across EWP in the short term. Compared with L2, which has a lower probability of interstate transfer, L1 has a greater likelihood of transfer to a higher level. This paper provides suggestions for the optimal allocation of ecological resources in Chinese cities through the analysis of EWP.

Keywords: urban eco-welfare performance; two-stage DEA modeling; social network analysis method; Markov chain

1. Introduction

Urbanization is a multifaceted process with profound implications for sustainable development. While it drives economic and social development, it simultaneously poses significant challenges to sustainability. The rapid urbanization witnessed in China exemplifies this dual nature. Since the implementation of reform and opening-up policies, China has made significant strides in urbanization. Data from the National Bureau of Statistics of China (2024) show that the urbanization rate rose from 17.92% in 1978 to 66.16% in 2023 [1], contributing to economic and social development. However, the urbanization process suffers from the neglect of essential factors, such as the quality of urbanization, social development, and environmental protection [2]. This has resulted in slow progress in building sustainable cities and communities and less progress than expected [3]. Regarding the quality of urbanization, some cities have overly pursued scale expansion while neglecting to improve urban quality [4]. Infrastructure development needs to be commensurate with the level of urbanization, leading to issues such as traffic congestion and inadequacies in public services, which affect the normal functioning of cities and residents’ quality of life [5]. This suggests that more than just quantitative growth is needed...
in the urbanization process; the quality and sustainability of cities are equally crucial. On the social front, rapid urbanization can exacerbate the risk of emergencies, such as natural disasters and public health events [6], threatening the stability of cities. In contrast, the widening income inequality associated with urbanization exacerbates social tensions and conflicts and hinders the building of stable, cohesive cities [7]. At the environmental level, China’s long-term rough urbanization has relied on massive resource inputs and land expansion, relatively neglecting environmental protection [8]. Vast expanses of natural land have been converted into urban construction areas, have depleted large amounts of resources, and have generated pollution emissions, which have exerted multiple pressures on ecosystems and led to serious environmental problems [9]. Ecological issues such as air pollution, climate change, and extreme weather conditions threaten urban residents’ lives and health [10–12]. Enhancing environmental protection and further integrating the concept of sustainable development into urban planning and construction is imperative to achieving the sustainable development of cities and communities. Consequently, accurately measuring a country or region’s capacity for sustainable development has become a focal point of interest among most scholars.

During its general debate, the 78th session of the United Nations General Assembly reaffirmed the importance of Sustainable Development Goal (SDG) 11 for making cities and communities sustainable. Drawing on the Sustainable Development Goals (SDGs) introduced by the United Nations in 2015 and embraced globally, the session specifically addressed the sustainability challenges facing cities. [13]. Sustainable Development Goal 11 aims to achieve inclusive, resilient, and sustainable urban development through policies and practices that emphasize essential services, affordable housing, efficient transportation, and green spaces [14]. However, the current monitoring and assessment of SDG 11 indicators suffer from several accounting deficiencies, including challenges related to indicator definitions, the timing of data, and missing data, which impede the effective monitoring and assessment of SDG 11 indicators [15]. This reduces the effectiveness of urban sustainable development policymaking, thus affecting the timely realization of SDG 11 objectives. Therefore, to make up for the shortcomings of the SDG 11 assessment system, we adopt EWP as a measure of the sustainable development capability of Chinese cities, which is used by most scholars at present [16], and conduct an in-depth examination of the spatial distribution features of EWP, the attributes of its evolution, and its spatio-temporal transfer paths at each city’s level of EWP. This paper focuses on EWP, and our research framework follows the logical structure of “EWP evaluation, network analysis and spatial evolution” (Figure 1).

Ecological welfare performance (EWP) evaluates the efficiency of converting ecological resource consumption into enhanced welfare. It reflects the welfare benefits per unit of ecological resources used, aiming to continuously improve human well-being without surpassing the current carrying capacity of ecosystems. EWP is highly relevant to sustainable urban development and provides a framework for assessing how efficiently cities can convert ecological resource consumption into improvements in residents’ well-being. By incorporating EWP into urban planning, policies and practices that improve residents’ quality of life, preserve the ecological environment, and ensure the sustainable use of resources can be improved to support long-term human and ecological well-being, in line with SDG 11’s overall objective. EWP differs from traditional welfare indicators. Traditional welfare indicators measure human well-being primarily through economic and social parameters (GDP, income levels, health, and education) and typically ignore long-term impacts on the environment. In contrast, EWP not only includes these traditional welfare indicators but also integrates ecological factors to evaluate the efficiency of converting ecological resource consumption into higher levels of well-being. Thus, it provides a more comprehensive assessment framework for balancing economic development and environmental protection. EWP is critical for policymakers, providing an integrated framework that combines ecological sustainability and socioeconomic well-being to help inform decision making for sustainable development. Traditional welfare indicators often
prioritize short-term economic growth, which can lead to ecological degradation and resource depletion. In contrast, EWP emphasizes the efficient use of ecological resources to enhance human well-being while maintaining or improving ecosystem health. This dual focus ensures that policy decisions contribute to long-term environmental sustainability and social equity, balancing immediate welfare needs with the preservation of natural resources for future generations. The significance of comprehensively assessing urban EWP is that it can help cities formulate more scientific and rational development strategies, optimize resource allocation, enhance environmental quality, promote social equity and inclusiveness, and facilitate the transformation of urbanization from crude to high-quality development. Meanwhile, by continuously improving EWP, a city can address various ecological challenges while improving the overall well-being of its residents and realizing SDG 11.

Figure 1. Research framework.

2. Research Implications

This paper makes several contributions as follows: (1) This paper avoids the limitations of the traditional EWP single-indicator ratio method of measurement, constructs a multivariate input–output indicator system, and incorporates environmental factors into the traditional Human Development Index (HDI) to develop a new framework for assessing EWP; this framework adopts per capita finance and gross domestic product (GDP) as the intermediate variables for economic measurement, which are more in line with pursuing high-quality economic growth and sustainability. (2) Adopting a two-stage DEA model for analyzing EWP and its subdivision into ecological-to-economic and economic-to-welfare stages facilitates a comprehensive understanding of the overall EWP level and the coherence between its stages. This method allows for the consideration of multiple
input and output variables, thereby mitigating the bias that may arise from reliance on the ratio of a single indicator. Additionally, it enables further exploration into the constraints on enhancing EWP, contributing valuable insights for policy formulation and implementation aimed at sustainable development. (3) Combining an SNA and spatial Markov chain, we further study the spatial distribution characteristics of the sub-stages of EWP, the transmission mechanism affecting its spatial distribution characteristics, and its evolution characteristics under the effect of spatial lag to provide a scientific foundation and decision-making references for the targeted formulation of EWP synergistic enhancement strategies and policies in Chinese cities.

3. Literature Review

3.1. Defining EWP Performance

EWP is a crucial indicator of a country’s or region’s capacity for sustainable development [17]. Theoretically, EWP is defined as the ratio of benefits gained to the consumption of ecological resources, typically using the per capita ecological footprint as the denominator. The numerator of EWP is primarily quantified by the Human Development Index (HDI), a comprehensive measure of the benefits received [18,19]. This is because the HDI, published by the United Nations Development Programme (UNDP), is a relatively authoritative indicator of social welfare, including economy, education, and health [20], that is simple and easy to use and effectively measures the level of well-being from economic and social dimensions. As the importance of the ecological environment in social development has become more and more prominent, the previous HDI, which focuses only on the economic, educational, and health aspects and ignores the environmental dimension, is no longer able to accurately reflect people’s growing demands for a better life. Regarding the measurement of ecological consumption, ecological footprint is usually considered the most representative indicator [21,22]. Due to the absence of detailed ecological footprint data at the city level, researchers have adapted by utilizing alternative indicators, such as resource consumption and environmental pollution, to gauge ecological resource utilization [23].

3.2. Accounting and Assessment of EWP Performance

The accurate determination of EWP values serves as a foundational step for subsequent investigations into their spatial distribution patterns and evolutionary characteristics. Regarding the measurement method of EWP, scholars are increasingly inclined to construct a multivariate input–output indicator system, and some scholars mostly use data envelopment analyses (DEAs), building a single-stage DEA or its improved method, the Super-SBM method [24], to measure EWP values. However, employing a single-stage DEA model fails to accurately capture the complex relationships between resource environments and economic development levels, and it cannot fully reveal the interactions between economic growth and well-being. Due to this model’s limitations, we cannot grasp the nuanced dynamics of the eco-welfare transformation process thoroughly, and it is difficult to identify the effectiveness of each stage in-depth, which undoubtedly makes it more challenging to understand the weaknesses in the EWP enhancement process. Therefore, there is a need to seek more comprehensive and in-depth modeling or methodologies to reveal these relationships more accurately to better contribute to sustainable development and enhanced well-being. In this regard, some scholars use the two-stage DEA model, which considers the impact of intermediate outputs. The model divides EWP into the ecological–economic transition and economic welfare transition stages, thereby elucidating the “black box” of the urban EWP conversion process. It reflects the effectiveness of inputs and outputs at each stage, reveals the efficiency loss and potential for improvement [25], and takes into account desired outputs, such as the output pollution and emissions, etc., which correspond closely with the reality of the EWP conversion process, thereby facilitating a more accurate quantification of emissions and other related metrics.
during the EWP transformation. This evaluation method adheres tightly to the actual circumstances of the EWP modification process, rendering the assessment of EWP more precise [26].

3.3. Advances in Spatio-Temporal Research on EWP Performance

Studies on the spatial aspects of EWP can generally be divided into three main categories. The initial category of research is dedicated to comparing and dissecting the levels of EWP across various regions, employing data collection and analysis methodologies to lay a foundational basis for policymaking and further research. Some scholars have built an ISGA indicator system for assessments and comparative analyses to investigate the growth effect of ISGA and GTFP on EWP, using the EWP and three-dimensional industrial ecological footprint (3DIEF) theories [27]. Other scholars have investigated the effects of forest ecological security (FES) on human EWP from the perspective of forest ecosystems [28], providing multiple guarantees for EWP enhancement. Some scholars, studying cities in the Yangtze River Delta (YRD) region, also discovered that the gradual decline in ecological consumption per unit of well-being output, along with resource consumption, technology, and welfare effects, significantly inhibited the reduction in regional ecological intensity of well-being (EIWB). The economic impact played a prominent role in promoting it, while the environmental depletion effect, the scale effect, and the efficiency effect had no visible influence. Economic and technological factors were the primary drivers of changes in urban EIWB [29], and all of the above studies support the idea that EWP has spatial effects. The second category of studies centers on an in-depth exploration of spatial correlations. Most of the existing literature utilizes exploratory spatial data analysis methods, and one study explores the impact of the economy on EWP through provincial panel data from the perspective of income distribution [30]. The last category of studies focuses on the spatial dimension to explore the evolutionary state of the EWP and its future development. Some studies have concluded that there is a two-way interaction between technological innovation and industrial agglomeration and that there are regional differences in their impacts on EWP [31]. Some studies investigate the effect of green innovation on EWP based on policy differences [32], which provide useful lessons for this study. However, there is an insufficient number of studies conducting spatial and temporal analyses and predictions of EWP with municipal data. At present, many studies tend to ignore the influence of spatial-level correlations when exploring the evolution of EWP, which makes it impossible to study their evolution accurately. Therefore, this neglect of spatial-level correlations is unfavorable for the synergistic enhancement of EWP.

3.4. Research Gap

The established literature has made some progress in studying EWP and its spatio-temporal properties, but there are still some prominent areas for improvement. Firstly, within the framework of the EWP assessment system, applying the data envelopment analysis (DEA) model to evaluate EWP leads to the challenge of refining the construction of the indicator system. Additionally, there is a dilemma in choosing between the Charnes, Cooper, and Rhodes (CCR) model, which assumes constant returns to scale, and the Banker, Charnes, and Cooper (BCC) model, which assumes variable returns to scale. Secondly, existing studies tend to study EWP as a whole but lack an in-depth exploration of the ecological welfare transformation’s “black box” process. Furthermore, most of the literature has explored the measurement of EWP and its influencing factors. However, the spatial variability in its sub-stages has yet to be investigated. Given the above gaps, this paper studies 284 Chinese cities, adds ecological factors to the traditional HDI, constructs an EWP evaluation system with per capita finance and per capita GDP as intermediate economic measurement variables, avoiding bias from using the ratio of a single indicator. The two-stage DEA divides the EWP into the ecological–economic transition stage and economic welfare transition stage to explore the overall level of EWP, the coordination of
its phases, and the ability to consider multiple inputs and outputs simultaneously. Secondly, the temporal and spatial variability in and transfer paths of the sub-phases of the EWP are investigated by combining the SNA and the Markov chain to offer a scientific foundation and a decision-making reference for the targeted formulation of the synergistic enhancement strategies and policy optimization of EWP for the Chinese cities studied.

4. Study Regions and Data Sources

4.1. Study Regions

China is not only the world’s largest developing country but also maintains a leading position among the world’s major economies and is the primary stabilizer and power source of the world’s economic growth. Its strategies and effectiveness in sustainable development have significant global impacts. Therefore, the study of the development of urban EWP in China is of enormous importance for the sustainable development of other developing countries. Based on our research goal and data availability, 284 cities in China were chosen as research objects in this paper.

4.2. Data Sources

In this paper, we use the two-stage DEA method of the related literature to measure the EWP of 284 cities in China [33], in which input indicators are represented by energy consumption and pollution emissions. In this paper, a multidimensional HDI incorporating ecological factors is constructed based on the traditional HDI and used as an output indicator. Further, this EWP indicator system includes consumption level, education, healthcare, and environmental benefits and uses GDP per capita and fiscal revenue as proxies for economic development level [34,35]. In evaluating the comprehensive level of EWP, we adopted the whole-process evaluation method, which fully considered the inputs of the first stage and the outputs of the second stage. Concurrently, we developed an indicator system for each stage of the EWP transformation process, as detailed in Table 1. This study examines 284 cities in China over the period from 2007 to 2022. The data of the evaluation indicators come from the China Statistical Yearbook and the statistical yearbooks of each city-region in 2007–2022.

Table 1. Evaluation index system of EWP.
5. Methods

5.1. Two-Stage DEA Model

The DEA is a non-parametric efficiency assessment method. Traditional DEA models, however, struggle with efficiency issues that involve undesired outputs. The SBM model relaxes the assumption that inputs and outputs change proportionately. As a non-radial DEA model, the SBM model avoids the directional bias inherent in radial approaches and more effectively captures the essence of efficiency evaluations.

Given the limitations of traditional DEA existence measurements and the advantages of two-stage DEA measurements of EWP existence, in this paper, we divide EWP into two sub-stages of efficiency to uncover the “black box” of the transformation process between ecological inputs and welfare outputs. In the first stage, we examine L1, in which the primary objective is to efficiently convert ecological inputs into economic outputs. In the second stage, we shift our focus to L2, aiming to optimize the efficiency of converting economic inputs into welfare outputs. The specific transformation process is detailed in the following formula:

\[ E = \frac{I}{C} = \frac{G}{C} \times \frac{I}{G} \]  

where \( E \) is the EWP; \( C \) represents the initial input of ecology; \( G \) represents economic development, which is the intermediate variable of the whole transformation process and plays the role in the first stage as an output indicator as well as the input indicator in the second stage; and \( I \) is the HDI, which represents the final output indicator of the whole process.

The advantage of the DEA over entropy weights and other evaluation methods is that it does not require a predefined production function and can adequately handle the inputs and outputs of multiple indicators, so it can comprehensively and accurately measure the EWP system constructed in the previous section. However, traditional DEA methods such as Super-SBM can only determine the final efficiency and ignore the efficiency of each sub-stage in the actual production process and the impact of each sub-stage on the overall efficiency. To address this shortcoming, some scholars [36] have enhanced the classic single-stage DEA model and built a two-stage DEA model, which can effectively evaluate the actual efficiency of the system operating process, fully reflect the effectiveness of inputs and outputs in each stage as well as the correlation of sub-stages, which is more in line with the reality of the eco-welfare transformation process.

Assume that there are \( n \) homogeneous decision-making units (DMUs) and that each \( DMU_i = (i = 1, 2, \ldots, n) \) is divided into two phases. Where \( x_{ij} = (x_{i1}, x_{i2}, \ldots, x_{im})^T (j = 1, 2, \ldots, m) \) denotes the \( DMU_i \) input variable at L1; \( z_{id} = (z_{i1}, z_{i2}, \ldots, z_{ir})^T (d = 1, 2, \ldots, r) \) denotes the intermediate variable at \( DMU_i \), which serves as the output of L1 with the inputs of L2; and \( z_{ik} = (z_{i1}, z_{i2}, \ldots, z_{ip})^T (k = 1, 2, \ldots, p) \) denotes the output variable at \( DMU_i \) of L2.

5.1.1. Ecological–Economic Transformation Phase

In L1, this paper uses an input-oriented model as follows:

\[ \min E_1 = \frac{\sum_{j=1}^{m} W_{pj} + \beta_1}{\sum_{d} \varphi_d Z_{id}} \]  

\[ \text{s.t.} \quad \sum_{j=1}^{m} W_{pj} x_{ij} + \beta_1 \leq 1, \quad i \in [1, n] \]  

\[ V_{k}, \varphi_d \geq 0, \beta_2 \in R \]
5.1.2. Economic Welfare Transformation Stage

In L2, this paper uses the output-oriented DEA-CCR model as follows:

\[
\begin{align*}
\max E_2 & = \sum_{k=1}^{p} v_k y_{ik} - \beta_2 \\
\text{s.t.} & \quad \frac{\sum_{k=1}^{p} v_k y_{ik} - \beta_2 \sum_{d=1}^{r} \varphi_d z_{id}}{\sum_{d=1}^{r} \varphi_d z_{id}} \leq 1, i \in [1, n] \\
V_k, \varphi_d & \geq 0, \beta_2 \in R
\end{align*}
\] (5)

5.2. Kernel Density Estimate

Kernel density estimation (KDE) is a nonparametric method for estimating the probability density function of a random variable. It is often used to estimate an unknown distribution function for a dataset to help understand and analyze its distributional characteristics. Due to the abundance of urban data in studying urban ecological welfare transformation, this paper utilizes the Gaussian function to estimate the kernel density curve of the EWP distribution pattern. This approach offers a deeper understanding of the EWP’s evolution and serves as a reference for relevant policy formulation and optimization. We assume that the kernel density function for the random variable allows the kernel density at any point to be estimated as follows:

\[
\begin{align*}
f(x) & = \frac{1}{Nh} \sum_{i=1}^{N} K \left( \frac{X_i - \bar{X}}{n} \right) \\
K(x) & = \frac{1}{\sqrt{2\pi}h^2} e^{-\frac{x^2}{2h^2}}
\end{align*}
\] (8)

where \( N \) indicates the number of cities in the country; \( X_i \) is the observed value of the EWP; \( \bar{X} \) is the mean value of EWP observations; \( h \) is the window width; and \( K(x) \) is the Gaussian kernel function.

5.3. SNA Method

The SNA approach mainly uses a quantitative analysis to research the structural aspects of social networks, focusing on the distributional characteristics of the networks. This paper evaluates the structural characteristics and evolutionary patterns of spatially connected networks in EWP s in terms of network density, hierarchy, efficiency, and number of ties. At the same time, this paper also explores the urban clustering of EWP s using the block model, among other things.

5.3.1. Modified Gravitational Modeling and Network Calculations

Identifying the spatial correlations for EWP is a prerequisite for social network analyses. Utilizing pertinent studies derived from the literature, the correlation matrix of the EWP of Chinese prefecture-level cities is computed in this article using the modified gravity model [37]. The formula is given below:

\[
\begin{align*}
F_y & = K_y \times \frac{\text{EWP}_i \times \text{EWP}_j}{D_{ij}^2}, K_y = \frac{\text{EWP}_i}{\text{EWP}_i + \text{EWP}_j}, D_{ij}^2 = \left( \frac{\text{dis}_y}{\text{pgdp}_i - \text{pgdp}_j} \right)^2
\end{align*}
\] (10)

where \( F_y \) is the strength of the EWP link between urban area \( i \) and \( j \); \( K_y \) indicates the contribution of urban area \( i \) in the EWP link \( i \) with urban area \( j \); EWP denotes the EWP index; \( D_y \) is the distance between the urban area and the “integrated economic geography N”; \( \text{dis}_y \) indicates the spherical distance between cities; and pgdp represents the
city’s per capita gross regional product. According to Equation (10), the gravitational matrix of inter-city EWP can be calculated and binarized to obtain the spatial binary matrix of the EWP.

The SNA contains an overall network and a local network. Firstly, the connection density of the cities forming the network is indicated by the network density, which rises as the number of connections within the network grows. In addition, network efficiency and hierarchy are commonly used to measure network instability and vulnerability. Furthermore, the presence of direct or indirect connecting paths between any two cities in the network indicates a stronger correlation between their EWPs. Network efficiency refers to the effectiveness of inter-city connectivity. A decrease in network efficiency presupposes the presence of numerous spatial spillover pathways, which can make the network more stable. The network hierarchy provides information on the location of the cities in the network. All the shortest paths of any two nodes in the network are calculated for the local networks. If any of these shortest paths pass through a particular node, then this node is considered to have high centrality. The above calculations are shown in Table 2.

Table 2. Calculation formulae for overall network structural characteristics and degree of centrality.

<table>
<thead>
<tr>
<th>Norm</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global network</td>
<td></td>
</tr>
<tr>
<td>Network density</td>
<td>( D = \frac{M}{N(N - 1)} )</td>
</tr>
<tr>
<td>Network hierarchy</td>
<td>( H = 1 - \frac{T}{\text{max} (T)} )</td>
</tr>
<tr>
<td>Network efficiency</td>
<td>( G = 1 - \frac{E}{\text{max} (E)} )</td>
</tr>
<tr>
<td>Personal network</td>
<td></td>
</tr>
<tr>
<td>Degree centrality</td>
<td>( A_i = \sum_{j=1}^{N} x_{ij} / (N - 1) )</td>
</tr>
<tr>
<td>Betweenness centrality</td>
<td>( B_i = \frac{2}{N^2 - 3N + 2} \sum_{j=1}^{N} \sum_{k=1}^{N} \frac{g_{jk}(i)}{g_{jk}} )</td>
</tr>
</tbody>
</table>

Notes: \( M \) is the number of relationships owned in the network, \( N \) is the total number of nodes, \( T \) is the number of symmetric and accessible nodes in the network, \( F \) is the total number of redundant connections in the network (there is a spatial correlation between nodes \( i \) and \( j \), \( x_{ij} = 1 \), or \( x_{ij} = 0 \)), \( d_{ij} \) is the shortest path distance between nodes \( i \) and \( j \), and \( g_{jk} \) is the number of shortest paths passing through nodes \( i \) between nodes \( k \) and \( j \).

5.3.2. QAP Model

Scholars have demonstrated a substantial correlation between the strength of the spatial association of EWP and geographic proximity and that geographically proximate cities may exhibit more EWP spillovers between them [37]. Therefore, this paper considers the magnitude of differences in EWP between regions regarding industrial structure, level of external openness, level of urbanization, geographic distance, technological innovation, environmental regulation, and level of healthcare. At the same time, this paper makes the following theoretical assumptions: The spatial correlation of EWP in Chinese cities is mainly influenced by eight drivers. These are ecological resource endowment (EC), urbanization level (UB), geographical distance (D), industrial structure (IS), technological innovation (TI), environmental regulation (ER), openness to the outside world (FD), and medical care level (ML). The specific measures for each driver are shown in Table 3.

Table 3. Specific measures for each driver.

<table>
<thead>
<tr>
<th>Driving Factor</th>
<th>Alphanumeric</th>
<th>Introduction to Indicators</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ecological resource endowment</td>
<td>EC</td>
<td>Urban green coverage</td>
</tr>
<tr>
<td>Urbanization level</td>
<td>UB</td>
<td>Urbanization</td>
</tr>
<tr>
<td>Geographic distance</td>
<td>D</td>
<td>Geographic distance between cities</td>
</tr>
<tr>
<td>Industrial structure</td>
<td>IS</td>
<td>Secondary sector’s value added as a percentage of GDP</td>
</tr>
</tbody>
</table>
In addition, the spatial network of EWP linkages is influenced by factors such as geographic distance and environment, which flow between cities in the form of resources such as capital, technology, and information, creating different ecological and welfare effects, which in turn generate EWP linkages and spillover effects. Considering the above mechanism analysis and the structural characteristics of the EWP correlation network, this paper selects the variables described in the previous section as the driving factors affecting the spatial correlation network of the EWP sub-stage. This paper adopts the data of 2007 and 2022 as a research example and constructs a QAP analytical model to carry out regression analyses on the generating mechanism of the spatial network structure of the EWP sub-stage. The specific models are as follows:

\[
EW = F(D, EC, UB, IS, TI, ER, FD, ML)
\]

(11)

where \(EW\) is the spatial correlation network of EWP.

5.4. Markov Chain Model

Given the spatial influence of urban EWP on the EWP of neighboring cities, this section employs the Markov chain method to construct both a traditional Markov chain and a spatial Markov chain, conditioned on the type of spatial lag. This approach further elucidates the direction and probability of EWP state transfers and examines the spatio-temporal evolution pattern of national EWP, building on previous research.

5.4.1. Traditional Markov Chain Model

We classify the EWP from 2007 to 2022 into \(k\) groups, and then the constructed \(k \times k\) matrix reflecting the probability of state transfer records the probability distribution of EWP transferring from one group to another, which is used to describe the process of the spatio-temporal transfer of EWP. The expression formula is as follows:

\[
M_{ij} = \frac{n_{ij}}{n_i}
\]

(12)

where:

\[
M_{ij} = \begin{bmatrix}
n_{11} & \cdots & n_{1j} \\
\vdots & \ddots & \vdots \\
n_{i1} & \cdots & n_{ij} \\
\end{bmatrix}_{k \times k}
\]

(13)

where \(M_{ij}\) is the state transfer probability matrix of \(k \times k\), \(n_{ij}\) is the sum of the number of all spatial units that have transformed the EWP from state \(i\) in year \(t\) to state \(j\) in year \(t+1\) during the study period, and \(n_i\) is the sum of the number of all spatial cells in which the EWP was at state \(i\) for the entire sample period.

5.4.2. Spatial Markov Chain

The first law of geography states that all things are related to geographical location. Therefore, we study the EWP and its sub-phases in relation to our cities’ geographical location. Geographical location affects the distribution, development, and interaction of things, and these interactions increase with factors such as distance. However, the traditional Markov chain cannot accurately take into account inter-city interactions, so the traditional Markov chain is combined with space to introduce the concept of “spatial lag” and construct the spatial Markov chain [38].
In contrast to conventional Markov chains, spatial Markov chains are composed of \( k \times k \) transfer matrices and require the introduction of spatial weight matrices. In this paper, a neighborhood matrix is used to reflect the geographical interactions between cities, and the value of the spatial lag determines the type of spatial lag to which a spatial unit belongs. Its expression is as follows:

\[
Lag = \sum_{i=1}^{n} y_i w_{ij}
\]  

(14)

In the above equation, \( Lag \) denotes the spatial lag value, \( n \) denotes the number of spatial units, \( y_i \) denotes the attribute value of spatial unit \( i \), and \( w_{ij} \) denotes the neighborhood spatial weight matrix.

To determine the significance of spatial factors on the EWP of our cities, we apply the chi-square test to verify the following formula:

\[
p = -2 \log \left( \prod_{m=1}^{2} \prod_{i=1}^{k} \prod_{j=1}^{k} \frac{Q_{ij}^{t,t+1} Q_{ij}^{t,t+1}(m)}{Q_{ij}^{t,t+1}(m)} \right)^{n_{ij}(m)}
\]  

(15)

In the above equation, \( Q_{ij}^{t,t+1}(m) \) and \( n_{ij}(m) \) denote the sum of the values of the two types of transfer matrix elements and the number of regions belonging to this type of transfer when the length of time is \( d \), respectively, \( Q_{ij}^{t,t+1}(m) \). The value of the transfer probability is calculated by combining the two types of data. \( p \) asymptotically obeys the chi-square distribution with degrees of freedom of \( k \times (k - 1) \) minus the number of transfers, whose probability is zero.

Then, \( M_{ij} \) needs to include the spatial lag effect, so we use \( M_{ij}^{k} \) to represent the spatial lag factor \( k \) that the spatial unit has in year \( t \) as a condition and the spatial transfer probability that the EWP level is type \( i \) in year \( t \). By changing this to type \( j \) in year \( t + 1 \), we can consider the spatial effect, construct a spatial Markov chain model on the basis of the traditional Markov chain model, and obtain the spatial Markov transfer matrix to further explore the influence of the spatial relationship on the spatial and temporal transfer of types of EWP in China and the characteristics of the spatial effect.

6. Results

6.1. Features of the Overall EWP and Sub-phase Distribution

Based on the EWP evaluation index system, this paper uses a two-stage DEA model to evaluate the EWP of Chinese cities in stages from 2007 to 2022, obtaining L1, L2, and the integrated levels and exploring their distribution characteristics in time and space dimensions.

The results of the EWP measurements are shown in Figure 2; in the sample period before 2011, the EWP and L1 levels synchronously declined from 0.8732 to 0.8198, indicating that at this time, the changes in the EWP were caused by L1; after 2011, the two rose to around 0.9913 and 0.9987, respectively, and fluctuated up and down, indicating that the EWP and L1 showed a positive trend in general. L2 declined from 1 in 2011 to 0.8692 in 2013, then rose to 0.9744 and fluctuated up and down. A possible reason for this lies in the fact that before 2011, the construction of eco-cities was imperfect, and the efficiency of eco-economic transformations was low; after 2011, Chinese cities responded to the national call to promote the eco-city construction model, rationally allocate ecological resources, and fully safeguard the ecological environment, which improved the efficiency of eco-economic transformations. Still, the previous crude eco-economic growth mode at the expense of the environment was constrained, affecting the efficiency of economic welfare transformations. After 2013, cities focused on sustainable development, building on the relationship between ecology, economy, and welfare, which all began to show growth. Further, L1 grew year by year, with its most significant increase being 13.4%, while L2
only realized growth in 2013, 2018, and 2020. This suggests that L1 is a key link in promoting EWP. Meanwhile, the uneven development of economic growth and welfare enhancement in L2 restricts the overall level of EWP, so improving the efficiency of economic welfare transformations is the key to further enhancing EWP.

Figure 2. The performance of EWP in each stage in Chinese Cities.

By analyzing the EWP and the results of the two-stage measurements, this paper initially discusses the differences in EWP between the cities. In this regard, this paper adopts the Kernel density estimation method to explore further the absolute differences in EWP among the cities and their evolutionary trends in the time dimension. The kernel density estimation results are shown in Figures 3 and 4.

Figure 3. Efficiency of ecological and economic transformation stages.
As can be seen from Figures 3 and 4, for L1, the central peak initially shifts to the right and then slightly to the left, suggesting that the EWP in L1 experienced growth followed by a minor decline, with an overall upward trend. In addition, the width of the EWP curve shows a slight widening trend, and the right trailing phenomenon is relatively more evident at the end of the study, which indicates that the absolute variation in EWP among municipalities in L1 tends to widen and that the cities with a higher level of EWP maintain a leading position. It was further observed that lateral peaks with lower peaks exist to the right of the central peak of EWP at the end of the study period, suggesting a weak polarization of EWP at L1. This is because the cities that are the forerunners in implementing energy conservation and emissions reduction policies greatly improved the efficiency of ecological and economic transformations, thus widening the gap between them and other cities. For L2, the distribution curve’s center point generally shifts to the left throughout the study period, indicating a declining trend in EWP for L2. This observation aligns with the trend of the mean value of L2. Secondly, the width of the distribution curve in L2 is slightly widened. It shows a slight right-tailed phenomenon, indicating that the absolute difference between cities in L2 also tends to be widened somewhat and that very few cities have an absolute lead. Overall, EWP is low in L2, meaning that economic growth does not inherently result in increased welfare, and cities with inferior levels of economic development fail to promote effective policies to improve people’s livelihoods.

To further examine the characteristics of the EWP’s spatial distribution, we averaged the values of the EWP and its two sub-stage efficiencies, presenting the results in Figure 5.

Figure 5 illustrates that the distribution of EWP and its sub-stages is uneven, with higher values in the central-eastern region and lower values in the northwestern region of the country. This imbalance may be due to urban agglomerations in the central and eastern regions actively implementing relevant environmental and welfare policies, resulting in a more favorable EWP and sub-stage situation. Furthermore, the concentration of high-energy-consuming businesses in the country’s north resulted in excessive natural resource consumption and a failure to increase welfare levels considerably. Some of the cities in the northern part of the country have lower EWPs, but L1 shows a higher trend, and L2 shows a lower trend. Therefore, the development of EWP in L1 and L2 of each city could be more balanced, but there are still significant differences.

6.2. EWP Sub-phase Network Characterisation and Drivers

In this study, we construct the urban EWP sub-phase network structure using the modified gravity model and the SNA approach, and the results are visualized below.
6.2.1. Features and Evolutionary Trends of the Overall Network Structure in the EWP Sub-Phase

Data from 2007 to 2022 were selected to plot the overall network characteristic indicators for both phases of the EWP, as shown in Figures 6–9:

**Figure 6.** Network hierarchy and efficiency in the ecological–economic transition stage.

**Figure 7.** Network density and number of ties in the ecological–economic transition stage.

**Figure 8.** Network hierarchy and efficiency in the economic welfare transition stage.
According to the measurement results of Figures 7 and 9, the network density and association coefficient of L1 and L2 from 2007 to 2022 both show an initial decreasing trend followed by an increasing trend. Both reached the final inflection point in 2021, and the association coefficient of L1 decreased from 8459 at the beginning of the period to 8178. The network density declined from 0.1053 to 0.1018, and the association coefficient of L2 from 8979 to 8365, and the network density decreased from 0.1117 to 0.1041. In comparison, the network density and association coefficients of L1 decreased less while those of L2 decreased more, suggesting that economic welfare transformation is a crucial constraint on EWP enhancement. In addition, measures specific to network hierarchy show an overall increasing trend in both the L1 and L2 phases. Specifically, the network hierarchy of L1 gradually increases from 0 in 2007 to 0.0282 in 2022, while the network hierarchy of L2 grows from 0 in 2007 to 0.0144 in 2022. This trend offers a crucial reference for understanding the hierarchical differences in the network development of the two phases. Also, it suggests a specific hierarchical structure exists between the high-EWP regions and the low-EWP regions and that the city’s position in the network is characterized by unevenness. Figures 6 and 8 also present the two phases’ network efficiency, respectively. The overall level of network efficiency of the two phases is high, remaining above 0.85, which is at the upper level, indicating that the EWP spatial correlation network has a low number of multiple superposition phenomena and redundant relationships. It is worth noting that in 2013, the network density and number of ties in the L1 and L2 phases suddenly decreased, and the network hierarchy in the L2 phase suddenly increased, which implies that inter-city ecological and economic cooperation and connections decreased and the regional economic development imbalance intensified. This may be due to the changes in environmental protection policies or economic policies in 2013 which affected the flow of resources and cooperation projects in cities, such as the “Action Plan for Prevention and Control of Air Pollution”, which restricts cross-regional ecological cooperation in terms of standards and investments, and the deleveraging policy, which leads to credit tightening and restricts inter-city economic cooperation and investment projects. Additionally, the reduction in inter-regional cooperation leads to imbalances in resources and economy and ultimately exacerbates the imbalance of the position of Chinese cities in the network in the L2 stage.

To determine the spatial correlation between regions, this paper builds a relationship matrix based on the improved gravity model to map the spatial correlation network of the two stages of EWP in China. The spatial correlation network maps of L1 and L2 in 2007 and 2022, respectively, are presented in Figure 10.
In the central-eastern region, the YRD has the highest number of linkages and the most robust connections with other cities and is at the network’s core. In addition, Guangzhou has more linkages in the southern region. It occupies an essential position in connecting the linkage networks of South and Southwestern China, whereas the cities in the northwestern and northeastern areas lack linkages to other cities. Overall, the spatial network of EWP sub-stages in China shows an uneven situation of “dense in the east and sparse in the west”, with the core structure of the YRD featuring significantly. Secondly, according to our comparative analyses, within the same stage, the degree of network accumulation in 2022 is considerably higher than that in 2007. Meanwhile, within the same year, the spatial network of L1 shows a more complex and dense network structure than that of L2.

6.2.2. Individual Network Characteristics in the EWP Sub-Stage

To examine the central position and influence of the selected cities in the EWP sub-stages’ spatial association network, this paper employs quantitative indicators such as degree centrality and betweenness centrality to analyze their centrality. By comparing the data from 2007 and 2022, we aim to reveal the dynamic changes in each city in this network and the differences between the two phases.

(1) Degree centrality

After an in-depth analysis of the data at the L1 level, we found that the average betweenness centrality of the 284 cities in 2007 and 2022 are 0.339 and 0.414. Looking at Figure 11 in detail, we can identify 34 and 45 towns whose centrality exceeds this average value. These cities are primarily situated in the central and eastern regions. Due to their unique geographic locations and convenient transportation conditions, they play a crucial role in the network.
role as hubs in the spatial correlation network. For example, Shanghai, is located in the center of the eastern seaboard, backed by the vast hinterland of economically developed areas such as Suzhou and Zhejiang, and is the world’s largest aviation hub and port city, comprising the core of the YRD. In contrast, the remaining 244 and 239 cities with below-average betweenness centrality values are primarily located in the northeast and southwest regions. Due to these regions’ relatively close transportation networks, they play a more peripheral role in the spatial correlation network. However, these cities still play an essential role as “bridges” and “conduits” in the ecological development spatial linkage network. Through close cooperation and interaction with other cities, they jointly promote the development and progress of the whole network. Therefore, enhancing and upgrading the hub transportation network is essential. This would also enhance the node cities’ connectivity and influence and promote regional ecological and economic integration development.

Figure 11. Degree centrality.

The results from the analysis of L2 indicate that the mean degree centrality values in 2007 and 2022 are 12.907 and 11.835, respectively. Looking closer, in Figure 11b,d, we can see that 97 and 104 cities have degrees of centrality exceeding this mean level, respectively. Suzhou, Wuxi, and Guangzhou are among the top ten cities in both years. Among the top twenty cities in both years, there are six provincial capitals, Guangzhou, Wuhan, Jinan, Changsha, Nanjing, and Hangzhou, which geographically radiate from the provincial capitals to the surrounding areas in L2. These cities, as the administrative centers of the provinces, have the advantages of resource allocation and policymaking and are regional economic centers. Over time, the overall layout of the cities’ centrality values from 2007 to 2022 increasingly shifted towards the YRD region. In summary, the EWP spatial correlation network of L2 shows prominent radiating characteristics. A core city or region will
have a more significant impact on surrounding areas. It is necessary to take advantage of core cities’ radiating effects to realize regional synergistic development through improving transportation infrastructure and enhancing the connectivity of areas that are far apart.

(2) Betweenness centrality

The mean betweenness centrality values for the 284 cities in L2 are 0.410 and 0.415 for 2007 and 2022. Figure 12 illustrates that the betweenness centrality values for 49 and 50 cities are more significant than the mean value. Guangzhou City, Beijing City, and Changsha City are in the top ten cities in both years. The top 20 cities in these two years included the four provincial capitals of Wuhan, Guangzhou, Changsha, and Nanjing. These cities are economically developed and are sources of industry, talent, policy, and other resources. In L2, the EWP of the capital city radiates to the surrounding areas, and the capital city is in the center of the network due to the transmission of information that radiates to other cities of the node and its ability to guide and control the nodes to give full play to its role in “conduction”. Therefore, capital cities should support the industry, talent, and policies of other cities and enhance their role as bridges and radiating centers in the regional economic, social, and policy network.

Figure 12. Betweenness centrality.

6.2.3. Sub-stage Block Model Analysis

This paper employs block modeling to investigate cluster characteristics and individual roles, referencing the block model proposed by Li et al. [39] and other research methods. We categorize the cities into four significant blocks at different transition stages and at the same time, categorize these four blocks according to the level of EWP, naming the first to the fourth blocks from the highest to the lowest. We also rank them according to
the number of members as follows: Panel II > Panel III > Plate I > Panel IV. We divide the spatial correlation network of EWP sub-stages into four blocks: net benefit block, two-way spillover block, broker block, and net spillover block. Then, the interactions among the blocks are further analyzed. This paper employs the CONCOR iterative method, selecting a maximum block depth of two and a concentration criterion of 0.2 to divide the 284 cities into four blocks. As shown in Figure 13, the classification of each block is determined by analyzing the internal relationships within the block along with the number of external spillovers.

![Figure 13. Distribution of two-phase spatial network relationship panels in 2022.](image)

As shown in Table 4, China’s EWP sub-stages in 2022 show significant spillover effects between cities and regions. The interregional spillover effect is primarily driven by inter-city spillovers, which both complement and enhance the impact of these inter-city interactions.

<table>
<thead>
<tr>
<th>Stage</th>
<th>Plate</th>
<th>Number of Members</th>
<th>Percentage in the East</th>
<th>Percentage in the Central Region</th>
<th>Percentage in the West</th>
<th>Percentage in the North East</th>
<th>Board Connections</th>
</tr>
</thead>
<tbody>
<tr>
<td>L1</td>
<td>Plate I</td>
<td>44</td>
<td>61.36%</td>
<td>27.27%</td>
<td>6.82%</td>
<td>4.55%</td>
<td>Net spillover</td>
</tr>
<tr>
<td></td>
<td>Panel II</td>
<td>107</td>
<td>27.10%</td>
<td>29.91%</td>
<td>16.82%</td>
<td>26.17%</td>
<td>Two-way spillover</td>
</tr>
<tr>
<td></td>
<td>Panel III</td>
<td>89</td>
<td>25.84%</td>
<td>41.57%</td>
<td>32.59%</td>
<td>0.00%</td>
<td>Broker</td>
</tr>
<tr>
<td></td>
<td>Panel IV</td>
<td>44</td>
<td>15.91%</td>
<td>0.00%</td>
<td>77.27%</td>
<td>6.82%</td>
<td>Net benefit</td>
</tr>
<tr>
<td>L2</td>
<td>Plate I</td>
<td>52</td>
<td>53.85%</td>
<td>32.69%</td>
<td>7.69%</td>
<td>5.77%</td>
<td>Net spillover</td>
</tr>
<tr>
<td></td>
<td>Panel II</td>
<td>102</td>
<td>31.37%</td>
<td>31.37%</td>
<td>22.55%</td>
<td>14.71%</td>
<td>Two-way spillover</td>
</tr>
<tr>
<td></td>
<td>Panel III</td>
<td>79</td>
<td>24.05%</td>
<td>40.51%</td>
<td>35.44%</td>
<td>0.00%</td>
<td>Broker</td>
</tr>
<tr>
<td></td>
<td>Panel IV</td>
<td>51</td>
<td>13.73%</td>
<td>0.00%</td>
<td>72.54%</td>
<td>13.73%</td>
<td>Net benefit</td>
</tr>
</tbody>
</table>

As shown in Figure 13, in L1, Plate I is primarily centered in the central and eastern coastal cities with high levels of development, such as Beijing, Tianjin, Shanghai, etc. Panel II is distributed primarily in the eastern and central areas. Panel III is mainly in the western and central regions, such as Lijiang and Taizhou, and it continuously occurs in Jiangxi and other places, such as Ganzhou and other areas. Panel IV is predominantly located in the western areas, including cities like Anshan and Jincheng.

In L2, Plate I is mainly concentrated in the eastern and central areas. Panel II is distributed primarily in the central and eastern areas, such as Xiamen City, Foshan City, etc.
Panel III is mainly in the central and western areas with contiguous occurrences, such as Anqing, Shaoxing, etc., and Panel IV is primarily in the western region, with sporadic occurrences in the northeast, such as Yinchuan and Tongchuan.

From Figure 14:

(1) After analyzing the results, we find that the net spillover block is Plate I. In L1, the spillover relationships between Plate I and Panel II, III, and IV are 1621, 1497, and 77, respectively. At the same time, there are 241 correlations within the plate, representing cities such as Beijing, Wuxi, and Guangzhou, which are at the forefront of economic development and are subject to the EWP spillover effect on the areas around them. In L2, on the other hand, there are 1408, 1135, and 49 correlations between Plate I and Panel II, Panel III, and Panel IV, respectively, and 253 correlations within the plate. Representative cities such as Beijing, Wuhan, and Nanjing receive a greater economic income and absorb technology from surrounding cities. This data distribution shows that the net spillover block performs well in maintaining and enhancing its own EWP level and has a solid radiating effect, which can effectively promote linkages and interactions with other blocks.

(2) We identify the two-way spillover block as Panel II. In L1, Panel II establishes 1365, 156, and 79 spillover relationships with the first, third, and fourth plates, respectively. There are also 566 spillover relationships within the plate, such as those of Huainan and Jilin. These cities have more ecological resources and better ecological policymaking, which drives environmental policymaking in the surrounding cities. After entering L2, Panel II has 1814, 119, and 61 overflow affiliations to Panel II, Panel III, and Panel IV, respectively, while the number of overflow relationships within the plate is 843, with Shenyang and Xuzhou being representative cities. This type of city has a more complete implementation of welfare policies and influences the development of welfare policies in surrounding cities. The second block shows a high degree of activity in its internal operation and has quite strong external spillover linkages with other blocks. As a result, the second block has more significant development potential, and its EWP mean is relatively high.

(3) The broker block is Panel III, receiving 303 internal relationships in L1, transmitting 1324 and 176 affiliations to Panel I and Panel II, respectively, transmitting 304 affiliations to Panel IV, and receiving a total of 1907 affiliations from all blocks, with representative cities such as Anqing, Sanya, etc. In L2, it receives 243 internal relations, transmits 1430, 129, and 336 associative ties to Panel I, Panel II, and Panel IV, respectively, and receives a total of 1552 associative relations from each board, with Guilin, Tianshui, etc., being representative cities in this interval. It can be seen that the broker plate receives external relations in the spatial association network and is also responsible for transmitting them to other blocks.

(4) Panel IV is the net benefit block. In L1, Panel IV aggregates 460 associative relationships from the first three blocks and constructs 100 associative relationships internally, with Lhasa and Lanzhou being representative cities. In L2, Panel IV receives 457 affiliations and maintains 122, with Yinchuan and Mianyang being representative cities. This demonstrates the duality of factor flows between blocks, with spillovers from high-level cities to low-level cities and reverse flows from low-level cities to high-level cities due to the siphon effect.
6.2.4. QAP Regression Analysis

Table 5’s regression results demonstrate that the standardized coefficients of UB and ML of L1 are positive and successfully passed the test at a 1% significance level in 2007 and 2022. This indicates that with the increase in urbanization and level of medical care, the differentiation of towns and cities and differences in medical care level gradually appear. Differences between the cities regarding their pollutant discharge regulations and medical resources have widened. The well-performing cities gradually spread the transformation method of the ecological economy to other cities, which strengthens their spatial relationships and advances their urban ecological economy. The standardized coefficients for L1’s D are all negative and significant, indicating that as the geographical distance between cities increases, the ecological-economic connections become less tight. Reducing these differences may be more beneficial for the spatial relationships between cities. Widening differences could be more conducive to the spatial relationships between cities. However, for IS, FD, and TI, L1 behaved differently in 2007 and 2022, and FD and TI were insignificant in 2005. Still, the standardized coefficients of D pass the significance test and are both positive at the 1% and 5% levels, respectively, in 2022, which suggests that the early stage of the cities does not rely on their receptivity to the external environment or their degree of technology to influence the spatial relevance of L1. Also, it suggests
that in the later stage of the cities, their receptivity to the external environment and their degree of technology increases with the increase in the spatial tightness of L1. The standardized coefficients of IS in 2007 and 2022 are positive and successfully passed the 10% and 1% significance level tests, indicating that with a city’s continuous development, its industrial structure in L1 becomes more and more prominent. A city with a better industrial structure can lead to surrounding cities improving their ecological and economic efficiency and increasing network correlations.

Table 5. Results of QAP regression analysis of prefecture-level cities in 2007 and 2022.

<table>
<thead>
<tr>
<th>Stage</th>
<th>Variable</th>
<th>2007 Un-Stdized Coefficient</th>
<th>2007 Stdized Coefficient</th>
<th>Significance</th>
<th>2022 Un-Stdized Coefficient</th>
<th>2022 Stdized Coefficient</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>L1</td>
<td>IS</td>
<td>0.152 *</td>
<td>0.015 *</td>
<td>0.011</td>
<td>0.002 ***</td>
<td>0.048 ***</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>UB</td>
<td>0.213 ***</td>
<td>0.030 ***</td>
<td>0.000</td>
<td>0.006 ***</td>
<td>0.235 ***</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>D</td>
<td>-0.013 ***</td>
<td>-0.069 ***</td>
<td>0.000</td>
<td>-0.018 ***</td>
<td>-0.408 ***</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>FD</td>
<td>-0.013</td>
<td>-0.001</td>
<td>0.431</td>
<td>0.005 **</td>
<td>0.033 **</td>
<td>0.021</td>
</tr>
<tr>
<td></td>
<td>ER</td>
<td>-0.013</td>
<td>-0.002</td>
<td>0.364</td>
<td>-0.006</td>
<td>-0.008</td>
<td>0.261</td>
</tr>
<tr>
<td></td>
<td>TI</td>
<td>0.008</td>
<td>0.001</td>
<td>0.387</td>
<td>0.008 **</td>
<td>0.030 **</td>
<td>0.037</td>
</tr>
<tr>
<td></td>
<td>EC</td>
<td>-0.031</td>
<td>-0.025</td>
<td>0.368</td>
<td>-0.001</td>
<td>-0.023</td>
<td>0.104</td>
</tr>
<tr>
<td></td>
<td>ML</td>
<td>0.218 ***</td>
<td>0.0201 ***</td>
<td>0.002</td>
<td>0.027 ***</td>
<td>0.063 ***</td>
<td>0.001</td>
</tr>
<tr>
<td>Intercept</td>
<td></td>
<td>0.115</td>
<td></td>
<td>0.168</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L2</td>
<td>IS</td>
<td>0.225 **</td>
<td>0.014 **</td>
<td>0.018</td>
<td>0.001 ***</td>
<td>0.038 ***</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>UB</td>
<td>0.255 ***</td>
<td>0.023 ***</td>
<td>0.001</td>
<td>0.006 ***</td>
<td>0.239 ***</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>D</td>
<td>-0.016 ***</td>
<td>-0.054 ***</td>
<td>0.000</td>
<td>-0.019 ***</td>
<td>-0.431 ***</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>FD</td>
<td>-0.020</td>
<td>-0.001</td>
<td>0.452</td>
<td>0.006 ***</td>
<td>0.039 ***</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>ER</td>
<td>-0.0001</td>
<td>-0.00001</td>
<td>0.554</td>
<td>-0.005</td>
<td>-0.007</td>
<td>0.278</td>
</tr>
<tr>
<td></td>
<td>TI</td>
<td>-0.032</td>
<td>-0.002</td>
<td>0.345</td>
<td>0.004 *</td>
<td>0.017 *</td>
<td>0.098</td>
</tr>
<tr>
<td></td>
<td>EC</td>
<td>-0.127 *</td>
<td>-0.007 *</td>
<td>0.061</td>
<td>-0.001 *</td>
<td>-0.023 *</td>
<td>0.072</td>
</tr>
<tr>
<td></td>
<td>ML</td>
<td>0.295 **</td>
<td>0.018 **</td>
<td>0.001</td>
<td>0.025 ***</td>
<td>0.056 ***</td>
<td>0.001</td>
</tr>
<tr>
<td>Intercept</td>
<td></td>
<td>0.151</td>
<td></td>
<td>0.189</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note 1: ***, **, and * denote significance tests at the 1%, 5%, and 10% levels, respectively.

In 2007 and 2022, the standardized coefficients of IS, UB, and ML for L2 are positive and significant. This suggests that as industrial structure, urbanization, and medical care levels increase, industrial disparities, urban differentiation, and differences in the level of medical care gradually emerge. The differences in the types of industries, towns’ investments in welfare, and medical services widen across cities. Well-performing cities pass on better welfare policies to other cities, driving up the economic welfare of these cities and increasing the closeness of their spatial linkages. D has the same effect on L2 as L1. For FD and TI, L2 behaved differently in 2007 and 2022, but FD and TI were not significant in 2005. The standardized coefficients passed the significance test and were both positive at the 1% and 10% levels, respectively, in 2022, which suggests that the impact of investment and technological innovation differentiation on economic welfare transformations is insignificant at the early stage of city growth, whereas in the later stage of urban development, the impact of the two increases as the investment and technology differentiation becomes increasingly prominent. This also reflects the importance of FD and TI in the development of each city. The continuous improvement of technology and investment is conducive to increasing the spatial correlation of economic welfare. The correlation coefficients of EC are negative and significant in both 2005 and 2022, which suggests that inter-city linkages are insufficient. As the differences in ecological resource endowments decrease, the communication and linkages between the cities in L2 become stronger. The widening of their differences is not conducive to inter-city spatial linkages.
6.3. Markov-Chain-Based EWP Transfer Path Prediction

6.3.1. Research on the Spatio-Temporal Transfer Path of China’s Urban EWP Level Based on Traditional Markov Chain

This paper divides the EWP level into five levels: "low", "lower", "medium", "higher", and "high." We obtain a traditional Markov transfer probability table for fifth-order matrices, as shown in Table 6.

Table 6. Traditional Markov chain transfer probability table for fifth-order matrices.

<table>
<thead>
<tr>
<th>t/t + 1</th>
<th>1 (Low)</th>
<th>2 (Lower)</th>
<th>3 (Medium)</th>
<th>4 (Higher)</th>
<th>5 (High)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (low)</td>
<td>213</td>
<td>0.671</td>
<td>0.315</td>
<td>0.014</td>
<td>0.000</td>
</tr>
<tr>
<td>2 (lower)</td>
<td>1803</td>
<td>0.023</td>
<td>0.776</td>
<td>0.194</td>
<td>0.006</td>
</tr>
<tr>
<td>3 (medium)</td>
<td>1578</td>
<td>0.000</td>
<td>0.167</td>
<td>0.714</td>
<td>0.114</td>
</tr>
<tr>
<td>4 (higher)</td>
<td>464</td>
<td>0.000</td>
<td>0.017</td>
<td>0.321</td>
<td>0.541</td>
</tr>
<tr>
<td>5 (high)</td>
<td>202</td>
<td>0.000</td>
<td>0.010</td>
<td>0.069</td>
<td>0.228</td>
</tr>
</tbody>
</table>

Table 6’s diagonal line shows the likelihood that each city will retain its initial EWP level, and the off-diagonal line is the probability of the temporal shift occurring in each city. According to Table 6, we can learn the following: (1) The stability of EWP, which is maintained at the level of the original status quo for each city in China, is high. Within the initial category that spans from low to high, the diagonal probability is higher than the non-diagonal probability, and the lowest probability for each city maintaining the original status quo is 54.1% and the highest probability is 77.6%, which indicates that the stability of the EWP in each city is more robust, but does not exclude the occurrence of spatio-temporal transfer. (2) China’s cities have a greater likelihood of maintaining their original status quo at both low and high levels of EWP. In contrast, the likelihood of maintaining the original status quo across low, medium, and high levels is relatively low, ranging from 0.6% to 77.6%, indicating that China’s cities have polarization in EWP and show the phenomenon of “club convergence”. This suggests persistent regional disparities in the level of EWP across different cities over the long term. This indicates that a polarization of EWP exists among cities in China, with the phenomenon of “club convergence” indicating a long-term regional difference in EWP levels among cities. (3) From the point of view of the transfer probability of each path, the probability of the path from low is 31.5%. The probability of the path from the low is 2.3%, which means that the likelihood of a city with a low level of EWP transitioning to an even lower level is higher than that of a city with a lower level of EWP shifting to a higher level. A city shifting to a medium level of EWP is higher than the probability of a city with a medium EWP level shifting to a city with a low level of EWP. The probability of the medium → higher path is 11.4%, and the probability of the higher → medium path is 32.1%, which indicates that the probability that a city with a medium EWP shifts to a high level of EWP is lower than the probability that a city with a high EWP shifts to a low level of EWP. The probability of the higher → higher path is 12.1%, and the probability of the high → higher path is 22.8%, indicating that the probability of cities with higher EWP levels shifting to higher levels is lower than that of cities with higher EWP levels shifting to higher levels. This shows that China’s EWP has experienced a high level of growth, but after reaching a certain level, it will be limited and tend to be low. (4) From the point of view of the crossing path, when the EWP of each city occurs across the transfer, the probability gradually decreases. For example, the low → medium path probability is 1.4%, the low → higher path probability is 0%, the low → high path probability is 0%, and the probability of transitioning to other EWP levels is low, indicating that China’s cities are subject to local locking, the probability of neighboring transitions is greater, and the probability of crossing the transfer is lower.

6.3.2. Research on Spatial and Temporal Transfer Paths of EWP Levels in Chinese Cities Based on Spatial Markov Chain
We divided the spatial lag into five groups: none, low–low aggregation (LL), low–high aggregation (LH), high–low aggregation (HL), and high–high aggregation (HH). Firstly, the test indicator \( p = 0.01 < 0.05 \) demonstrates the significance of establishing a spatial Markov chain to account for the spillover effect. Since the traditional Markov chain inadequately explains interactions between neighboring regions, incorporating the spatial dimension allows for a more nuanced understanding of this phenomenon. Consequently, we derive the spatial Markov chain path transfer probability matrix results, as shown in Table 7.

### Table 7. Spatial Markov chain path transfer probability matrix.

<table>
<thead>
<tr>
<th>Regional Background</th>
<th>t ( n )</th>
<th>Low</th>
<th>Lower</th>
<th>Medium</th>
<th>Higher</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>HH(_t) low</td>
<td>19</td>
<td>0.789</td>
<td>0.211</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>HH(_t) lower</td>
<td>33</td>
<td>0.030</td>
<td>0.879</td>
<td>0.091</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>HH(_t) medium</td>
<td>44</td>
<td>0.000</td>
<td>0.000</td>
<td>0.659</td>
<td>0.318</td>
<td>0.023</td>
</tr>
<tr>
<td>HH(_t) higher</td>
<td>140</td>
<td>0.000</td>
<td>0.021</td>
<td>0.243</td>
<td>0.660</td>
<td>0.136</td>
</tr>
<tr>
<td>HH(_t) high</td>
<td>101</td>
<td>0.000</td>
<td>0.001</td>
<td>0.059</td>
<td>0.248</td>
<td>0.683</td>
</tr>
<tr>
<td>HL(_t) low</td>
<td>24</td>
<td>0.750</td>
<td>0.167</td>
<td>0.083</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>HL(_t) lower</td>
<td>55</td>
<td>0.055</td>
<td>0.891</td>
<td>0.055</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>HL(_t) medium</td>
<td>0</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>HL(_t) higher</td>
<td>0</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>HL(_t) high</td>
<td>0</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>LH(_t) low</td>
<td>0</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>LH(_t) lower</td>
<td>157</td>
<td>0.637</td>
<td>0.357</td>
<td>0.006</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>LH(_t) medium</td>
<td>1666</td>
<td>0.022</td>
<td>0.769</td>
<td>0.202</td>
<td>0.007</td>
<td>0.000</td>
</tr>
<tr>
<td>LH(_t) higher</td>
<td>1520</td>
<td>0.000</td>
<td>0.169</td>
<td>0.718</td>
<td>0.109</td>
<td>0.005</td>
</tr>
<tr>
<td>LH(_t) high</td>
<td>301</td>
<td>0.000</td>
<td>0.013</td>
<td>0.359</td>
<td>0.522</td>
<td>0.106</td>
</tr>
<tr>
<td>LH(_t) high</td>
<td>70</td>
<td>0.000</td>
<td>0.000</td>
<td>0.086</td>
<td>0.271</td>
<td>0.643</td>
</tr>
</tbody>
</table>

According to Table 7, we can derive the following: (1) There is a high correlation between the EWP type shift and regional context; a significant difference in the spatio-temporal shift probability of EWP in different regional contexts; and a difference in the results of the traditional Markov chain, indicating a spatial spillover effect of the EWP shifts among the cities in China. (2) The diagonal probability is greater than the non-diagonal probability in some regional contexts. Still, in the high–low, low–low, and low–high aggregation categories, there is a situation in which the diagonal is smaller than the non-diagonal probability, which indicates that some of the cities in our country have the problem of keeping their original state. Still, some of them have pathway transfer, a case of jumping transfer. (3) In the regional background of high–high aggregation, the probability of a high level of EWP is 68.3%, which is higher than that of 64.3% in the absence of a regional background. (4) The change in the regional background does not affect the transfer of EWP in each city. (5) Compared with the traditional Markov chain, for the spatial Markov chain, without setting the regional background, that is, without setting the spatial
lag, the EWP of each city in China has an original status quo that appears slightly lower, considering that space increases the path selection and reduces spatial locking. Additionally, the probability of certain transfer paths is increased, suggesting that considering the spatial lag better reflects the transfer of EWP in each city in China.

Since EWP and its sub-stages have a spatial spillover effect, this paper establishes traditional Markov and spatial Markov models, respectively, to further study the transfer direction of urban EWP and its sub-stages and comprehensively examine the spatio-temporal evolution law of EWP within cities. Under the influence of spatial effect, this paper obtains the Q-test value of L1, which is 65.645, while the Q-test value of L2 is 110.9, and the corresponding significance p-value of the two is less than 0.05. The spatial effect of the sub-stage is significant, which indicates that L1 or L2 experiences the phenomenon of neighboring cities interacting with each other in space. We categorize the status of the EWP sub-stages into four grades: low (1), medium–low (2), medium–high (3), and high (4) according to their measurement values, thus obtaining the conditional EWP state transfer probability matrix with a one-year lag, as shown in Table 8.

<table>
<thead>
<tr>
<th>Spatial Hysteresis</th>
<th>t/t + 1</th>
<th>L1 n</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>L2 n</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traditional Markov</td>
<td>1</td>
<td>1093</td>
<td>0.711</td>
<td>0.243</td>
<td>0.038</td>
<td>0.007</td>
<td>1099</td>
<td>0.828</td>
<td>0.146</td>
<td>0.022</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1072</td>
<td>0.191</td>
<td>0.503</td>
<td>0.255</td>
<td>0.051</td>
<td>1054</td>
<td>0.128</td>
<td>0.646</td>
<td>0.187</td>
<td>0.039</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1037</td>
<td>0.032</td>
<td>0.221</td>
<td>0.535</td>
<td>0.212</td>
<td>1053</td>
<td>0.018</td>
<td>0.175</td>
<td>0.624</td>
<td>0.183</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>1058</td>
<td>0.009</td>
<td>0.034</td>
<td>0.192</td>
<td>0.765</td>
<td>1054</td>
<td>0.003</td>
<td>0.032</td>
<td>0.178</td>
<td>0.787</td>
</tr>
<tr>
<td>Markov-I</td>
<td>1</td>
<td>172</td>
<td>0.727</td>
<td>0.250</td>
<td>0.012</td>
<td>0.012</td>
<td>391</td>
<td>0.857</td>
<td>0.128</td>
<td>0.013</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>84</td>
<td>0.179</td>
<td>0.560</td>
<td>0.226</td>
<td>0.036</td>
<td>166</td>
<td>0.247</td>
<td>0.608</td>
<td>0.108</td>
<td>0.036</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>62</td>
<td>0.000</td>
<td>0.210</td>
<td>0.532</td>
<td>0.258</td>
<td>43</td>
<td>0.116</td>
<td>0.302</td>
<td>0.624</td>
<td>0.183</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>40</td>
<td>0.050</td>
<td>0.025</td>
<td>0.100</td>
<td>0.825</td>
<td>13</td>
<td>0.077</td>
<td>0.154</td>
<td>0.308</td>
<td>0.462</td>
</tr>
<tr>
<td>Markov-II</td>
<td>1</td>
<td>493</td>
<td>0.738</td>
<td>0.215</td>
<td>0.037</td>
<td>0.010</td>
<td>416</td>
<td>0.825</td>
<td>0.149</td>
<td>0.022</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>413</td>
<td>0.189</td>
<td>0.540</td>
<td>0.211</td>
<td>0.061</td>
<td>390</td>
<td>0.126</td>
<td>0.690</td>
<td>0.159</td>
<td>0.026</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>285</td>
<td>0.011</td>
<td>0.193</td>
<td>0.575</td>
<td>0.221</td>
<td>223</td>
<td>0.018</td>
<td>0.238</td>
<td>0.605</td>
<td>0.139</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>246</td>
<td>0.016</td>
<td>0.033</td>
<td>0.228</td>
<td>0.724</td>
<td>138</td>
<td>0.002</td>
<td>0.036</td>
<td>0.188</td>
<td>0.775</td>
</tr>
<tr>
<td>Markov-III</td>
<td>1</td>
<td>363</td>
<td>0.675</td>
<td>0.267</td>
<td>0.055</td>
<td>0.003</td>
<td>202</td>
<td>0.762</td>
<td>0.193</td>
<td>0.035</td>
<td>0.010</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>476</td>
<td>0.202</td>
<td>0.468</td>
<td>0.288</td>
<td>0.042</td>
<td>378</td>
<td>0.093</td>
<td>0.635</td>
<td>0.222</td>
<td>0.050</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>508</td>
<td>0.045</td>
<td>0.254</td>
<td>0.500</td>
<td>0.201</td>
<td>562</td>
<td>0.011</td>
<td>0.149</td>
<td>0.646</td>
<td>0.194</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>480</td>
<td>0.006</td>
<td>0.042</td>
<td>0.188</td>
<td>0.765</td>
<td>527</td>
<td>0.002</td>
<td>0.036</td>
<td>0.188</td>
<td>0.774</td>
</tr>
<tr>
<td>Markov-IV</td>
<td>1</td>
<td>41</td>
<td>0.659</td>
<td>0.293</td>
<td>0.049</td>
<td>0.047</td>
<td>766</td>
<td>0.17</td>
<td>0.064</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>77</td>
<td>0.143</td>
<td>0.453</td>
<td>0.338</td>
<td>0.065</td>
<td>103</td>
<td>0.087</td>
<td>0.602</td>
<td>0.291</td>
<td>0.019</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>171</td>
<td>0.035</td>
<td>0.181</td>
<td>0.579</td>
<td>0.205</td>
<td>217</td>
<td>0.014</td>
<td>0.143</td>
<td>0.627</td>
<td>0.217</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>244</td>
<td>0</td>
<td>0.02</td>
<td>0.209</td>
<td>0.77</td>
<td>339</td>
<td>0.003</td>
<td>0.009</td>
<td>0.165</td>
<td>0.823</td>
</tr>
</tbody>
</table>

Using the Markov transfer probability matrix presented in the above table, we can derive the final steady-state table for L1 and L2 through Markov fitting, as shown in Table 9.

<table>
<thead>
<tr>
<th>State Type</th>
<th>L1</th>
<th>L2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Traditional Markov</td>
<td>Initial state</td>
<td>0.243</td>
</tr>
<tr>
<td></td>
<td>stationary</td>
<td>0.214</td>
</tr>
<tr>
<td>Spatial Markov</td>
<td>Stationary</td>
<td>1 0.585</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2 0.259</td>
</tr>
</tbody>
</table>
The following can be concluded: (1) The probability values of both the L1 and L2 diagonals are higher than the non-diagonal probability values in a matrix, and both stages are characterized by club convergence. Among them, L1 maintains the original level, with a minimum of 50.3% and a maximum of 76.5%, while L2 is at the original level, with a minimum of 62.4% and a maximum of 82.8%. (2) The cities in the L1 and L2 stages are subject to local locking, and the probability of crossing paths is lower than the probability of neighboring paths, with a maximum of only 5.1%. This suggests that achieving short-term leapfrog-type development for EWP in both L1 and L2 poses significant challenges. (3) The probability of maintaining the original status quo at low and good levels is higher than the probability of retaining the original status quo at medium–low and medium–high levels in each of the cities in L1 and L2, indicating that there is a polarization in the probability of path shifting. (4) It is necessary to be aware of the fact that the probability of L2 being at a low level is relatively high, amounting to 82.8%, which constitutes a “low-level trap”. (5) In the initial situation, L1 is concentrated at a low level, with the highest path probability at only 5.1%. (5) In the initial situation, L1 is concentrated at the low level, and the probability of being at the high level is low. In the steady state, both L1 and L2 are concentrated in the middle–high and high levels, which indicates that both tend to increase.

According to the spatial Markov chain results, (1) L1 and L2 exhibit spatial dependence. Due to the differences in spatial geographic patterns, the transfer probability matrices of L1 and L2 significantly differ in different spatial lag backgrounds. This deviation from traditional Markov transfer probability matrices further confirms the critical influence of geographic dependence on the evolutionary transfer process of L1 and L2. (2) Considering the influence of the spatial lag effect, Table 9 shows that the probabilities of upward or downward transfer in the two sub-stages of urban EWP vary in magnitude. Generally, a higher level of EWP can drive neighboring cities to shift to a higher level. In comparison, a lower level of EWP may inhibit neighboring cities from moving to a higher level. We hypothesize that this phenomenon can be attributed to the spatial spillover effect of EWP concerning ecology, economy, and other related factors. (3) The diagonal probability values of L1 and L2 are higher than the non-diagonal probability values, and there is a bifurcation, with the phenomenon of “club convergence”. (4) In the steady state, under different spatial lag backgrounds, the evolution of L2 has a heterogeneous nature, that is, under each type of lag background, the evolution of L2 has the same value. Under each lag background, the probability distribution of the welfare performance level shows different trends when reaching the steady state. At the L1 level, the welfare performance levels all have an upward trend. At the L2 level, the heterogeneity is more significant.

7. Discussion, Conclusion, and Recommendations
7.1. Discussion
7.1.1. Methodological Insights

During the extensive debates at the 78th session of the United Nations, the necessity of achieving SDG 11 was emphasized. However, the prevailing lack of accountability has led to significant challenges in monitoring and evaluating SDG 11 indicators. This paper focuses on calculating EWP to assess regional SDG 11 weaknesses and internal gaps at the aggregate level to facilitate eco-city planning and management, potentially increasing city dwellers’ well-being.

Firstly, this paper incorporates environmental factors into the traditional HDI, constructs an assessment system for urban EWP, evaluates it to identify weaknesses and internal gaps, and explores the stages that constrain the improvement of EWP. Economic variables are constructed as intermediate variables in this indicator system, emphasizing
their role in the EWP assessment system. In addition, this paper adopts both finance per capita and GDP per capita as metrics for our economic analysis, moving beyond solely relying on GDP per capita. The rationale for this approach is that GDP per capita primarily reflects individual income levels, whereas government finance underpins public welfare. High-quality economic development necessitates the simultaneous consideration of both individual and public progress. Therefore, employing per capita finance and GDP per capita as metrics offers a more accurate representation of economic growth. This dual measure provides fresh insights for further developing the EWP system, aligning it more closely with real-world conditions.

Secondly, this study employs the modified gravity model and the SNA method to create spatial correlation networks across various scales, from the global to the local level. A key innovation of this paper is the incorporation of economic disparities and geographical distances between cities, which significantly improves the study’s reliability. This methodological approach enables a detailed examination of the spatial distribution patterns of EWP sub-stages. Consequently, it offers crucial insights for the debate on strategies to enhance EWP, thereby contributing to a more nuanced understanding of economic development dynamics. The work structure of China’s EWP sub-stages is complex, multi-threaded, and increasingly evolving into a more complicated pattern. The YRD urban agglomeration emerges as the nexus with the densest urban connections, positioning it at the heart of the network. This trait is most pronounced in the YTD’s coastal cities, notably Shanghai and Suzhou, which have effectively disseminated their influence outward. The region is evolving from a “dual-core” model centered around these two cities to a more decentralized, polycentric structure. The polycentric network is conducive to the economic resilience of the cities [40]. Guangzhou’s number of related relationships in the southwest is also at the forefront, occupying the center of the network. In contrast, the northwestern and northeastern parts of the network, along with other cities, relatively lack links. Overall, the phenomenon of EWP sub-stages can be summarized as the “East is dense and the West is sparse”. From a local perspective, the degree of centrality of the cities in the southeast region of L1 is higher and clustered, which can be seen in the L1 EWP of the spatial structure of the network. In L1, the southeastern region has more directly related correlations and plays a vital role as a “bridge” and in “conduction” in the spatial correlation network of ecological development. The EWP in L2 tends to spread from the capital city to the surrounding area. In L1, the provincial capital cities occupy a central position within the network, in which their guiding and controlling capabilities are fully manifested through the “conduction” role of their nodes. Investigating the driving effects of EWP within the spatial correlation network of L2 holds significant importance. This exploration is crucial for understanding the dynamics of regional development and sustainability efforts, providing insights into how provincial capitals can influence and enhance environmental welfare across broader geographical scales. This study provides a more nuanced analysis of the EWP enhancement in each city, which can serve as a reference for policymakers in terms of ecology and welfare. In addition, to delve deeper into the underlying causes behind spatial correlation formation in the EWP sub-stages, we conducted a QAP regression analysis for each sub-stage. The findings reveal that the variance in industrial structure, urbanization levels, geographic distance, degree of openness to external influences, technological innovation, and healthcare quality significantly impact the development of spatial correlation networks within the EWP sub-stages. This analysis underscores the multifaceted influences shaping the spatial dynamics of EWP, highlighting the importance of considering a broad spectrum of factors in understanding and enhancing environmental welfare outcomes across different regions. This highlights the significance of improving the construction of urbanization, strengthening technological exchanges, and improving industrial structure and medical care. These measures have a positive significance for EWP enhancement, consistent with previous research findings [41]. Therefore, it is suitable for this paper to present our analysis here.
To delve deeper into the pathways for enhancing EWP, this study employs the Markov chain model to investigate the transition dynamics of EWP and its sub-stages. In predicting the spatial and temporal evolution trends of EWP and its sub-stages in China, our traditional Markov chain analysis findings reveal that the EWP of China’s cities demonstrates a solid propensity to preserve their initial state, exhibiting significant stability and bifurcation. There are varying degrees of club convergence in both stages of the EWP, which makes it challenging to achieve a short-term leap forward, and the space could be stronger than the original state. The outcomes of the Markov chain analysis indicate that EWP exhibits a spatial spillover effect, its sub-stages have spatial dependence, and high-level cities can help promote EWP enhancement in neighboring cities. This observation underscores the phenomenon that a city’s EWP level can exert spillover effects on the EWP of neighboring cities and that the EWP of a municipality evolves significantly depending on its geographic location, which is inconsistent with the results of previous studies [42]. This paper distinguishes itself from earlier perspectives by innovatively exploring China’s EWP transfer paths from the perspective of EWP sub-stages, providing a reference for analyzing EWP enhancement from a more nuanced perspective.

7.1.2. Limitations and Future Directions

First, ecological resources and the levels at which they are consumed by humans vary, so in constructing EWP evaluation indicators, more indicators can be used to measure ecological inputs to achieve a more objective EWP system. Future research should concentrate on refining and enhancing the EWP evaluation framework. In addition, we are limited in considering the transfer path of EWP in our EWP path study, and future research should explore the transfer path of EWP in other situations to improve the accuracy and breadth of the results. The following methods are proposed for future research. First, the indicator system needs to be more comprehensive, and constructing a more decadal indicator system and expanding the sample research period should be considered. Second, multiple spatial models can be used to explore the spatial dimension of EWP’s influence mechanism by combining attribute data and panel data. In addition, numerical simulation and other methods can be used to analyze the transfer path of EWP. The results of these studies are expected to deepen our understanding of urban EWP.

7.2. Conclusions and Recommendations

This study uses panel data from 284 Chinese cities from 2007 to 2022. A two-stage DEA model measures EWP, divided into the ecological-economic transition and the economic-welfare transition. We use a modified gravity model and the SNA method to construct spatial correlation networks and examine their structures. We employ a block model analysis that identifies the diverse city roles within the network. Additionally, a QAP model is used to explore the factors influencing EWP spatial networks, and Markov chains are used to investigate EWP transfer paths. The study’s conclusions are as follows:

(1) Throughout the observed period, levels of EWP in urban China have generally improved, rising from 0.8732 in 2007 to 0.9913 in 2022. Both sub-stages, L1 and L2, show upward trends. L1 demonstrates consistent annual growth, peaking at 13.4%, while L2 only shows growth in 2013, 2018, and 2020. Post 2016, L2 and the overall EWP moved inversely, indicating that the economic welfare transition stage is a key constraint for EWP advancement, suggesting new areas for future research and improvement.

(2) Exploring the overall network structure of the EWP sub-stage, this study found that the spatial correlation of EWP in China forms a complex, multi-threaded network, with the YRD region having a clear single-core structure. China’s EWP network is imbalanced, being “dense in the east and sparse in the west”. More developed eastern cities act as core “bridges” and “intermediaries.” The L1 network is denser and more complex than the L2 network. Overall network density is low with many redundant
relationships, indicating a need to enhance network tightness and stability. The hierarchical structure reveals disparities between high- and low-EWP regions, with an imbalance in cities’ network positions. Understanding these characteristics, improving the EWP transmission mechanism, and broadening the spillover channels of EWPs are crucial for China to achieve SDG11. The government should enhance L2 network compactness by promoting inter-city resource mobility, ultimately strengthening the EWP network.

(3) Analyzing the spatial network of the EWP sub-stages reveals an agglomeration pattern with “local clustering” and “global connections”, centered mainly in the eastern coastal regions. This has led to a significant Matthew effect, concentrating advantages and resources in these prosperous areas. In contrast, the central-western and northeastern regions have lower network densities, functioning primarily as bridges within the network. This disparity indicates an opportunity to enhance the EWP spatial network’s structure and connectivity by better integrating these regions. Increasing network density in these areas can promote balanced resource distribution, knowledge exchange, and environmental welfare practices, contributing to more equitable and sustainable development. Strengthening these “bridge” regions is crucial for improving the overall effectiveness and resilience of the EWP spatial network.

(4) The EWP sub-phase local network study found that cities in the southeast region of L1 have higher and more clustered degree centrality values, while those below average are mostly in the western fringe. Provincial capitals hold central positions and lead in terms of network relevance in L2. The betweenness centrality indicates that the north-central region, with its geographic and transportation advantages, acts as a hub, while the northeastern and southwestern areas are more peripheral. In L2, provincial capitals play a crucial role by transmitting information to other cities, enhancing network cohesion. The L1 network is mainly influenced by eastern cities, while provincial capitals dominate L2. Future improvements in the EWP spatial network should focus on provincial capitals and city clusters.

(5) Our block model analysis shows that cities within the two-way spillover segment of EWP are mainly in central and Northern China, such as Huainan and Jilin in L1, and in central and eastern regions, like Shenyang and Xuzhou in L2. In L1, these cities focus on ecological protection and have high ecological economy conversion efficiency, influencing surrounding cities to adopt better environmental policies. In L2, these cities have economic advantages, leading others to develop economically and improve social welfare. Both stages have significant spillover effects on and from other cities. The net beneficiary block includes cities that gain more resources and benefits from EWP spillover effects.

(6) To explore the construction of spatial correlation networks in the EWP sub-stages, this study uses the QAP model. The formation and development of these networks are significantly influenced by IS, UB, D, FD, TI, ML, and EC. However, L1’s network is not affected by EC, indicating it has a greater impact on L2 concerning technological innovation. To improve EWP network relevance, cross-regional EWP networks and regional EWP cites should be built, promoting a new development pattern of “promoting the whole with the local”. Geographic proximity (D) is crucial as it decreases cooperation time and reduces costs, enhancing city collaboration. In addition, there are obvious differences in the economic development patterns of the eastern, central, and western regions, which require the active promotion at the national level of the formation of a regional ecological engineering pattern of “point by point, overall promotion” to promote the flow of regional ecological resources and the spillover of EWP dynamics.

(7) Our study of EWP transfer paths found that the level of EWP in each city remained stable in both stages, showing spatially positive correlations. “Club convergence” was observed, with the traditional Markov chain analysis indicating varying levels of convergence and difficulty in short-term leaps. Although L2 showed cross-state
transfer with a maximum probability of 0.357, L1 had a higher likelihood of transitioning to a high level. Urban EWP transfer is influenced by neighboring cities’ differentiation, suggesting a spatial spillover effect in which high-EWP cities enhance adjacent cities. Future optimization of EWP paths should start from L2, promoting capital and technology cooperation, enhancing high-level and lagging cities, and avoiding downward transfers to improve overall EWP. Higher EWP levels drive neighboring cities higher, while lower levels inhibit upward movement, indicating polarized transfer probabilities.

7.3. Recommendations

The policy implications of this study are as follows: (1) The unification of ecological resource inputs and welfare outputs is advised. It is recommended that the government consider the unification of ecological resource inputs and welfare outputs in urban planning and distinguish between high-value and low-value ecological welfare aggregation areas through EWP assessments. We recommend strengthening the mechanism of urban EWP assessment, considering both ecological resource inputs and welfare outputs to guide urban planning and development. We recommend cultivating successful experiences in high-EWP areas, promoting eco-city construction models, and improving ecological welfare. This will help formulate differentiated urban planning strategies, rationally allocate ecological resources, and effectively protect the environment. (2) Forecasting future development trends is advised. By observing the dynamic changes in EWP, the government can predict future development trends and provide a scientific basis for long-term planning. This helps to formulate sustainable development strategies for healthy urban development. For example, we recommend developing and implementing climate change adaptation plans to improve urban infrastructure resilience and reduce extreme weather events’ impact on cities. We recommend promoting the transition of cities to renewable energy sources to reduce reliance on traditional energy resources, lower carbon emissions, and mitigate the impacts of climate change. (3) Ecological and economic transformation and economic welfare transformation are advised. The government can conduct research to reveal the specifics of Chinese cities in ecological–economic and economic welfare transformation stages and identify weaknesses and internal gaps. The government can promote sustainable urban development by formulating the stages’ shortcomings to implement enhancement strategies, such as implementing more ecological protection work in low-EWP areas and promoting successful eco-city building experiences in high-value agglomeration areas. (4) To enhance EWP, government authorities can devise policy interventions to optimize the balance among economic expansion, ecological preservation, and the improvement of societal welfare. By implementing strategic frameworks and regulations prioritizing sustainable development, governments can effectively address the multifaceted aspects of EWP. Such measures could include incentivizing green technologies, enforcing stricter environmental regulations, and promoting policies that integrate economic, environmental, and social objectives. Through these comprehensive strategies, it is feasible to foster an environment in which economic growth does not come at the expense of ecological integrity or human well-being, thereby ensuring a sustainable and prosperous future for all stakeholders involved. We recommend formulating strict urban planning regulations to ensure that ecologically protected areas are not eroded by urban expansion and to protect the integrity of ecosystems around cities. We recommend urban green space construction and ecological landscape planning to increase urban green coverage and improve the ecological environment. We recommend prioritizing ecological and environmental protection, promoting green development, and enhancing residents’ quality of life in urban planning. (5) Multi-party cooperation and the radiating effect of cities should be encouraged. We recommend giving full play to the radiating effect of cities with a high level of EWP, and by sharing experiences, technology, and resources, enabling neighboring areas to promote and apply corresponding environmental protection technologies and policies. This promotes the development of green industries.
and enhances the level of public services and social welfare, thus leading to the enhancement of EWP and the sustainable development of the entire region. By promoting intercity cooperation and exchanges, the overall level of ecological welfare in Chinese cities can be effectively improved, and the construction of sustainable urban communities can be promoted.

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**References**


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