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Spatial Analysis and Prediction of Ecological Welfare Performance: Evidence from 284 Prefecture-level Cities in China

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Abstract: The general debate of the 78th session of the United Nations reaffirmed the importance of the Sustainable Urban and Community Development Goal (SDG 11), however, the pervasive accounting gaps still lead to significant challenges in the monitoring and evaluation of SDG 11 indicators. This paper focuses on ecological welfare performance accounting, aiming to assess the weaknesses and internal gaps of regional SDG 11 at the aggregate level, so as to promote eco-city planning and management, improve the well-being potential of urban residents, and reduce the adverse impact on the ecological environment. Taking China as a developing country as a case, the two-stage DEA model is used to measure the ecological welfare performance of 284 cities in China from 2007 to 2022, and the spatiotemporal pattern of efficiency at each stage of the ecological welfare transformation process is described, a modified gravitational model is constructed to transform the "attribute data" of ecological welfare performance into "relationship data", and the characteristics of network structure are described with the help of social network analysis, and the formation mechanism of the spatial correlation network of ecological welfare performance is revealed and its dynamic evolution characteristics are revealed through the spatial Markov chain.

Keywords: Ecological Welfare Performance; Two-stage DEA Model; Social Network Analysis; Space Markov Chain.

1. Background

Following the Millennium Development Goals, the United Nations adopted the 2030 Agenda for Sustainable Development in September 2015, which covers 17 interrelated Sustainable Development Goals (SDGs) and 169 related targets in three dimensions of economy, society and environment, and plans to implement these goals by 2030 by UN members[1]. SDG 11 aims to achieve inclusive, resilient and sustainable urban development policies and practices that prioritize basic services for all, affordable housing, efficient transport and green spaces.

At the same time, the current global environmental problems, such as climate change, resource depletion, biodiversity reduction, and environmental pollution, pose severe challenges to the sustainable development of cities [3]. Extreme weather events brought on by climate change threaten the resilience of urban infrastructure [4] and can cause severe economic losses and social unrest. The over-exploitation and consumption of resources not only leads to the deterioration of the ecological environment, but also increases the economic cost of urban operation and affects the long-term economic competitiveness of cities [5]. The loss of biodiversity weakens the services provided by ecosystems, such as air and water purification, climate regulation and soil conservation, and reduces the quality of life of residents [6]. At the same time, environmental pollution, including air pollution, water pollution, and soil pollution, degrades the quality of the urban environment, and threatens the health of urban residents [7]. Moreover, more than half of the world's population lives in urban areas, and this proportion is expected to reach 68% by 2050 [8]. In 2015, about 1.2 billion people lived in urban slums or slum-like conditions, which is expected to increase to 2.5 billion in the next 15 years [9]. However, as of 2022, only half of city dwellers have easy access to public transport, and problems such as urban sprawl, air pollution, and limited public space remain. [10], Cities are considered to be the main platforms for the Sustainable Development Goals (SDGs) such as poverty eradication, healthy living, and quality education [11-13], so "Building inclusive, safe, resilient and sustainable cities and human settlements" (SDG 11) not only focuses on the sustainability of cities per se, but also has an important impact on the achievement of all SDGs and is at the heart of achieving the SDGs [14], The general debate of the 78th session of the United Nations reaffirmed the importance of the Sustainable Urban and Community Development Goal (SDG 11).

At present, most scholars use Ecological Well-being Performance (EWP), an important indicator to measure the sustainable development capacity of a country or region [27]. In the context of global environmental governance and sustainable development, China has actively explored the path of urban green transformation under the Sustainable Development Goals, with significant improvements in urban air quality [28], steady increase in carbon emission performance [29], and an increase in biodiversity [30], while China's smart cities have actively explored renewable energy and resources [31], contributing Chinese wisdom and solutions to the global urban ecological welfare performance and sustainable urban development.

2. Data Sources, Indicator System and Model Construction

2.1. Data Sources and Processing

In this paper, 284 cities in China are taken as the research unit, and the study period is from 2007 to 2022. The evaluation index data are from the China Statistical Yearbook, China Energy Statistical Yearbook, China Education Statistical Yearbook, China Environment Statistical Yearbook and urban statistical yearbooks from 2001 to 2022. The data of influencing factor variables are from China

Statistical Yearbook, China Science and Technology Statistical Yearbook, China Environment Statistical Yearbook and statistical bulletins of various urban areas. The original data of the EWP input-output indicators are derived from the China Urban Statistical Yearbook and the China Urban Construction Statistical Yearbook.

2.2. Ecological Welfare Performance Evaluation Index System

In this paper, a two-stage DEA method is used to measure the ecological welfare performance of 284 cities in China, and the premise is to clarify the input and output indicators of each stage. In this paper, a two-stage DEA method is used to measure the ecological welfare performance of 284 cities in China, and the premise is to clarify the input and output indicators of each stage. Drawing on the research of [51-52], this paper shows that the input indicators are expressed in terms of energy consumption and pollution emissions. In this paper, a multi-dimensional HDI based on economic welfare, social welfare, and environmental welfare is constructed as output indicators, including consumption level, education, medical and health care, and environmental benefits. The comprehensive level of ecological welfare performance is evaluated through the first stage input and the second stage output. The evaluation index system of each stage in the process of ecological welfare transformation was constructed.

2.3. Two-stage DEA Model

This paper refers to [53] to decompose the efficiency of EWP into two sub-stages, in order to open the "black box" of the transformation process of ecological input and welfare output. Among them, the first stage is the ecological economic transformation stage (L1), that is, the efficiency of transforming ecological input into economic output; The second stage is the economic welfare transformation stage (L2), that is, the efficiency of transforming economic inputs into welfare outputs, and the formula is as follows:

$$E = \frac{I}{C} = \frac{G}{C} \times \frac{I}{G} \tag{1}$$

In the above formula:

E – Ecological welfare performance;

C - ecological consumption, which is the initial input indicator;

G - the level of economic development is the intermediate variable in the transformation process of ecological welfare, which is not only the output index of the first stage, but also the input index of the second stage, and plays a mediating role.

I – Human Development Index, which indicates the level of welfare, is an indicator of final output.

Compared with other measurement methods, the DEA method does not need to pre-set the production function, and can handle the input and output of multiple indicators, so it can fully reflect the consumption of resources and the improvement of economic, social and environmental well-being in the process of ecosystem operation. However, the traditional DEA method ignores the stage efficiency in the production process and the impact of each sub-stage on the overall efficiency. In view of this shortcoming, some scholars [54] have improved the traditional single-stage DEA model and constructed a two-stage DEA model, which can effectively evaluate the real efficiency of the system in the process of operation, fully reflect the effectiveness of input and output at each stage and the correlation of sub-stages, and is more in line with the actual situation of the transformation process of ecological welfare.

Suppose there are n homogeneous decision units (DMUs) and each DMUi (i=1,2,... n) are all broken down into two phases. where xij = (xi1, xi2,... xim)T(j=1,2,… m) denotes the DMUi input variable at L1; zid=(zi1,zi2,… zir)T(d=1,2,… r) denotes the intermediate variable of DMUi, which is both the output of L1 and the input of L2; yik=(yi1,yi2,… yip)T (k=1,2,… p) denotes the output variable of DMUi at L2. In L1, this paper adopts the input-oriented DEA-BCC model, and the goal of this stage is to minimize input and maximize output, with input/output as the evaluation index, and the minimum value of the evaluation index is the optimal value.

2.3.1. Ecological Economic Transformation Stage

$$minE_1 = \frac{\sum_{j=1}^{m} w_j x_{ij} + \beta_1}{\sum_{d=1}^{r} \varphi_d z_{id}} \tag{2}$$

$$s.t. \frac{\sum_{d=1}^{r} \varphi_d z_{id}}{\sum_{j=1}^{m} w_j x_{ij} + \beta_1} \le 1, i \in [1, n] \tag{3}$$

$$w_j, \varphi_d \ge 0, \beta_1 \in R \tag{4}$$

2.3.2. Transformation Stage of Economic Welfare

In L2, this paper adopts the output-oriented DEA-BCC model, and the goal of this stage is to maximize output and minimize input, with output/input as the evaluation index, and the maximum value of the evaluation index is the optimal value.

$$maxE_2 = \frac{\sum_{k=1}^{p} v_k y_{ik} - \beta_2}{\sum_{d=1}^{r} \varphi_d z_{id}} \tag{5}$$

$$s.t. \frac{\sum_{k=1}^{p} v_k y_{ik} - \beta_2}{\sum_{d=1}^{m} \varphi_d z_{id}} \le 1, i \in [1, n] \tag{6}$$

$$v_k, \varphi_d \geq 0, \beta_2 \in R \tag{7}$$

2.4. Social Network Analysis

2.4.1. Modified Gravitational Models and Network Calculation

The determination of the spatial correlation of EWP is the premise of social network analysis. Drawing on the research of [55] et al., this paper uses a modified gravitational model to determine the correlation matrix of EWP in prefecture-level cities in China. The formula is as follows:

$$F_y = K_y \times \frac{EWP_i \times EWP_j}{D_{ij}^2}, K_y = \frac{EWP_i}{EWP_i + EWP_j}, D_y^2 = \left(\frac{dis_y}{pgdp_i - pgdp_j}\right)^2 \tag{8}$$

where: is the strength of the ecological welfare performance link between urban area and ; It represents the contribution rate of urban areas in the relationship with inter-city ecological welfare performance; Represents the ecological welfare performance index; for urban areas and "comprehensive economic geography N distance" (km/yuan); Represents the spherical distance between cities (km); Indicates the per capita GDP of the city (RMB). According to equation (1), the gravitational matrix of inter-city ecological welfare performance can be calculated,

The "mean principle method" was used to binarize the matrix to obtain the spatial binary matrix of ecological welfare performance.

2.4.2. Characteristics and Evolution Trend of the Overall Network Structure

Data from 2007 to 2022 are selected to plot the overall network characteristics of the two phases of EWP, as shown in Figures 1 to 4.

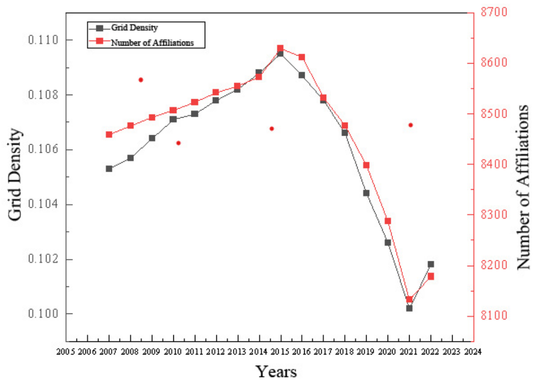

Figure 1. Network density and relationships in 2007

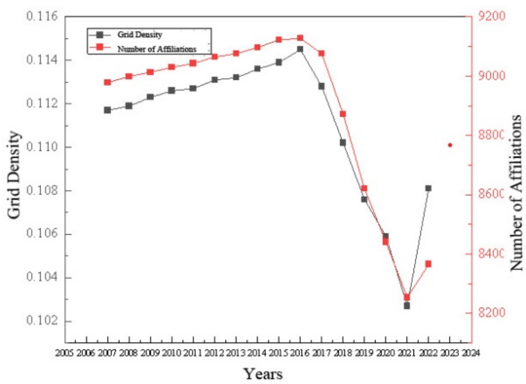

Figure 2. Network densities and relationships in 2022

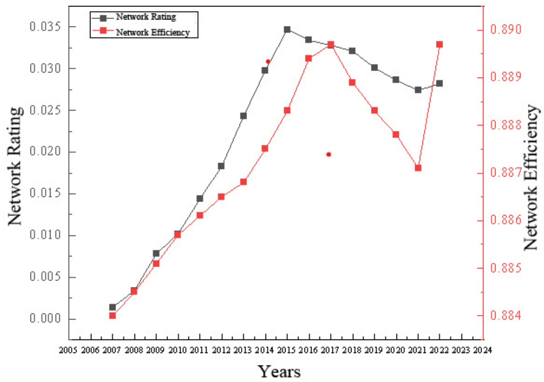

Figure 3. Network level and efficiency in 2007

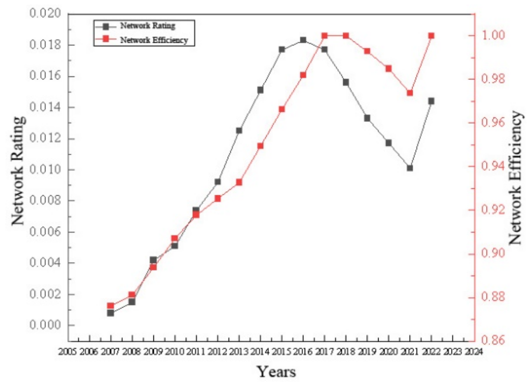

Figure 4. Network level and network efficiency in 2022

According to the results of Figure 6 to Figure 9, the network density and correlation coefficient of L1 and L2 showed a steady increase and then decrease from 2007 to 2022, and as of 2021, the association coefficient of L1 decreased from about 8500 at the beginning of the period to about 8100, and the association coefficient of L2 decreased from about 9000 to about 8200. In contrast, the network density and correlation coefficient of L1 decreased slightly, while L2 decreased greatly, indicating that the transformation of economic welfare is the key link restricting the improvement of EWP. From the perspective of dynamic evolution trend, the network density and relationship number of L1 in the same year are larger than those of L2, as shown in Figures 6 and 8. The results of the quantitative analysis are consistent with the results of the previous intuitive experience. The network rating of L1 increased from 0.0014 in 2007 to 0.0282 in 2022, and the network rating of L2 increased from 0.0008 in 2007 to 0.0144 in 2022, as shown in Figures 8 and 9. The results indicate that there is a certain hierarchical structure between the areas with high ecological welfare performance and the areas with low ecological welfare performance, and the potential of each province in the network is uneven. Figures 8 and 9 also show the network efficiency of two stages: the overall level of network efficiency in the two stages is high, which remains above 0.85, which is at the upper level, indicating that there are multiple superposition phenomena and redundant connections in the spatially related network of EWP, and the network stability needs to be further improved.

3. Prediction of the Horizontal Transfer Path of Ecological Welfare Performance based on Markov Chain

3.1. Research on the Spatiotemporal Transfer Path of Ecological Welfare Performance Level of Cities in China Based on the Traditional Markov Chain

The traditional Markov chain [57] is based on a stochastic process under the condition that both time and state are continuous, and no aftereffect is an important feature of it. In this model, the transition of state of a system depends only on its most recent state, regardless of its earlier state. This property makes the Markov chain a powerful tool that can be applied in a variety of fields. There are two main reasons for using traditional Markov chains: first, Markov chains can accurately predict the dynamic changes in the state of a system with relatively little computational complexity, which is especially important when dealing with large-scale data or making long-term predictions; Second, the Markov chain is able to describe many real-world processes in a formal way, providing them with an efficient way to model them. To use a traditional Markov chain, the following requirements need to be met:

(1) The state state of regional economic development level at any time series node during the study period is random.

(2) The type of regional economic development level is transferred from this time series node to the next time series node according to the path of different probabilities.

(3) The type of regional economic development level only depends on the probability of the transfer path and the state under the time series node, and has nothing to do with the state before the node, that is, the evolution of the regional economic development state has no aftereffect.

After satisfying the above conditions, we divided the EWP from 2007 to 2022 into groups, and then constructed a matrix reflecting the probability of state transition, and recorded the probability distribution of ecological welfare performance from one group to another, so as to describe the process of spatiotemporal transfer of EWP. The expression formula is as follows:

$$M_{ij} = \frac{n_{ij}}{n_i} \tag{9}$$

Thereinto:

$$M_{ij} = \begin{bmatrix} n_{11} & \cdots & n_{1j} \\ \vdots & \ddots & \vdots \\ n_{i1} & \cdots & n_{ij} \end{bmatrix}_{k\times k} \tag{10}$$

where is the state transition probability matrix of , which is the sum of the number of spatial units in the study period when the level of economic development changes from the state of year to the state of j of year. is the sum of the number of all spatial units with a state of economic development throughout the study period.

According to the Markov chain principle, the year-by-year changes of ecological performance types in cities in China from 2007 to 2022 were recorded and analyzed, and the EWP and economic development level were set into five groups: "low", "low", "medium", "high" and "high", and the traditional Markov transfer probability table of the fifth-order matrix was obtained, as shown in Table 1.

Table 1. Probability table of traditional Markov chain transfer in fifth-order matrix

t/t+1	n	1 (Low)	2 (lower)	3 (Medium)	4 (Higher)	5 (High)
1 (Low)	886	0.727	0.221	0.043	0.009	0.000
2 (lower)	869	0.183	0.490	0.251	0.062	0.014
3 (Medium)	840	0.017	0.202	0.452	0.262	0.067
4 (Higher)	829	0.004	0.051	0.221	0.510	0.215
5 (High)	836	0.002	0.008	0.044	0.202	0.743

The diagonal line in Table 9 shows the probability of each city maintaining the original economic development level, and outside the diagonal is the probability of spatiotemporal transfer in each city. According to Table 9, we can know that: (1) The stability of EWP in the original state of each city in China is strong, the initial category is from low to high, the diagonal probability is greater than the non-diagonal probability, and the lowest probability of each city to maintain the original state is 45.2%, and the highest probability is 74.3%, indicating that the stability of the economic development of each city is strong, but the occurrence of spatiotemporal transfer is not excluded. (2) The probability of maintaining the original status quo at a low level and a high level of ecological efficiency in cities in China is relatively low, while the probability of maintaining the original status quo at a low, medium and high level is relatively low, ranging from [49% to 51%], indicating that there is a polarization of EWP in cities in China and a phenomenon of "club convergence", indicating that there is a long-term regional difference in EWP level among cities.

3.2. Research on the Spatiotemporal Transfer Path of Ecological Performance Level of Cities in China based on Spatial Markov Chain

Since economic phenomena are not random, according to the first law of geography, everything is related to geographical location, so we study the EWP of each city in China, which is related to its geographical location, and geographical location will affect the distribution, development and interaction of things, and this interaction will become closer with distance and other factors. However, the traditional Markov chain cannot accurately take into account the interaction between cities, so the traditional Markov chain is combined with local space to introduce the concept of "spatial lag" and construct a spatial Markov chain.

Compared with the traditional Markov chain, the spatial

Markov chain is composed of transition matrices, and the spatial weight matrix needs to be introduced to reflect the interaction between cities, and the size of the spatial lag value determines the spatial lag type to which the spatial unit belongs. The expression is:

$$Lag = \sum_{i=1}^{n} y_i w_{ij} \tag{11}$$

In the above equation, denotes the spatial lag value, denotes the number of spatial units, denotes the attribute value of spatial units, and denotes the adjacency space weight matrix based on the QueenXX rule.

In order to test whether the spatial factors have a significant impact on the EWP of cities in China, we use the chi-square test to verify the situation, and the formula is as follows:

$$p = -2\log\left\{\prod_{m=1}^{2}\prod_{i=1}^{k}\prod_{j=1}^{k}\left[\frac{Q_{ij}^{t,\ t+1}}{Q_{ij}^{t,\ t+1}(m)}\right]^{n_{ij}(m)}\right\} \tag{12}$$

In the above equation, and denotes the sum of the elements of the two types of transition matrix and the number of regions belonging to this type of transition when the duration is , respectively, and the transfer probability value is calculated by combining the two types of data, p asymptotectively obeys the chi-square distribution, and its degrees of freedom are minus the number of transfer probabilities of 0.

In order to take the spatial lag factor of the spatial unit in the year as the condition, and the economic development level of the year is the type, and the spatial transition probability of the year into the type, we consider the spatial effect on the basis of the traditional Markov chain, construct the spatial Markov chain model, obtain the spatial Markov transfer matrix, and further explore the influence and spatial effect characteristics of the spatial relationship team in China.

We set the spatial lag to 5 groups, named none, low-low aggregation, low-high aggregation, high-low aggregation, and high-high aggregation, and we first set up the spatial Markov chain according to the test index p=0.01<0.05, which shows that it is meaningful to consider the spillover effect in the establishment of spatial Markov chains, and the traditional Markov chain cannot well explain the interaction between the leading regions, and the results of the path transfer probability matrix of spatial Markov chains are shown in Table 2.

Table 2. Spatial Markov chain path transition probability matrix

Regional context	t	n	t+1				
			Low	Lower	Medium	Higher	High
Gather high High and low gathering Low and high clusters	low	0	0.000	0.000	0.000	0.000	0.000
	Lower	0	0.000	0.000	0.000	0.000	0.000
	medium	0	0.000	0.000	0.000	0.000	0.000
	Higher	23	0.000	0.043	0.087	0.478	0.391
	high	270	0.000	0.004	0.033	0.115	0.848
Low low aggregation Regional context	low	0	0.000	0.000	0.000	0.000	0.000
	Lower	0	0.000	0.000	0.000	0.000	0.000
	medium	0	0.000	0.000	0.000	0.000	0.000
	Higher	2	0.000	0.500	0.000	0.000	0.500
	high	78	0.013	0.013	0.013	0.115	0.846
Gather high High and low gathering	low	129	0.791	0.155	0.047	0.008	0.000
	Lower	47	0.234	0.574	0.170	0.021	0.000
	medium	5	0.200	0.400	0.400	0.000	0.000
	Higher	0	0.000	0.000	0.000	0.000	0.000
	high	0	0.000	0.000	0.000	0.000	0.000
Low and high clusters Low low aggregation	low	33	0.939	0.030	0.030	0.000	0.000
	Lower	8	0.125	0.625	0.250	0.000	0.000
	medium	1	0.000	0.000	1.000	0.000	0.000
	Higher	0	0.000	0.000	0.000	0.000	0.000
	high	0	0.000	0.000	0.000	0.000	0.000
Regional context	low	724	0.706	0.242	0.043	0.010	0.000
	Lower	814	0.181	0.484	0.256	0.065	0.015
	medium	834	0.016	0.201	0.452	0.264	0.067
	Higher	804	0.004	0.050	0.225	0.512	0.209
	high	488	0.002	0.010	0.055	0.264	0.668

According to Table 10, we can see that: (1) There is a high correlation between EWP type transfer and regional background, and the probability of spatiotemporal transfer of EWP in different regional backgrounds is quite different, and the results are quite different from those of the traditional Markov chain, so there is a spatial spillover effect of EWP transition among cities in China. (2) In the context of most regions, the probability of diagonals is greater than that of non-diagonals, but in the case of high-high aggregation and high-low aggregation, there is a situation where the diagonal is equal to the probability of non-diagonal, which indicates that most cities in China have the situation of maintaining the original state, but there are also some cases of pathway transfer, and it is the situation of jump transfer. (3) The probability of high EWP level was 84.8% in the regional background of high aggregation, which was higher than that in the non-regional background (66.8%). The probability of low EWP level was 93.9% in the regional context of low and low aggregation, which was higher than that in the non-regional background (70.6%). This suggests that there is a "club convergence" phenomenon at the EWP level. (4) The change of regional background does not absolutely affect the transfer of EWP in each city. (5) Compared with the traditional Markov chain, the spatial Markov chain maintains the original status quo of the EWP in each city in China without setting the regional background, that is, without setting the spatial lag, and the path selection will be increased and the spatial lock will be reduced. Moreover, the probability of some transfer paths has been improved, indicating that after considering the spatial lag, it can better reflect the EWP transfer situation of various cities in China.

4. Conclusion

Based on the improved HDI index, economic development level and natural consumption index, this paper constructs an EWP evaluation index system, decomposes the ecological welfare performance into two stages: ecological economic transformation and economic welfare transformation, and calculates the EWP level of 284 cities in China from 2007 to 2022 through the two-stage DEA method, and depicts the spatiotemporal differentiation characteristics of each stage, and then uses social network analysis and Markov chain to explore the dynamic evolution trend of EWP from the perspective of distribution characteristics and space. The main conclusions of the study include: (1) EWP generally showed a trend of first increasing and then decreasing during the sample period, and its decline in L1 was lower than that of L2, which shows that L2 is the key link restricting the improvement of EWP. (2) The agglomeration pattern of the spatial correlation network of ecological welfare performance is characterized by the coexistence of "local agglomeration" and "global association", and the network center is concentrated in the eastern coastal region, forming a significant Matthew effect, while the central and western regions and the northeast region mainly play a bridge role. (3) The formation and development of the spatial correlation network in the two sub-stages of EWP is affected by four mechanisms: resource endowment differences, market regulation, government macroeconomic regulation and control, and science and technology promotion.

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