The Decoupling Relationship Between Land Use Efficiency and Carbon Emissions in Beijing Ecological Conservation Areas, China

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Key words: Carbon emissions; Land use efficiency; Data Envelopment Analysis (DEA) model; Tapio model

SUMMARY

In the new development phase, clarifying the relationship between land use efficiency (LUE) and carbon emissions (CE) supports high-quality development and coordinated economic-ecological progress. Based on land use and socio-economic data of Beijing Ecological Conservation Areas (BECA) from 2010 to 2021, this paper analyzes the decoupling relationship between LUE and CE using carbon emissions calculation coefficients, Data Envelopment Analysis model, and Tapio decoupling model. The findings are as follows:

(1) Net CE of the areas showed fluctuating declines, with overall carbon sequestration increasing in 2021. Pinggu and Miyun districts had carbon sink ecological carrying capacity coefficients greater than 1. While Huairou, Mentougou and Yanqing districts had relatively low LUE. (2) During the 12th Five-Year Plan period, driven by policies for ecological protection and industrial transformation, the decoupling status showed a sharp fluctuation trend of "strong decoupling-strong negative decoupling-recessive decoupling". In the 13th Five-Year Plan period, with the deepening of green development policies, the decoupling relationship evolved toward a moderate and coordinated trend of "weak decoupling – expansive connection". Taken together, this reflects the response law and evolution logic of the relationship between LUE and CE in ecological conservation areas, shifting from "transformation pains" to "mature development" across different policy stages. Overall, promoting low-carbon development, high technology, and scientific innovation is essential for the region in future.

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1 Introduction

The efficient use of land resources is crucial to sustainable regional development. China currently suffers from both land scarcity and severe ecological pollution, amid mounting pressure to achieve its dual carbon goals. Neither the conventional "develop first, clean up later" model nor sacrificing economic growth to cut emissions is sustainable. Although economic growth has traditionally correlated with rising CE, neither of these two paths aligns with today's climate objectives—making them unviable solutions. Therefore, it is urgent to explore mechanisms that simultaneously enhance LUE and reduce CE.

As a physical concept originally referring to the separation of interrelated quantities, "decoupling" was introduced into socio-environmental research by the German scholar Weizsäcker to describe asynchronous changes between economic growth and resource use or environmental pressure. Challenging the notion that economic growth requires environmental sacrifice, decoupling theory provides a quantitative tool for assessing regional sustainability.

The theory was initially applied to energy consumption and economic output (e.g., CE vs. GDP growth). Now, it has been extended to land use studies. It now serves as a key framework for analyzing conflicts such as land development intensity versus economic growth, urban expansion versus ecological degradation[2-4]. For example, decoupling elasticity helps assess sustainability between land use intensity and pollution, or between construction land expansion and demographic/industrial growth. International applications, such as studies on CE and energy policies in Portugal [5], further confirm its utility in examining interactions among human activities, land use, and environment.

It can be achieved through three synergies—rooted in intensive, rational, and ecological land allocation—to improve LUE and reduce CE. Firstly, it involves utilizing less land to generate higher value, such as by increasing industrial plot ratios, by centralizing industrial parks to minimize ecological encroachment, or by reducing CE through energy sharing. Secondly, it entails optimizing functional compatibility, such as locating high-value-added services in core areas and promoting a balance between jobs and housing to shorten commutes, thereby reduce mobile CE. Thirdly, it requires protecting ecological land by demarcating red lines and transforming idle land into green spaces and wetlands to enhance carbon sequestration. It is evident that improving LUE is not solely about maximizing spatial output; rather, it involves integrating carbon reduction into the entire process of land allocation. Decoupling theory can assess the extent to which improvements in LUE are decoupled from CE, facilitating the achievement of "economic growth without an increase in CE."

Currently, relevant research on urban land use efficiency (LUE) is continuously enriched [8, 9], with research methods evolving from directional description to quantitative analysis, forming two categories: non-parametric methods represented by Data Envelopment Analysis (DEA) and parametric methods represented by Stochastic Frontier Analysis (SFA) [10, 11]. Common DEA models include the BCC and CCR models, with research scales covering different spatial scopes such as the whole country, economic zones, urban agglomerations, and typical cities (e.g., prefecture-level cities) [12-14]. Overall, these studies mostly focus on LUE itself and its influencing factors. Meanwhile, research on the relationship between land use and carbon emissions (CE) mainly focuses on three aspects: the carbon effects caused by different land use structures and intensities [15-17], the spatiotemporal evolution of LUE and CE [18-20], and their influencing factors [18-20]. However, there is relatively little research on the correlation between LUE and CE. Most of these studies are concentrated in economically developed provinces in the central and eastern parts of China, as well as the Sichuan-Chongqing region, with fewer studies on typical functional zones. The research on the decoupling relationship between LUE and CE is an important extension of decoupling theory in the field of territorial space. There are two reasons for introducing decoupling theory into this correlation study. On the one hand, LUE integrates the comprehensive evaluation of economic output, resource input, and ecological benefits, while CE is one of the most critical negative environmental outputs in the process of land use. The decoupling state of the two directly reflects the coordination level of the regional "economic-ecological" system. On the other hand, through the dynamic calculation of decoupling elasticity coefficients, this approach can not only identify specific types such as "efficiency improvement and carbon emission reduction" (strong decoupling) and "efficiency improvement but faster carbon emission growth" (expansionary negative decoupling), but also reveal the supporting capacity of land use patterns for the low-carbon transformation of economic development in different stages. This analytical perspective not only provides a quantitative standard for evaluating the level of urban green and sustainable development but also offers a precise theoretical basis for formulating differentiated land management and carbon emission reduction policies. Especially for special areas such as ecological conservation zones, which bear the dual missions of "ecological protection" and "economic development", the theoretical guiding value of this perspective is even more prominent. Based on this, this paper takes BECA as its research area [6]. Through CE accounting models, DEA models, and Tapio decoupling model, it systematically analyses the distribution characteristics of CE, LUE levels, and the decoupling relationship between LUE and CE.

This research not only provides a “gradient reference” case for other functional zones in Beijing (such as urban development new districts) in collaboratively promoting land use transformation and CE reduction but also offers theoretical and practical insights for exploring coordination mechanisms linking ‘ecological conservation, land use, and CE reduction’ in similar ecologically sensitive zones or functional zones nationwide.

2 Overview of the Study Area and Data Sources

2.1 Overview of the Study Area

In 2005, Beijing designated Huairou, Mentougou, Pinggu, Miyun, and Yanqing as ecological conservation zones, covering 8,747 km² (53.3% of the city’s area). As Beijing’s largest functional zone under the "Four Centers" strategy, it serves as a critical ecological barrier, emphasizing water conservation and biodiversity. The area is predominantly mountainous (over 85%), with a temperate monsoon climate and rich ecological resources—including Miyun and Huairou reservoirs, which supply over 70% of Beijing’s water. Forest coverage exceeds 60%, and ecological land accounts for 82% of the area, with over 40% under strict ecological protection red lines.

In 2022, the zone's CE were around 20 million tons (8% of Beijing's total), primarily from residential energy (40%), agriculture (25%), and transportation (20%). Its annual carbon sequestration reaches 12 million tons, yielding a carbon sink-to-emission ratio of 0.6—making it Beijing's only functional zone nearing carbon neutrality. This study examines the period 2010–2021 to analyze LUE and CE decoupling trends.

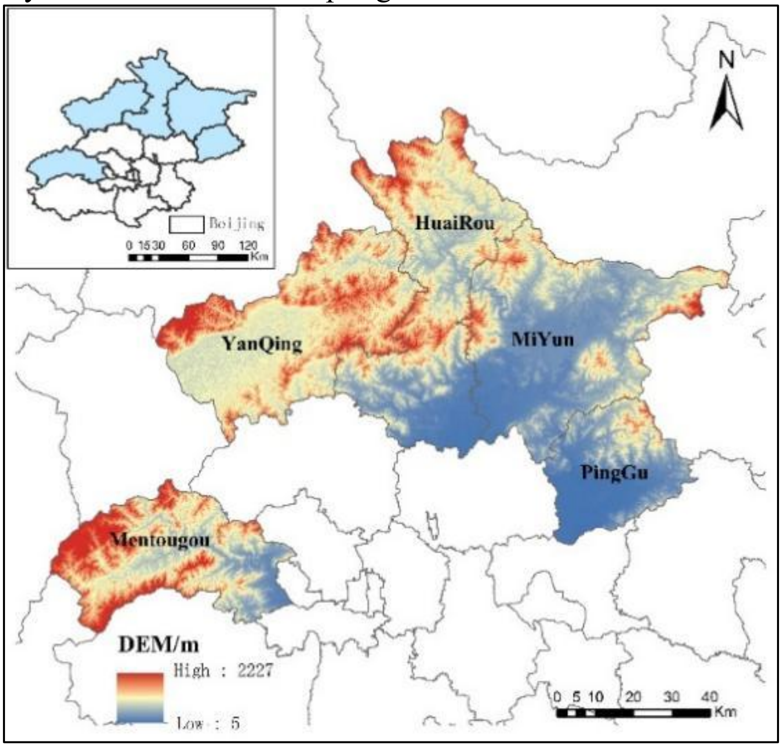

Fig.1 Geographical location of ecological conservation area in Beijing

2.2 Data Sources

The data used in this article includes land use data, socio-economic data, etc. The land use data from 2010 to 2021 is sourced from the Landsat's annual China Land Cover Dataset (CLCD) and a research paper titled "30m annual land cover and its dynamics in China from 1990 to 2019" co-authored by Professor Yang Jie and Professor Huang Xin from Wuhan University, with a data accuracy of 30m [7] (land cover data for 2020-2021 has been subsequently updated). The socio-economic data is sourced from the "Beijing Regional Statistical Yearbook" and the "China City Statistical Yearbook". Missing data for individual years were supplemented by consulting government bulletins and contacting relevant government departments.

3 Research Methods

3.1 Methods for Evaluating LUE

3.1.1 Development of a LUE Indicator System

The evaluation index system for LUE in this study is based on the core principle of the three production factors theory, and combines the diverse impacts of urban land use on economy, society, and ecology to establish a bidirectional input-output framework.

At the input level, indicators are primarily selected based on three major factors: land, capital, and labor. The built-up area (land factor) reflects the scale of urban land development and serves as the basis for measuring the intensity of land investment. The amount of social fixed assets investment (capital factor) encompasses infrastructure and industrial project investments, indicating the support of capital for intensive land development. The proportion of employees in the secondary and tertiary industries (labor factor) reflects the agglomeration of labor towards efficient industries, indirectly indicating the efficiency of land and human resource allocation.

At the output level, we must consider the comprehensive benefits of land use. Gross domestic product (GDP) (economic output) measures the total economic output per unit of land and is a key indicator of land economic efficiency. The total retail sales of consumer goods (social function) reflect the support provided by commercial and residential land to residents' consumption convenience. The average wage of employees on the job (livelihood benefit) reflects the impact of industrial added value on the income of employed individuals. Green coverage rate (ecological output) aligns with the "dual carbon" goals, reflecting the carbon sink and environmental regulation functions of land as well as ecological sustainability.

The specific indicator system is constructed as shown in Table 1.

Tab.1 Evaluation index system of LUE

Primary Indicators	Secondary Indicators	Tertiary Indicators
Input Indicators	Land Level	Built-up Area (km²)
	Capital Level	Total Social Fixed Asset Investment (¥ billion)
	Labour Level	Proportion of Employment in Secondary and Tertiary Industries (%)
Output Indicators	Social Level	Total Retail Sales of Consumer Goods (¥ billion)
		Average Wage of Active Employees (¥)
	Economic Level	Gross Domestic Product (¥ billion)
	Ecological Level	Green Space Coverage Rate (%)

3.1.2 Evaluation Model

Data Envelopment Analysis (DEA) is a non-parametric efficiency evaluation technique founded on relative comparisons of evaluation subjects. Notably, its core advantage lies in its compatibility with complex evaluation scenarios involving multiple inputs and outputs, without the need for a predefined production function form. It accurately measures the relative efficiency of homogeneous decision-making units (DMUs), which closely matches the evaluation requirements of LUE—namely "multi-factor inputs and multi-dimensional outputs"—thus offering a scientific analytical tool for this study.

Given that the evaluated subjects in this study differ in developmental stages and resource endowments, they nevertheless collectively fall within a phase characterized by the pursuit of synergistic optimization of scale and technological efficiency. Consequently, the constant returns to scale (CRS) assumption inherent in the CCR model is more appropriately suited to analyzing two key aspects: whether the current scale has been optimized, and what implications scale adjustments may have for efficiency.

Suppose we wish to measure the technical efficiency of a set of n DMUs, denoted as DMU_j(j=1，2，⋯，n); Each DMU possesses m inputs and s outputs, denoted respectively as X_i(i=1，2，⋯，m)and Y_q(q=1，2，⋯，s).The weights of inputs and outputs are represented as v_i (i=1，2，⋯，m)and μ_q (q=1，2，⋯，s). The DMU currently under measurement is denoted as h_k, whose input-output ratio is expressed as:

$$h_k = \frac{\mu_1 y_{1k}+\mu_2 y_{2k}+\cdots+\mu_s y_{sk}}{v_1 x_{1k}+v_2 x_{2k}+\cdots+v_m x_{mk}} = \frac{\sum_{q=1}^{s} \mu_q y_{qk}}{\sum_{i=1}^{m} v_i x_{ik}} \quad (1)$$

Where $v \geq 0$ and $\mu \geq 0$. By constraining the efficiency values θ_j obtained for all DMUs using the aforementioned weights within the range 0–1, the CCR model (input-oriented) is derived [9].

3.2 Methodology for Calculating LUCE

LUCE encompasses both direct and indirect emissions. Direct emissions primarily stem from the land use category itself, whilst indirect emissions chiefly arise from anthropogenic activities conducted on cultivated land and construction land. The magnitude of net CE depends on the difference between CE (sources) and carbon sequestration (sinks). Carbon sources are reflected in CE intensity, while carbon sinks are reflected in carbon pool stocks and cumulative absorption. This paper designates cultivated land and construction land as carbon source areas; forested land, grassland, water bodies, and unutilized land as carbon sink areas [10, 11].

The formula for calculating direct CE is:

$$C_a = S_i \cdot V_i \tag{2}$$

In the formula: C_a denotes CE (t) for land use type i; S_i represents the area (hm²) of land use type i; V_i denotes the CE coefficient (t/hm²) for land use type i. Here, i=1,2,3,4,5, which respectively denote arable land, forest land, grassland, water bodies, and unutilized land. Considering that CE from these land uses exhibit minimal variation over extended periods, the emission factors established by scholars Fang Jingyun et al. [12] are adopted, sequentially as 0.497, -0.6125, -0.0205, -0.253, -0.005 (units: t/hm^2).

Indirect CE from construction land were calculated by reference to the China Energy Statistical Yearbook and the IPCC 2006 National Greenhouse Gas Inventory Guidelines (Tab.2), using the following formula:

$$E_j = \sum_{j=1}^{7}\left(e_j \times \theta_j \times \beta_j\right) \tag{3}$$

Where: E_j denotes CE from construction land (t); e_j denotes energy consumption of type j (t); θ_j denotes the standard coal conversion factor for energy type j; β_j denotes the CE factor for energy type j.

Tab.2 Conversion coefficient and CE coefficient of standard coal of various energy sources

	Raw coal	Coke	Petrol	Diesel	Fuel oil	Thermal energy	Electricity
Standard coal conversion factor(kg/kg)	0.7143	0.9714	1.4286	1.4571	1.4286	0.0341	0.1229
CE factor(t/t)	0.7559	0.855	0.5857	0.5921	0.6185	0.773	0.2132

The formula for calculating net CE is:

$$C = C_a + E_j \tag{4}$$

In the equation: C denotes net CE from land use (t), C_a represents carbon sequestration from each land use type (t), and E_j signifies total CE (t).

This study analyses the spatiotemporal distribution characteristics of CE in ecological conservation areas using representative years. Using land use data from 2010, 2015, and 2020, we calculated carbon sources and sinks by using the CE estimation formula to derive net CE. Using the natural breakpoint method, we categorized regions into four tiers (t): high carbon sink zones (-∞, -5), low carbon sink zones (-5, 0), low carbon source zones (0, 10), and high carbon source zones (10, +∞).

3.3 Methodology for Analyzing Regional Contributions to LUCE

The carbon sink ecological carrying capacity coefficient is employed to assess the contribution of land use CE to the region. This coefficient serves as a crucial parameter for evaluating carbon balance and sustainability, reflecting the relationship between an ecosystem's carbon sequestration capacity and CE from human activities. The carbon sink ecological carrying capacity coefficient represents the ratio of carbon sink capacity to CE within a region, calculated as follows:

$$ESC = \frac{E_m}{E} / \frac{C_m}{C} \tag{5}$$

In the formula: E_m and E denote the carbon sink capacity of region m and the entire area respectively; C_m and C denote the CE of region m and the entire area respectively. When $ESC > 1$, it indicates that region m exhibits a higher ecological contribution rate to carbon sinks, thereby alleviating the CE pressure across the entire area to a certain extent; conversely, a lower ESC implies a negative external effect.

3.4 Analytical Methods for the Decoupling Relationship Between LUE and CE

Employing the Tapio decoupling model to establish the decoupling relationship between LUE and CE yields the following expression [13]:

$$D_i(W_i, \ LE_i) = \frac{\Delta W_i/W_i}{\Delta LE_i/LE_i} = \frac{(W_{i,\ t} - W_{i,\ 0})/W_{i,\ 0}}{(LE_{i,t} - LE_{i,0})/LE_{i,0}} \tag{6}$$

In the formula: $D_i(W_i, \ LE_i)$denotes the decoupling elasticity between CE in region i and LUE in year i; ΔW_i represents the change in CE in region i during period t compared to the preceding period; ΔLE_i signifies the change in LUE in region i during period t relative to the prior period. Drawing upon the critical values for decoupling states categorised by scholars Chen Wanxu et al. [14], this study employs 0.8 and 1.2 as the dividing lines for decoupling types. This classification yields three major categories and eight distinct decoupling states, with the classification criteria illustrated in Fig.2 (using the strong decoupling state as an example, where $\Delta W < 0$, $\Delta LE < 0$ and $D \leq 0$).

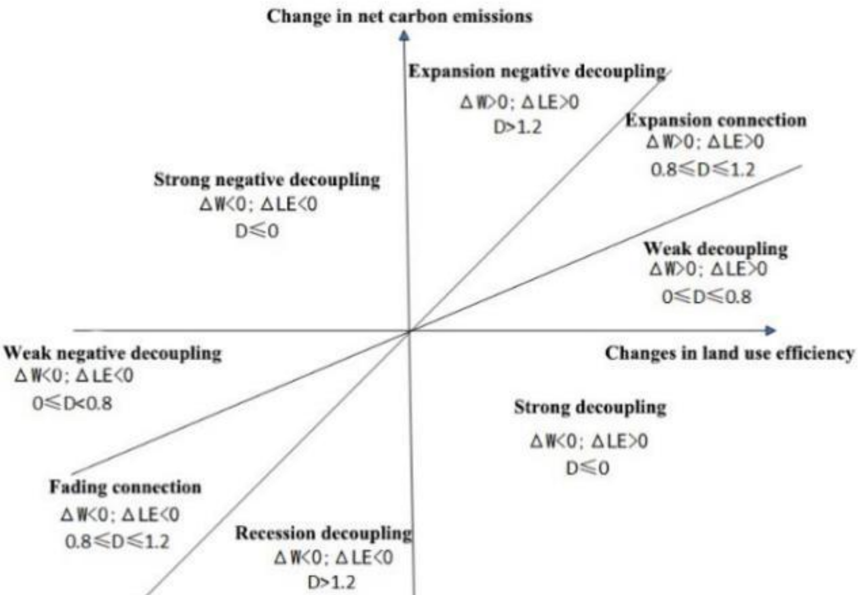

Fig.2 Decoupling state discrimination quadrant diagram

Specifically:

(1) Decoupling denotes a state where Net CE changes are largely unrelated to LUE shifts, with efficiency improvements not increasing emissions (favorable carbon reduction performance). Based on the relationship strength between the two, it is subdivided into three states: strong, weak, and declining decoupling. Strong decoupling—the most desirable state—occurs when emissions decrease as efficiency improves, defined as low-carbon friendly development.

(2) Negative decoupling occurs when Net CE and LUE show a positive correlation. Based on their relative change rates, it is further subdivided into strong, weak, and expansive negative decoupling. Strong negative decoupling—the most unfavorable scenario—involves rapid emission growth with falling efficiency, indicating ineffective land use and inadequate carbon reduction measures (defined as inefficient development).

(3) Coupled state: Net CE and LUE progress largely in tandem, subdivided into expansive and regressive coupling. Expansive coupling means synchronous growth of both, while regressive coupling means synchronous decline—defined as conventional development.

4 Analysis of Results

4.1 Spatiotemporal Variations in LUE in BECA

From 2010 to 2021, there were significant regional gradient differences in LUE in ecological conservation areas (see Tab.3), with a spatial pattern characterized by "higher efficiency in the north than in the middle and greater fluctuations in the east". Although there were fluctuations in the medium term, the overall trend showed an optimization from "local high efficiency to global high efficiency, and from significant differences to converging disparities". After 2015, with the precise implementation of ecological policies and the improvement of land management levels, the efficiency of the entire region steadily increased, achieving "global high efficiency" in 2021, providing support for the construction of an ecological security barrier and sustainable land use in Beijing-Tianjin-Hebei region.

Over the years, in terms of the average LUE across various regions, Yanqing has been the best, followed by Pinggu and Mentougou, with all three having an average efficiency exceeding 1.0. Miyun and Huairou have relatively lower efficiency, with Huairou having the lowest across the entire region. The significant difference between the highest and lowest values among regions reflects the uneven level of land resource allocation and utilization.

From the perspective of temporal evolution, the characteristics of each district show differentiation. Among them, Mentougou has the best stability, with high efficiency and small fluctuations in most years, indicating a stable operation of the land use system. Yanqing is the only district in the entire region that has never experienced a year of low efficiency, with efficiency consistently exceeding 1.0, showing significant improvement in the later period and ranking first in peak values. Huairou has the most prominent fluctuations, reaching the lowest level in the early stage and gradually rising to a higher level towards the end of the period, showing a trend of "low-level rebound" (possibly related to ecological policy adjustments and phased implementation of land consolidation projects). Miyun experiences frequent fluctuations and a concentration of low-efficiency years in the middle period, but tends to stabilize and steadily rise in the later period. Pinggu is stable in the early stage and experiences explosive growth in the later period, with a significant jump in efficiency at the end of the period, making it the most significantly improved district besides Yanqing.

Tab.3 Evaluation of LUE in ecological conservation area

Year	Huairou	Mentougou	Miyun	Pinggu	Yanqing
2010	1.0113	1.0445	1.0118	1.0443	1.0281
2011	0.621	1.0212	0.8201	0.9056	1.0182
2012	0.6549	0.916	0.8506	1.0029	1.0096
2013	0.7362	1.0071	1.0376	1.0055	1.0104
2014	1.0142	0.9385	0.8577	1.0047	1.0022
2015	1.0193	1.0167	1.023	1.0183	1.0285
2016	1.0259	1.0018	1.0018	0.9174	1.0016
2017	1.0275	1.0201	1.0216	1.0889	1.0226
2018	1.0206	1.0053	0.9284	0.9361	1.0014
2019	1.0259	1.0241	1.0176	1.0214	1.0433
2020	1.004	1.0108	1.0184	1.0061	1.0064
2021	1.0446	1.0433	1.0301	1.199	1.2993
Average	0.9338	1.0041	0.9682	1.0125	1.0393

4.2 Spatiotemporal Variation in LUCE in BECA

By 2020, high carbon source zones had largely disappeared across the region (see Fig.3). Significant carbon source fluctuations were mainly observed in eastern Mentougou and the border area between Huairou and southern Miyun. High carbon sources were concentrated in urbanized areas with dense population and economic activity, surrounded by ring-shaped low carbon source zones, while high carbon sink areas were primarily located in forest-covered regions such as Huairou, Mentougou, and Yanqing.

During the 12th Five-Year Plan period (2010–2015), industrial upgrading in southern Huairou reduced CE, transitioning it from a high to a low carbon source. Similar declines occurred in southwestern Yanqing and Pinggu due to policy interventions. After 2015, eastern Miyun and Mentougou also became low carbon source zones, with southwestern Miyun gradually following this trend.

Changes in carbon sinks were most notable in Yanqing, where forest carbon sequestration weakened after 2015, turning it into a low-carbon sink area. Mentougou consistently maintained net carbon absorption, with emissions limited mainly to eastern Yongding Town, demonstrating a positive overall transition toward lower emissions.

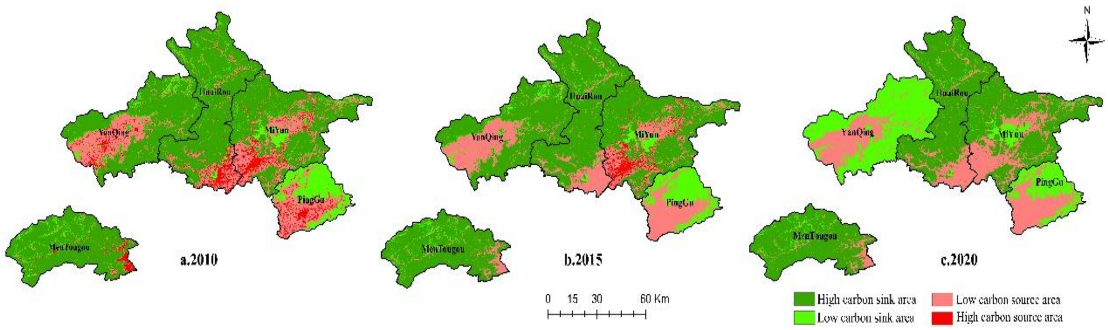

Fig.3 Spatial distribution of net CE in ecological conservation area

From 2010 to 2021, Net CE in BECA exhibited an overall fluctuating yet decreasing trend (Fig.4), with carbon sink capacity increasing after 2017. The average annual reduction rate of CE between 2010 and 2015 was 16.74%, while the average annual growth rate of carbon sink capacity from 2015 to 2021 reached 64.32%. Prior to 2015, Mentougou and Huairou recorded the steepest declines in Net CE within the ecological conservation zones, achieving average annual reduction rates of 30.03% and 22.41% respectively, followed by Pinggu .

Yanqing had the slowest CE deceleration, with the weakest low-carbon reduction effect (only 6.69%), followed by Miyun . Compared to other areas, Yanqing and Miyun are more dependent on traditional industries such as agriculture and tourism—these industries are energy- and resource-intensive, thus exerting greater CE impact. Their land use structures may also contribute to weaker CE reduction. Mentougou, located in the ecological conservation zone of western Beijing, has distinct location advantages. Since its designation as an ecological conservation area, mines of various scales have been closed, and comprehensive remediation of abandoned mining sites has been carried out district-wide. After nearly a decade of restoration, its ecological environment has recovered.

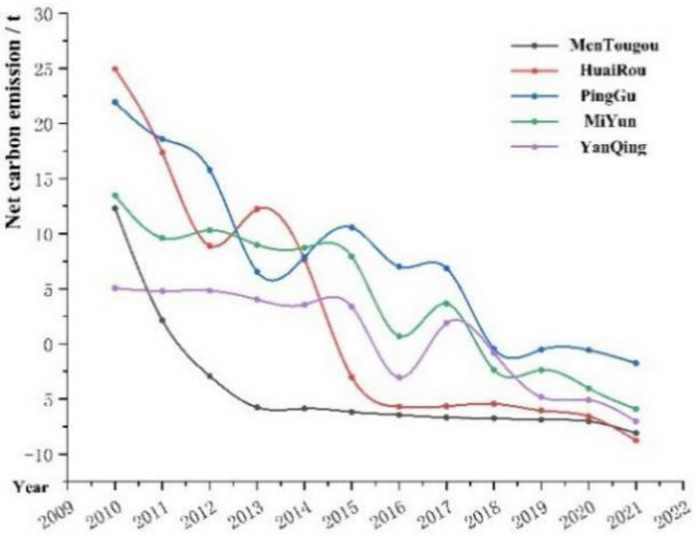

Fig.4 Changes in net CE

4.3 Analysis of Regional Contributions to CE in BECA

Results of regional CE contributions in BECA (Fig.5) show significant disparities in carbon sink capacity across the five districts. The carbon sink ecological carrying capacity coefficients of Pinggu and Miyun districts are greater than 1, indicating that these two districts have strong carbon absorption capabilities and can positively impact the carbon emissions of the entire region. In contrast, Yanqing also exhibited high carbon sink capacity in some years, but its stability was not as good as the former two. Pinggu showed significant fluctuation throughout the study period, with its carbon sink ecological carrying capacity coefficient reaching a maximum of 9.635 in 2015. This fluctuating change may reflect factors such as changes in land use patterns and climate change in the region. It is worth noting that the large area of forest land in Pinggu is the main reason for its high carbon sink capacity, as forest ecosystems are one of the largest terrestrial carbon sinks on Earth. The carbon sink ecological carrying capacity coefficient of Mentougou is the lowest and has shown a downward trend year by year, falling to 0.1314 in 2021. This indicates that the carbon sink capacity of this region is facing serious challenges and effective measures need to be taken to improve it. Considering that carbon sink capacity is closely related to land use patterns, this trend may be related to land use changes in Mentougou.

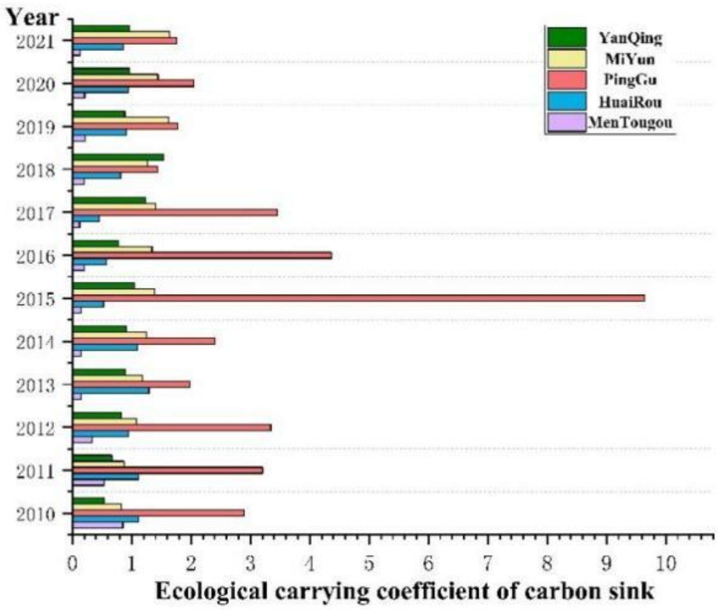

Fig.5 Ecological carrying coefficient of carbon sink in each district

4.4 Analysis of Decoupling of LUE and Net CE in BECA

As can be seen from Fig.6, the decoupling relationship between LUE and CE in BECA from 2010 to 2021 exhibits significant temporal fluctuations and regional differentiation characteristics, with no single dominant decoupling type, reflecting the dynamic adjustment of collaborative management and control between the two in the region..

During the 12th Five-Year Plan period (2010–2015), a critical period for ecological protection and industrial transformation, five districts in Beijing—Huairou, Mentougou, Miyun, Pinggu and Yanqing—were driven by policies such as the delineation of ecological conservation areas and the elimination of high-energy-consuming industries. The decoupling status between their LUE and CE showed a phased fluctuation trend, alternating between strong decoupling, strong negative decoupling, recessive decoupling, and expansive negative decoupling. This phenomenon reflects the "painful period of incoordination" in the early stage of industrial transformation and ecological construction.

On the contrary, during the 13th Five-Year Plan period (2016–2020), a phase of deepened green and high-quality development, the implementation of the Regulations on Ecological Protection and Green Development of BECA and the large-scale advancement of high-end, precision, and advanced industries as well as ecotourism led to an overall evolution of the decoupling status in various districts toward weak decoupling and expansive connection. In later stages, strong decoupling achieved a mature return in districts such as Yanqing, while the occurrence frequency of weak negative decoupling and expansive negative decoupling decreased significantly. This indicates that the relationship between LUE and CE has evolved from "sharp fluctuations" to "moderate coordination".

This evolutionary process not only highlights the direct driving role of policy orientations at different stages on the decoupling relationship between LUE and CE in ecological conservation areas, but also reveals the common dynamic characteristic of regional transformation—shifting from "transformation pains" to "mature development".

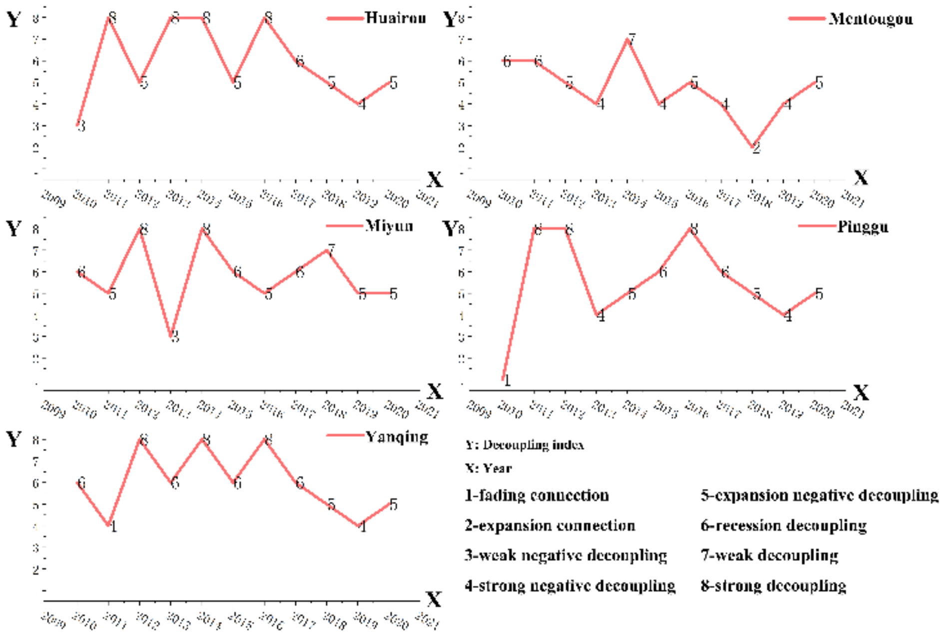

Fig.6 Evolution of decoupling state between LUE and CE in ecological conservation areas

5 Conclusions and Discussion

5.1 Conclusions

Based on data from 2010 to 2021 for BECA, this study systematically analyzed LUE, CE, and their decoupling relationship. The main conclusions are drawn:

LUE across the zones initially fluctuated before steadily improving after 2015, with significant regional variation. By 2021, all districts had exceeded an efficiency value of 1.03, indicating high-efficiency performance. Yanqing has consistently performed the best (average 1.0393), while Mentougou has remained the most stable. Huairou and Miyun have showed greater fluctuations and slightly lower averages, placing them in the “near-efficient” category. Pinggu has improved markedly in later years, becoming the second-most efficient district by 2021. The decline in efficiency is mainly attributed to natural constraints, traditional agriculture, and unbalanced urban expansion.

Despite the persistence of spatial differences, the carbon sink capacity has been enhanced, and the CE has shown a gradual downward trend overall. Policies supporting ecological conservation contributed to increased carbon sequestration and reduced net emissions. Pinggu and Miyun maintain the strongest carbon sink capacity, whereas Mentougou—impacted by its historical reliance on coal—has the lowest, highlighting a need for focused improvement. Yanqing has the slowest emission reduction rate, reflecting uneven progress across regions.

The decoupling relationship between LUE and CE primarily exhibits weak decoupling or significant negative decoupling, indicating that a stable synergistic relationship has not yet been formed. Huairou has shifted to a significant negative decoupling of high emission growth. Pinggu demonstrates a relatively stable decoupling state, while Yanqing exhibits strong decoupling, reflecting strong ecological protection efforts but low land use efficiency. Mentougou remains in a strong negative decoupling state ("high emission, low efficiency"), urgently requiring economic structural reform.

5.2 Discussion

This study provides important support for understanding the dynamics of regional carbon cycle and formulating targeted environmental protection policies by revealing the evolution laws of LUE, CE, and their decoupling relationship in BECA from 2010 to 2021. Its practical significance and policy implications are mainly reflected in three aspects. Firstly, in response to the spatial imbalance of carbon sink capacity, policymakers can focus on strengthening forest protection in high carbon sink areas such as Pinggu and Miyun, consolidating existing carbon sink advantages, and exploring effective ways to enhance carbon sink capacity such as forest land restoration and ecological industry cultivation, in combination with the transformation needs of coal-based cities in Mentougou, to improve the current situation of low carbon sink ecological carrying capacity. Secondly, the research results emphasize the importance of monitoring and quantifying regional carbon sources, carbon sink distribution, and net CE. It is necessary to establish a normalized monitoring mechanism to accurately assess the ecological carrying capacity of carbon sinks in different regions, provide scientific data support for regional low-carbon development planning, and assist in achieving global climate goals. Thirdly, based on the differences in decoupling status among districts and counties, differentiated collaborative development strategies should be formulated: for Huairou, the experience of "efficiency-emission reduction" collaborative development can be summarized and promoted within the region; for Mentougou, priority should be given to reducing carbon emissions through industrial structure adjustment (such as reducing the proportion of high-carbon industries and cultivating low-carbon industries) to alleviate the contradiction of "high carbon and low efficiency"; for Yanqing , on the basis of maintaining ecological protection achievements, land use efficiency can be improved through optimizing land use structure and enhancing industrial added value, avoiding the imbalance problem of "emphasizing ecology and neglecting development".

Overall, optimizing the industrial structure, actively developing the tertiary industry, and industrial upgrading are important driving forces that directly promote regional economic development and change the mode of economic development. Adapting measures to local conditions, actively developing green ecological agriculture, taking multiple measures to persist in afforestation in ecological conservation areas, promoting regional carbon trading and carbon sink work, improving relevant policies, and establishing a reasonable compensation mechanism can effectively promote the green development of ecological conservation areas.

Although this study provides a new perspective for the research on LUE and low-carbon development in BECA, there are still three aspects for optimization that need further improvement in the future. Firstly, this study did not conduct regression analysis on the influencing factors of LUE, and thus cannot accurately quantify the intensity of the interaction between LUE and CE influenced by factors such as natural conditions, industrial structure, and policy interventions. In future, models such as panel regression and spatial econometrics can be introduced to enhance the robustness and explanatory power of the research results. Secondly, due to limitations in data availability, the research period only covers 2010-2021, while both land use efficiency and carbon emissions are dynamic evolutionary processes. Short-term data are difficult to fully reveal long-term evolutionary patterns. In the future, it is necessary to expand the research period (for example, extending it to 2035) and combine longer-term data to conduct an in-depth analysis of the long-term trend of their relationship, thereby enhancing the timeliness and foresight of the research. Finally, the scope of the study is limited to BECA, while Beijing has diverse types of main functional areas (including urban functional core areas, urban development new areas, etc.). The characteristics of LUE and CE vary across different functional areas. In future, it is necessary to increase the number of research areas, incorporate collaborative development indicators of various functional areas into the research framework, and construct a multi-scale and multi-type analysis system to provide more comprehensive theoretical support for the overall high-quality development of Beijing.

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BIOGRAPHICAL NOTES

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