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# Green Low-Carbon Transition Efficiency in China's Yangtze River Economic Belt: A Global Super-Efficiency SBM Analysis with Implications for Land Use Management

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**Abstract:** Urban green low-carbon transition requires land use planning that coordinates construction-land development, redevelopment, and ecological protection. This study evaluates transition efficiency in 108 cities in China's Yangtze River Economic Belt during 2012–2023 using a global super-efficiency slacks-based measure model with undesirable outputs. Inputs comprise labor, electricity, construction land, capital stock, and water supply; desirable outputs include real GDP (gross domestic product) and a green-space-based carbon-sink proxy; undesirable outputs comprise wastewater, sulfur dioxide, dust, and carbon dioxide emissions. Temporal, distributional, regional, spatial, and city-typology analyses reveal initial fluctuations, subsequent adjustment, and recent recovery. Under the baseline land-data treatment, the 2023 rebound accompanies wider dispersion, with the proportion of observations scoring 1.3000 increasing from 6.48% in 2022 to 22.22% in 2023. Improvement is therefore concentrated in the upper tail. A comparison of reported scores through 2022 also identifies recovery between 2021 and 2022, although it does not isolate the frontier effects of extrapolated 2023 construction-land inputs. The lower reaches and eastern subregion generally outperform the middle reaches and central subregion. Global Moran's I is small and mostly insignificant, suggesting limited basin-wide spatial association. The coexistence of leading, catching-up, and lagging cities supports differentiated land use governance. Policy implications include linking discretionary construction-land quotas to verified green low-carbon performance, prioritizing redevelopment of underused land, and applying watershed-specific controls consistent with ecological protection red lines.

**Keywords:** Green Low-Carbon Transition Efficiency; Land Use Planning; Construction-Land Quotas; Ecological Protection Red Line; Yangtze River Economic Belt; Global Super-Efficiency SBM (Slacks-Based Measure)

## 1. Introduction

The green and low-carbon transition has become a central task for urban development. Cities are major carriers of economic production, population concentration, infrastructure investment and resource consumption. They are also major sources of conventional pollutants and carbon emissions. Whether cities can improve economic performance while reducing resource and environmental pressure has therefore become a key question in sustainable

development research. For China, this question is particularly important because the transition toward carbon peaking and carbon neutrality requires not only national policy commitment but also city-level improvement in production efficiency, environmental governance and low-carbon transformation capacity.

The Yangtze River Economic Belt provides a representative setting for examining this question. It is a long river-basin economic corridor that combines advanced coastal economies, major manufacturing bases, inland growth poles and ecologically sensitive upstream areas. The lower reaches have stronger innovation resources, market integration and service-oriented industrial systems. The middle reaches often face heavier pressure from traditional manufacturing and industrial restructuring. The upper reaches combine ecological-security responsibilities with uneven industrial foundations and growing regional development demands. This internal diversity makes the Yangtze River Economic Belt suitable for investigating whether urban green low-carbon transition is progressing in a balanced manner or whether transition gains are concentrated in specific cities and subregions.

Land use planning is central to this transition because construction land provides the spatial base for production, housing, and infrastructure, while its expansion can increase demand for energy and transport and displace ecological space. Redevelopment of underused built land, more efficient industrial layouts, and protection of connected green spaces offer distinct routes for improving the relationship between economic output and environmental pressure. Previous studies of land-use carbon efficiency and the green efficiency of urban construction land in the Yangtze River Economic Belt establish the relevance of this land-management perspective [1, 2]. The practical question is therefore how to accommodate necessary development within land and environmental constraints, rather than whether to maximize urban land expansion.

Ecological protection red line control provides a complementary spatial constraint. China's 2022 notice on ecological protection red line management identifies these lines as important territorial-spatial planning boundaries and specifies controls on construction activities, limited permitted human activities, and approval procedures [3]. Green low-carbon performance should consequently be considered alongside ecological red lines, permanent basic farmland protection, and urban development boundaries. An improvement in a composite efficiency score cannot itself justify conversion of protected ecological land. This distinction is especially relevant to a river basin, where upstream land conversion, riparian disturbance, and industrial siting can impose pressures beyond the jurisdiction in which development occurs.

Urban green low-carbon transition efficiency should not be understood as a single indicator such as carbon intensity, pollution emissions or gross domestic product. A city may reduce one pollutant while expanding other environmental pressures, or it may generate high output by relying on excessive inputs and emissions. A more comprehensive evaluation must therefore consider multiple inputs, desirable outputs and undesirable outputs simultaneously. From a production-theoretic perspective, a city is efficient when it can transform labor, energy, land, capital and water inputs into economic and green-development outputs while minimizing wastewater, sulfur dioxide, dust and carbon dioxide emissions. This integrated view is consistent with the practical logic of urban transition, where resource conservation, pollution abatement and carbon reduction should be coordinated rather than treated separately.

Existing evidence has improved understanding of green efficiency, eco-efficiency, carbon emission efficiency and green total factor productivity. However, three research issues remain important. First, studies at the provincial or urban-agglomeration level may conceal substantial heterogeneity among prefecture-level cities within a large river-basin economy. Second, many studies do not sufficiently cover the recent post-carbon-neutrality policy period, especially the years after 2021, during which green governance, carbon accounting and industrial adjustment have evolved rapidly. Third, efficiency measurement, distributional inequality and spatial dependence are often discussed separately. As a result, it remains unclear whether average improvement is accompanied by balanced convergence, spatial spillover or renewed city-level polarization. A related land-management gap is that city-level efficiency results are seldom translated into explicit rules for construction-land allocation, redevelopment, and watershed-sensitive development control. Such translation also requires distinguishing an integrated urban efficiency index from a direct measure of parcel-level land productivity or ecological compliance.

This study evaluates 108 prefecture-level and higher-level cities in the Yangtze River Economic Belt from 2012 to 2023 using a global super-efficiency SBM model with undesirable outputs. Its contribution is analytical. First, the observation window extends through 2023 and describes the recent rebound under the baseline land-data treatment. Second, mean efficiency is interpreted jointly with the coefficient of variation, Theil index, quantiles, and

the frequency of observations at 1.3000. Third, river-reach and eastern-central-western groupings are compared alongside alternative spatial-weight matrices. Fourth, long-run level, change, and volatility are combined into a policy-relevant city typology. This design connects intertemporal change, distributional structure, regional heterogeneity, spatial association, and city types in a unified assessment framework. By retaining construction land as an input and built-up green-space-based carbon-sink proxy as a desirable output, the framework also provides a basis for discussing how development-land demand can be evaluated jointly with economic, pollution, and carbon outcomes.

The study aims to answer five questions. First, what temporal trajectory did urban green low-carbon transition efficiency follow from 2012 to 2023? Second, did the recent recovery represent a broad-based improvement or a frontier-driven rebound concentrated in selected cities? Third, how did efficiency differ across the upper, middle and lower reaches and across eastern, central and western subregions? Fourth, did city-level efficiency exhibit stable spatial dependence or only weak and emerging local clustering? Fifth, how can cities be classified into policy-relevant types according to long-run efficiency, improvement and volatility? By answering these questions, the paper contributes city-level evidence on green low-carbon transition in a large river-basin economy and develops differentiated land-management implications for regional coordination, subject to ecological protection and the limits of the city-level evidence.

## 2. Literature Review

### 2.1. Green Development Efficiency and Low-Carbon Transition in the Yangtze River Economic Belt

Recent studies on the Yangtze River Economic Belt increasingly emphasize that green development efficiency should be evaluated through a multi-dimensional framework rather than through a single environmental or economic indicator. Peng and Yu measured green development efficiency in the Yangtze River Economic Belt and showed that efficiency improvement is shaped by both regional development conditions and environmental-governance capacity [4]. Jin et al. further analyzed the spatial-temporal evolution and driving factors of carbon emission efficiency, confirming that carbon efficiency differs markedly among cities and that transition performance is not spatially uniform [5]. Wang and Shao examined spatiotemporal interactions in city-level carbon emission efficiency and provided evidence that urban efficiency evolution is influenced by both local characteristics and spatial interactions [6].

Land, construction and urbanization-related dimensions have also received increasing attention. Zhang et al. investigated carbon emission efficiency of land use in urban agglomerations of the Yangtze River Economic Belt and highlighted the importance of measuring efficiency under both resource and carbon constraints [1]. Xu et al. assessed low-carbon city development from the dual perspective of effectiveness and efficiency, indicating that the level of low-carbon performance and the efficiency of achieving that performance may differ across cities [7]. Chen et al. used a three-stage SBM-ML framework to examine green total factor productivity in the Yangtze River Economic Belt and showed that dynamic productivity improvement depends on the interaction between technology, environmental constraints and regional development foundations [8].

Environmental regulation remains one of the major explanations for regional differences in green performance. Liu et al. found that environmental regulation can enhance green total factor productivity in cities of the Yangtze River Economic Belt, although the effects may vary across regions and development stages [9]. Li et al. focused on transportation green efficiency and spatial correlation, showing that sectoral green efficiency is closely related to the spatial organization of regional economic activity [10]. Zheng et al. emphasized the environmental-regulation effect on green total factor productivity, suggesting that regulatory intensity can reshape the efficiency frontier when cities face different industrial and institutional conditions [11].

Comparative regional studies deepen the understanding of the Yangtze River Economic Belt by placing it within broader national and river-basin contexts. Liu et al. compared green growth efficiency between the Yangtze River Economic Belt and the Yellow River Basin and found that green growth patterns are strongly conditioned by resource endowment and regional development stage [12]. Cui et al. explored regional differences in urban land green use efficiency and showed that land-use efficiency has dynamic spatial evolution rather than a fixed regional hierarchy [13]. Zhou identified spatial-temporal evolution and spatial spillover in the green efficiency of urban construction land, offering evidence that construction-land efficiency is a key component of urban green transition [2].

Industrial agglomeration, manufacturing structure and urban land use provide additional channels through which green efficiency may vary. Wang and Han found that industrial agglomeration affects urban green land-use efficiency in the Yangtze River Economic Belt, implying that agglomeration economies and environmental burdens may coexist [14]. Yu et al. examined efficiency evolution and risks of green development in the Yangtze River Economic Belt and emphasized that green development improvement can be accompanied by regional risks and unevenness [15]. Liu et al. found conditional  $\beta$ -convergence in green economic efficiency during 2003–2018, with different convergence rates across river reaches and spatial-network specifications [16]. Their results concern convergence in an earlier period and do not establish that intercity dispersion must decline in every subsequent year.

Manufacturing and resource-related sectors are particularly important in explaining why the middle reaches may lag behind more advanced downstream cities. Li et al. evaluated manufacturing green development efficiency with undesirable outputs and showed that regional differences remain significant even when undesirable outputs are incorporated [17]. He et al. investigated green total factor productivity in the Yangtze River Economic Belt under environmental regulation and confirmed that environmental regulation interacts with productivity improvement in complex ways [18]. Huang et al. studied the green efficiency of water resources and found that spatial and temporal differences are substantial, indicating that resource constraints should be incorporated into comprehensive green-efficiency measurement [19].

Studies on carbon-economic decoupling and sustainable urban efficiency further support the need to evaluate economic output and environmental pressure simultaneously. Li et al. analyzed the decoupling of economic growth from carbon dioxide emissions in Yangtze River Economic Belt cities and demonstrated that carbon reduction does not necessarily proceed at the same pace as economic expansion [20]. Yao et al. examined sustainable urban economic development efficiency in the Yangtze River Economic Belt and highlighted the importance of city-level comparison [21]. Tian et al. analyzed green innovation and efficiency-related coordination in the Yangtze River Economic Belt, showing that innovation and efficiency are jointly embedded in regional spatial systems [22].

The resource-environmental pressure perspective also reveals that growth, resource use and environmental pressure may decouple unevenly across cities. Yuan et al. studied the decoupling of economic growth from resource-environmental pressure and found that development pressure varies across subregions [23]. Zhang et al. analyzed urban land-use efficiency and its influencing factors in the Yangtze River Economic Belt, emphasizing the role of spatial-temporal heterogeneity [24]. Tan et al. focused on urban land green use efficiency in the Yangtze River Delta, showing that even within more developed downstream areas, internal differences remain significant [25].

Overall, this body of literature shows that green low-carbon transition in the Yangtze River Economic Belt is characterized by strong spatial and regional heterogeneity. However, many studies focus on a specific sector, a particular efficiency dimension or a shorter observation window. This leaves room for a comprehensive city-level framework that integrates multiple resource inputs, desirable outputs, conventional pollutants and carbon emissions over a longer recent period.

## 2.2. Efficiency Measurement Methods with Undesirable Outputs

Beyond the Yangtze River Economic Belt, national and regional studies provide methodological guidance for efficiency measurement under environmental constraints. Guo et al. examined green development efficiency and spatial spillover at the provincial scale, demonstrating that efficiency analysis can be combined with spatial diagnosis to reveal regional interactions [26]. Zhao et al. used a super-SBM model with undesirable outputs and a spatial Durbin model to evaluate green economic efficiency and its influencing factors, confirming the suitability of super-efficiency frameworks for ranking efficient decision-making units [27]. Wu et al. combined a super-efficiency model with DEA window analysis and showed that dynamic efficiency evaluation can reveal time-varying changes that are not visible in static comparisons [28].

Urban eco-efficiency and carbon-constrained efficiency studies further demonstrate the value of incorporating undesirable outputs. Long evaluated urban eco-efficiency using a super-efficiency SBM-DEA model with undesirable outputs and emphasized that environmental outputs should be directly included rather than treated as external explanations [29]. Niu et al. used a three-stage SBM-undesirable model and an LSTM model to examine carbon emission efficiency, showing that model-based correction and prediction can enrich traditional DEA analysis [30]. Ma et al. studied urban water-supply efficiency under carbon-emission constraints, suggesting that resource systems

and carbon constraints should be jointly considered in efficiency evaluation [31].

These methodological studies indicate that the SBM family of models is appropriate when inputs, desirable outputs and undesirable outputs cannot be assumed to change proportionally. In the urban green low-carbon transition, labor, energy, land, capital, water, economic output, green-service output and pollutants may move in different directions. Therefore, a non-radial and non-oriented framework can better capture the slack structure of inefficient cities. The global-frontier setting used in this study further strengthens intertemporal comparability by evaluating all city-year observations against a common production possibility set.

### 2.3. Digital Economy, Green Innovation and Transition Mechanisms

A growing literature links green efficiency and low-carbon transition to digitalization, data factors and green innovation. Li et al. studied the impact of the digital economy on industrial carbon emission efficiency at the city level and found that digital transformation can influence carbon efficiency through spatial movement and driving mechanisms [32]. Huang and Chen examined the effect of data factor-driven industries on green total factor productivity, showing that data factors can become new production elements for green development [33]. Huang et al. analyzed the impact of the digital economy on green total factor productivity while considering labor, technology and pollution factors, indicating that digitalization affects both production and environmental performance [34].

Spatial spillovers of digital transformation are also relevant for interpreting urban efficiency patterns. Zou et al. found that the digital economy can influence urban total factor productivity through mechanisms and spatial spillover effects, suggesting that digital capacity may shape the diffusion of green transition advantages [35]. Zhao et al. examined whether green innovation induces green total factor productivity and provided city-level evidence that innovation can improve green productivity [36]. Ma and Zhu showed that the digital economy can drive high-quality green development in emerging economies, reinforcing the idea that technological upgrading is a key pathway of green transition [37].

Environmental governance and low-carbon innovation add further explanatory channels. Luo et al. investigated the effect of environmental governance on green total factor productivity in the Yangtze River Economic Belt and suggested that governance systems can shape productivity improvement [38]. Ren et al. examined how low-carbon innovation drives urban green development efficiency and found that innovation is a critical source of efficiency improvement [39]. Huang et al. analyzed spatial-temporal evolution and influencing factors of carbon emission efficiency in Chinese cities, providing evidence that city-level carbon efficiency is affected by multiple economic, technological and environmental factors [40].

Recent studies using scenario and configurational methods broaden the methodological perspective on transition efficiency. Yu and Li conducted multi-scenario analysis of green water-resource efficiency under carbon constraints in the Chengdu-Chongqing urban agglomeration, highlighting the importance of scenario-based policy interpretation [41]. He examined spatial disequilibrium and influencing factors of carbon emissions in the Yangtze River Economic Belt using nighttime light data [42]. Min et al. applied a technology-organization-environment framework and fuzzy-set qualitative comparative analysis to provincial carbon emission efficiency, identifying alternative configurations associated with high efficiency [43].

The mechanism literature provides a basis for interpreting the observed efficiency patterns. Cities with stronger digital infrastructure, green-innovation capacity, environmental-governance systems, and financial resources may display better relative efficiency. Differences in these conditions can help explain why the regional mean and the upper tail evolve at different rates, motivating the temporal, regional, and typological comparisons developed below.

### 2.4. DEA, SBM and Spatial-Analysis Foundations

The formal methodological foundation of this paper is rooted in data envelopment analysis and its extensions. Tone proposed the slacks-based measure of efficiency, which directly incorporates input excesses and output shortfalls into efficiency evaluation [44]. Tone further developed a super-efficiency SBM model, making it possible to rank efficient decision-making units beyond the conventional frontier [45]. Charnes et al. established the original DEA framework for measuring decision-making-unit efficiency without specifying a parametric production function [46].

Banker et al. extended DEA by introducing models for technical and scale inefficiency, thereby enriching the

theoretical basis of efficiency decomposition [47]. Chung et al. proposed a directional distance function approach to productivity and undesirable outputs, offering a key foundation for environmental production analysis [48]. Färe et al. developed a nonparametric approach for productivity comparisons when some outputs are undesirable, which remains central to environmental-efficiency measurement [49].

Zhou et al. surveyed the application of DEA in energy and environmental studies and showed that nonparametric frontier methods are widely used for evaluating energy and environmental performance [50]. Anselin introduced local indicators of spatial association, providing a basis for identifying high-high, low-low, high-low and low-high local clusters [51].

These methodological foundations support the integrated design of the present study. The global super-efficiency SBM model provides a comparable efficiency score under undesirable-output constraints, while Global Moran's I and local indicators of spatial association reveal whether city-level efficiency is spatially clustered. The coefficient of variation and Theil index further help distinguish average improvement from distributional equity. Together, these methods allow the paper to evaluate not only whether urban green low-carbon transition efficiency improves but also whether improvement is spatially coordinated and regionally balanced.

## 2.5. Literature Gaps and Contribution of This Study

The reviewed literature provides a strong basis for analyzing green low-carbon transition efficiency, but four gaps remain. First, sector-specific studies do not always integrate multiple resource inputs, economic and ecological outputs, conventional pollutants, and carbon emissions in one city-level frontier. Second, comparatively few city-level studies cover the full 2012–2023 period under a common global frontier. Third, average improvement is often reported without jointly testing distributional divergence and the concentration of observations at 1.3000. Fourth, regional heterogeneity and spatial dependence are frequently assessed separately, obscuring whether apparent recovery represents broad convergence, localized clustering, or city-specific performance.

Accordingly, this study contributes a diagnostic architecture that links four levels of evidence: intertemporal stages, distributional inequality, two complementary regional classifications, and local-to-global spatial association. The city typology then translates these diagnostics into differentiated governance categories. The novelty lies in showing how a higher average, weak basin-wide spatial dependence, and widening intercity dispersion can coexist within the same transition process. The land-management contribution is to connect these diagnostics with the allocation and reuse of construction land while recognizing that ecological protection remains a separate requirement. The policy proposals are informed by the observed patterns rather than identified as causal effects of land-use regulation.

## 3. Theoretical Mechanism and Analytical Logic

### 3.1. Conceptualizing Urban Green Low-Carbon Transition Efficiency

Urban green low-carbon transition efficiency is not a simple environmental-quality indicator. It describes whether a city can transform labor, energy, land, capital and water inputs into economic and green-development outputs while suppressing conventional pollutants and carbon emissions. In this sense, a high-efficiency city is not necessarily the city with the lowest absolute emissions; rather, it is the city that achieves a more favorable input-output-environment relationship under a common production frontier. This distinction is important for the Yangtze River Economic Belt because cities along the corridor differ sharply in economic size, industrial structure, resource endowment and ecological function. A direct comparison of emission totals would therefore be misleading, whereas an efficiency-based comparison can evaluate whether each city uses its factor base in a cleaner and more productive manner.

The analytical logic of this section follows a production-system view. Each city is treated as a decision-making unit that consumes factor inputs, generates real economic output and an urban carbon-sink proxy output, and simultaneously produces undesirable environmental outputs. The transition problem therefore has three simultaneous requirements: reduce input redundancy, expand desirable outputs, and compress wastewater, sulfur dioxide, dust, and carbon dioxide emissions. A non-radial and non-oriented model is appropriate because these adjustments need not occur proportionally.

For a river-basin economy, efficiency also has a spatial meaning. The upper reaches are closely related to eco-

logical conservation and resource transformation, the middle reaches often face manufacturing restructuring and pollution-reduction pressure, and the lower reaches generally contain stronger innovation and service functions. These differences mean that the same efficiency score may reflect different transition pathways. A downstream city may improve efficiency through technological innovation and service-oriented upgrading, whereas an upstream city may improve efficiency through ecological value conversion and cleaner energy use. The methodological framework must therefore allow both overall comparison and regional interpretation.

Within this production system, construction-land input represents the urban land footprint supporting economic activity. With other conditions comparable, obtaining desirable outputs with less land and fewer emissions is consistent with more intensive land use. Urban green space contributes a separate ecological-service proxy through UCS. The two variables therefore represent different planning concerns: development-land demand and a limited component of urban ecological provision. Neither variable records the location of protected parcels, the quality of habitats, or the degree of compliance with ecological protection red lines.

### 3.2. Stage Mechanism of Efficiency Evolution

The temporal trajectory of green low-carbon transition efficiency is expected to be non-linear. In the early phase, some cities may obtain efficiency gains from infrastructure improvement and environmental investment, but these gains can be unstable because green governance systems and industrial adjustment mechanisms are still being formed. In the middle phase, stronger environmental standards, industrial restructuring and factor-cost changes may temporarily compress measured efficiency, especially in cities that rely heavily on traditional manufacturing or resource-intensive activities. In the recent phase, leading cities may recover more rapidly as green technologies, digital governance tools and carbon-management practices become more mature.

The staged framework links short-term restructuring pressure with longer-term capability accumulation. Section 5 evaluates whether the observed data follow an initial-fluctuation, adjustment, and recovery sequence by examining the annual mean together with dispersion, quantiles, and the frequency of observations at 1.3000.

A key theoretical distinction is between broad-based recovery and upper-tail-concentrated recovery. Broad-based recovery shifts low-, middle-, and high-efficiency cities upward together. Upper-tail concentration occurs when the annual mean rises mainly because a smaller group moves toward the highest observed scores while the center of the distribution changes more modestly. Because the number of observations at 1.3000 rises sharply in 2023, the empirical analysis examines the coefficient of variation, Theil index, quantiles, and the full-versus-excluded mean alongside the annual average.

### 3.3. Spatial Mechanism and Weak Spillover Possibility

The Yangtze River Economic Belt is spatially connected by hydrological, transport and industrial linkages, but spatial connection does not automatically produce mature green low-carbon spillovers. Technology diffusion, joint pollution control and carbon-data coordination require institutional compatibility and operational cooperation across city boundaries. If administrative segmentation, industrial heterogeneity or data-standard inconsistency remains strong, spatial autocorrelation may be weak even in a physically connected corridor.

This theoretical possibility is central to the interpretation of Moran's  $I$  and local spatial association. A positive and significant Moran's  $I$  would indicate that cities with similar efficiency levels cluster geographically. A weak or insignificant Moran's  $I$ , however, does not mean that the analysis fails; it may indicate that urban transition efficiency is still dominated by city-specific conditions rather than mature basin-wide spillovers. The local association analysis further distinguishes high-high, low-low, high-low and low-high configurations, allowing the paper to identify whether the spatial structure is stable or only exploratory.

### 3.4. Regional Heterogeneity and Differentiated Transition Pathways

Regional heterogeneity is not a residual issue but a substantive part of the transition process. The lower reaches usually have stronger innovation capacity, higher market integration and more developed environmental governance systems. These conditions can support higher desirable outputs and lower pollution intensity. The middle reaches often face a more difficult transition because manufacturing-oriented structures and traditional industrial bases may generate heavier input and emission pressure. The upper reaches combine ecological security responsibilities with uneven industrial foundations; some node cities may improve rapidly, whereas smaller cities

may face constraints in capital accumulation, infrastructure and green-technology diffusion.

For this reason, the study adopts two complementary grouping schemes. The river-reach grouping captures the ecological and hydrological logic of the Yangtze River Economic Belt, while the eastern-central-western grouping captures the broader economic-geographic gradient. The two schemes are not substitutes. If the eastern-central-western gradient is sharper than the upper-middle-lower gradient, the result suggests that administrative-economic development capacity explains part of the efficiency divergence beyond the river-basin position itself. This logic is developed empirically in Section 6. These are city groupings within an economic belt, not delineations of individual hydrological catchments. Their use in land policy therefore requires a further overlay with tributary watersheds, ecological function zones, and approved territorial-spatial plans.

### 3.5. From Efficiency Measurement to Policy Typology

The final analytical step is to transform measurement results into a policy-relevant classification. Cities with high long-run efficiency and positive improvement can be treated as high-level improving cities; cities with high efficiency but large volatility require stable governance mechanisms; cities with low initial performance but positive change can be regarded as catching-up cities; and cities with low efficiency and weak improvement require targeted support. This typology avoids a one-size-fits-all policy implication and links the empirical analysis with differentiated governance. For land management, the categories can guide priorities for redevelopment audits, infrastructure support, and screening of proposed new construction-land allocations. They do not determine the legal eligibility of a parcel for development.

The remainder of the paper proceeds sequentially. Section 4 defines the sample, indicator construction, data treatment, and formal methods. Section 5 evaluates temporal evolution and distributional change. Section 6 examines regional gradients, spatial distribution, global spatial dependence, and local spatial association. Section 7 develops the city typology and consolidates the sensitivity analyses. Section 8 discusses the findings and limitations. Section 9 develops policy implications for land management, and Section 10 concludes.

## 4. Research Design, Index System and Methods

### 4.1. Study Area and Sample Construction

The study uses a balanced city-level panel covering 108 prefecture-level and above cities in the Yangtze River Economic Belt from 2012 to 2023. The sample includes cities from Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, Chongqing, Sichuan, Guizhou and Yunnan. The final dataset contains 1,296 city-year observations. The balanced design ensures that annual averages, distributional indicators and spatial statistics are not affected by changes in the number of cities over time.

The study area has two analytical characteristics. First, it contains both highly developed downstream cities and less-developed inland cities, making it suitable for examining regional gradient effects. Second, it is a connected river-basin corridor where ecological protection, industrial transformation and low-carbon development are jointly emphasized. These characteristics justify the use of both river-reach grouping and eastern-central-western grouping. **Table 1** reports the sample structure.

**Table 1.** Sample structure by grouping scheme.

| Grouping Scheme | Group        | Number of Cities |
|-----------------|--------------|------------------|
| River reach     | Upper reach  | 31               |
| River reach     | Middle reach | 36               |
| River reach     | Lower reach  | 41               |
| Subregion       | Eastern      | 25               |
| Subregion       | Central      | 52               |
| Subregion       | Western      | 31               |

The river-reach grouping emphasizes the ecological and hydrological position of each city, whereas the sub-region grouping emphasizes the broader economic-geographic location. The two classifications are used jointly rather than interchangeably. In the empirical analysis, if both classifications point to the same pattern, the conclusion is relatively robust; if they differ, the difference itself becomes useful evidence about the source of regional

heterogeneity.

## 4.2. Evaluation Index System

The evaluation system follows the production logic of green low-carbon transition. Inputs comprise year-end employment, total electricity consumption, urban construction land, capital stock, and total water supply. The two desirable outputs are real GDP and the urban carbon-sink proxy (UCS). Wastewater, sulfur dioxide, dust, and carbon dioxide emissions are undesirable outputs. Built-up-area green space (Gre) is the source variable used to construct UCS and is not entered as a separate desirable output. **Table 2** reports the exact definitions, units, data sources, construction procedures, and frontier roles.

**Table 2.** Evaluation index system for urban green low-carbon transition efficiency.

| Dimension             | Indicator (Symbol)               | Exact Definition                                                                              | Unit                            | Primary Source or Construction                                                    | Frontier Role                                |
|-----------------------|----------------------------------|-----------------------------------------------------------------------------------------------|---------------------------------|-----------------------------------------------------------------------------------|----------------------------------------------|
| Input                 | Labor (Lab)                      | Year-end employed persons, harmonized to a common reporting unit                              | $10^4$ persons                  | China Statistical Yearbook; provincial and municipal yearbooks/communiqués        | Input; lower redundancy preferred            |
| Input                 | Electricity (Ene)                | Total citywide electricity consumption                                                        | $10^8$ kWh                      | Provincial and municipal statistical yearbooks/communiqués                        | Input; lower redundancy preferred            |
| Input                 | Construction land (Land)         | Area of urban construction land                                                               | $\text{km}^2$                   | China Urban Construction Statistical Yearbook; local yearbooks                    | Input; lower redundancy preferred            |
| Input                 | Capital stock (Cap)              | Perpetual-inventory estimate; investment deflated with the fixed-asset investment price index | $10^8$ CNY, 2012 prices         | Constructed from fixed-asset investment and price-index series                    | Input; lower redundancy preferred            |
| Input                 | Water supply (Wat)               | Total urban water-supply volume                                                               | $10^8$ $\text{m}^3$             | China Urban Construction Statistical Yearbook; local yearbooks                    | Input; lower redundancy preferred            |
| Desirable output      | Real GDP (GDP)                   | Nominal GDP deflated by the provincial GDP deflator, base year 2012                           | $10^8$ CNY, 2012 prices         | China Statistical Yearbook; provincial and municipal yearbooks                    | Desirable output; higher preferred           |
| Construction variable | Built-up green space (Gre)       | Green-space area in urban built-up districts                                                  | $\text{hm}^2$                   | China Urban Construction Statistical Yearbook; local yearbooks                    | Source of the area-based ecological output   |
| Desirable output      | Urban carbon-sink proxy (UCS)    | $c \times \text{Gre}$ ; $c = 0.0021156$ , uniform reporting normalization                     | $10^4$ t $\text{CO}_2$ -eq/year | Constructed from Gre; SBM scale-invariance justification [44,45]; see Section 4.2 | Desirable output; Gre not entered separately |
| Undesirable output    | Wastewater (Was)                 | Total wastewater discharge                                                                    | $10^8$ t/year                   | Urban-construction and local environmental statistics                             | Undesirable output; lower preferred          |
| Undesirable output    | Sulfur dioxide ( $\text{SO}_2$ ) | Total sulfur dioxide emissions                                                                | $10^4$ t/year                   | Local environmental statistics and statistical communiqués                        | Undesirable output; lower preferred          |
| Undesirable output    | Dust (Dus)                       | Total smoke and dust emissions                                                                | $10^4$ t/year                   | Local environmental statistics and statistical communiqués                        | Undesirable output; lower preferred          |
| Undesirable output    | Carbon dioxide ( $\text{CO}_2$ ) | Territorial city-level carbon dioxide emissions                                               | $10^4$ t/year                   | China Emission Accounts and Datasets (CEADs)                                      | Undesirable output; lower preferred          |

Compared with a single carbon-efficiency indicator, this index system better captures the compound nature of urban green low-carbon transition. A city can appear clean in carbon terms but still have high conventional pollution, or it can have high economic output at the cost of excessive resource consumption. The integrated input-output-undesirable-output framework avoids such one-dimensional interpretation.

Socioeconomic variables were compiled from the China Statistical Yearbook and the statistical yearbooks and annual statistical communiqués of the 11 provinces/municipalities and 108 cities. Construction-land, water-supply, green-space, wastewater, sulfur dioxide, and dust records were cross-checked against the China Urban Construction Statistical Yearbook and local environmental statistics. City-level carbon dioxide emissions were obtained from CEADs. Monetary variables were converted to 2012 constant prices, and capital stock was estimated by the perpetual inventory method. The finalized input-output panel contains all 1,296 city-year observations with no missing values. For 106 construction-land observations in 2023, the 2021–2022 proportional change was carried forward as  $\text{Land}_{i,2023} = \text{Land}_{i,2022}^2 / \text{Land}_{i,2021}$ . These 106 extrapolations cover 98.15% of the 2023 city observations. Section 7.3.2 reports a comparison ending in 2022 and distinguishes exclusion of the 2023 score summaries from re-estimation of a frontier without extrapolated inputs.

Gre denotes green-space area in urban built-up districts, measured in hectares. The ecological output is an area-based urban carbon-sink proxy,  $\text{UCS}_{it} = c \times \text{Gre}_{it}$ , with  $c = 0.0021156$  applied uniformly to all 1,296 city-year observations. Expressed in the baseline reporting units of  $10^4$  t  $\text{CO}_2$ -eq/year,  $c$  implies  $0.0021156 \times 10^4 \times 12/44 = 5.769818$  t C/( $\text{hm}^2 \cdot \text{year}$ ), approximately 5.77. This calculation is a unit conversion, not an empirical calibration of

annual carbon uptake. The fixed value is retained as a reporting normalization of the green-space output; it is not presented as a measured sequestration rate common to all cities and years. Gre is not entered separately into the model.

The methodological justification for a common positive coefficient is the unit invariance of the SBM and super-efficiency SBM formulations [44,45]. Let  $g_j$  be green-space area and  $y_j = c g_j$  the corresponding output. For any  $a > 0$ , replacing  $c$  with  $ac$  rescales this output for every evaluated and reference observation. Its output constraint and slack rescale together:  $y_j^* = a y_j$  and  $s^* = a s$ . Hence the normalized slack satisfies  $s^*/y_k^* = s/y_k$ ; the corresponding projected-output ratios in the super-efficiency formulation are unchanged. The feasible intensity vectors and the objective value therefore remain unchanged under this common rescaling, with all other model specifications held fixed. The result holds for the pooled global frontier and for exclusion of the evaluated observation from its reference set.

Accordingly, the numerical size of the common coefficient changes the reported UCS level but does not change the relative efficiency scores or rankings in the stated model. Using Gre directly as the sole ecological output is mathematically equivalent. This provides a methodological justification for uniform scaling, not a validation of the absolute carbon quantities. Species composition, vegetation age, climate, and maintenance can produce different actual uptake rates; city- or year-specific coefficients would change relative outputs and are not covered by the invariance result. UCS is therefore interpreted as a green-space-based ecological proxy, not a verified carbon inventory or an offset credit.

The land-related indicators require a bounded interpretation. Land is the observed stock of urban construction land in square kilometres, not the annual administrative quota for additional construction land. Gre and UCS describe green space in built-up districts; they do not measure all forest, wetland, soil, or protected-area carbon stocks within a city's administrative territory. Consequently, the composite efficiency score is relevant to urban land management but is not a land-only efficiency measure, a complete ecosystem valuation, or a test of ecological red line compliance. The proposed quota mechanism in Section 9 uses this score as one diagnostic input alongside independent land-use and ecological checks.

### 4.3. Descriptive Statistics and Data Features

**Table 3** reports the descriptive statistics of the input-output variables, the Gre construction variable, and the final efficiency score. All 1,296 city-year observations are retained in the baseline analysis. Lab ranges from 6.9741 to 22,764.9, with a P99 threshold of 890.244; the maximum occurs in Ya'an in 2023, and 13 observations exceed P99. Section 7.3 evaluates the stability of annual and regional summaries after excluding these 13 high-Lab observations.

**Table 3.** Descriptive statistics of variables and the final efficiency score.

| Variable                    | Mean     | Std. Dev. | Minimum | Maximum  | CV     |
|-----------------------------|----------|-----------|---------|----------|--------|
| Lab                         | 110.297  | 726.682   | 6.9741  | 22,764.9 | 6.5884 |
| Ene                         | 174.884  | 243.788   | 3.7361  | 1,848.81 | 1.394  |
| Land                        | 176.976  | 315.712   | 0.5     | 2,705.31 | 1.7839 |
| Cap                         | 10,853.1 | 11,862.5  | 734.363 | 112,431  | 1.093  |
| Wat                         | 2.0985   | 3.9415    | 0.1108  | 32.0385  | 1.8782 |
| GDP                         | 2,759.06 | 4,036.26  | 165.83  | 47,219   | 1.4629 |
| Gre (construction variable) | 6,327.8  | 8,333.46  | 187     | 69,499.9 | 1.317  |
| UCS (desirable output)      | 13.3871  | 17.6303   | 0.3956  | 147.034  | 1.317  |
| Was                         | 0.6187   | 0.7829    | 0.006   | 7.0754   | 1.2654 |
| SO <sub>2</sub>             | 2.547    | 4.0641    | 0.0068  | 50.9788  | 1.5957 |
| Dus                         | 2.1791   | 4.2618    | 0.0488  | 134.737  | 1.9558 |
| CO <sub>2</sub>             | 3,276.33 | 3,438.82  | 190.878 | 20,527.1 | 1.0496 |
| $\rho_k^G$ (final score)    | 1.0702   | 0.067     | 1.001   | 1.3      | 0.0626 |

The descriptive results show substantial differences in production scale, pollution pressure, and carbon emissions. Excluding the single Lab maximum changes the 2023 mean efficiency by 0.0006. Excluding all 13 observations above the Lab P99 threshold changes annual means by no more than 0.0023; the 2023 mean is 1.0971 compared with 1.0990 in the full sample, and the regional ordering remains unchanged under both grouping schemes. The temporal trajectory and regional gradient are therefore stable in the high-Lab sensitivity comparison.

#### 4.4. Global Production Possibility Set

Let each city-year observation be treated as a decision-making unit. For city-year observation  $j$ ,  $x_j$  represents the vector of inputs,  $y_j$  represents the vector of desirable outputs and  $b_j$  represents the vector of undesirable outputs. To ensure intertemporal comparability, all city-year observations from 2012 to 2023 are pooled into a global production possibility set. The global set can be expressed as follows:

$$T^G = \{(x, y, b) | x \geq X\lambda, y \leq Y\lambda, b \geq B\lambda, \lambda \geq 0\} \quad (1)$$

In Equation (1),  $X$ ,  $Y$  and  $B$  denote the pooled input, desirable-output and undesirable-output matrices, respectively. The vector  $\lambda$  represents the intensity vector used to construct feasible production combinations. The global frontier is preferable to annual frontiers because it places all observations under a common benchmark. Without this treatment, the efficiency score of a city in 2012 would be evaluated against a different annual frontier from the score of a city in 2023, which would weaken the interpretation of long-term transition dynamics.

#### 4.5. Global Super-Efficiency SBM with Undesirable Outputs

The slacks-based measure is suitable because the components of urban green low-carbon transition need not change proportionally. Electricity use may decline while capital rises, and carbon emissions may fall while real GDP or the urban carbon-sink proxy increases. A non-radial model can account directly for these asymmetric adjustments. For evaluated decision-making unit  $k$ , the global super-efficiency SBM objective with undesirable outputs is written as follows:

$$\rho_k^G = \frac{1 + \frac{1}{m} \sum_{i=1}^m s_i^- / x_{ik}}{1 - \frac{1}{s+q} (A_k + B_k)} \quad (2)$$

In Equation (2),  $A_k$  and  $B_k$  collect the relative desirable-output and undesirable-output slack terms. The corresponding constraints are:

$$\begin{cases} x_k \geq X_{-k}\lambda - s^-, \\ y_k \leq Y_{-k}\lambda + s^+, \\ b_k \geq B_{-k}\lambda - s_b, \\ \lambda \geq 0 \end{cases} \quad (3)$$

In Equations (2) and (3), the slack terms represent input excess, desirable-output shortfall, and undesirable-output excess. The notation  $k$  means that the evaluated decision-making unit is excluded from its own reference set. A higher  $\rho_k^G$  indicates stronger relative performance under the global frontier. The final efficiency indicator is denoted  $\rho_k^G$  throughout the text, tables, and figures.

The estimated efficiency scores range from 1.0010 to 1.3000. The value 1.3000 occurs in 86 of the 1,296 city-year observations and in 24 of the 108 observations in 2023. The annual comparison contrasts the full-sample annual mean with the mean calculated after excluding observations equal to 1.3000. In 2023, the two means are 1.0990 and 1.0416, respectively, showing that the recent increase is concentrated in the upper-score group.

The efficiency score measures each city-year observation relative to the common global production frontier. Subsequent analyses examine the score's temporal evolution, intercity distribution, regional differentiation, spatial association, and long-run city typology.

#### 4.6. Spatial Weight Matrices and Spatial Autocorrelation Statistics

Spatial autocorrelation requires a spatial weight matrix. The baseline specification uses the six-nearest-neighbor matrix because it provides enough neighbors for each city while avoiding an excessively broad neighborhood. To test matrix sensitivity, four-nearest-neighbor, eight-nearest-neighbor and inverse-distance matrices are also used. The  $k$ -nearest-neighbor matrix is defined as:

$$w_{ij}^K = \begin{cases} \frac{1}{k}, & j \in N_{ki}, i \neq j \\ 0, & j \notin N_{ki} \end{cases} \quad (4)$$

The inverse-distance matrix is defined as:

$$w_{ij}^D = \frac{d_{ij}^{-1}}{\sum_{j \neq i} d_{ij}^{-1}}, i \neq j \quad (5)$$

Global Moran's  $I$  measures whether cities with similar efficiency values are spatially clustered:

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \cdot \frac{\sum_i \sum_j w_{ij} (z_i - \bar{z})(z_j - \bar{z})}{\sum_i (z_i - \bar{z})^2} \quad (6)$$

Local Moran's  $I$  is used to identify local spatial association types:

$$I_i = \frac{(z_i - \bar{z})}{S^2} \sum_j w_{ij} (z_j - \bar{z}) \quad (7)$$

A high-high city has high efficiency and is surrounded by high-efficiency neighbors, while a low-low city has low efficiency and is surrounded by low-efficiency neighbors. High-low and low-high cities indicate spatial mismatch. Because local classification may be sensitive to the weight matrix and permutation threshold, the LISA evidence is interpreted as exploratory rather than definitive.

#### 4.7. Dispersion and Heterogeneity Measures

To examine whether average improvement is evenly distributed, the coefficient of variation and Theil index are used. The coefficient of variation is defined as:

$$CV_t = \frac{\sigma_t}{\mu_t} \quad (8)$$

The Theil index is defined as:

$$T_t = \frac{1}{n_t} \sum_{i=1}^{n_t} \frac{E_{it}}{\mu_t} \ln \left( \frac{E_{it}}{\mu_t} \right) \quad (9)$$

When cities are divided into regional groups, the Theil index can be decomposed into between-group and within-group components:

$$T = \sum_g \frac{n_g}{n} \frac{\mu_g}{\mu} \ln \left( \frac{\mu_g}{\mu} \right) + \sum_g \frac{n_g}{n} \frac{\mu_g}{\mu} T_g \quad (10)$$

Equations (8)–(10) complement Moran's  $I$ . Moran's  $I$  answers whether efficiency values are spatially clustered, whereas CV and Theil answer whether cities are becoming more unequal. These two dimensions may diverge. A region can display increasing inequality without strong geographical clustering, and this possibility is important for interpreting the 2023 recovery.

## 5. Efficiency Measurement Results and Temporal Evolution

### 5.1. Overall Temporal Trajectory

The first empirical question is whether urban green low-carbon transition efficiency in the Yangtze River Economic Belt follows a stable upward path or a more complex staged trajectory. **Table 4** reports the annual mean, dispersion, share recorded at 1.3000, and score-level exclusion sensitivity. The overall mean rises from 1.0760 in 2012 to 1.0990 in 2023, but the path is clearly non-linear. Efficiency improves slightly from 2012 to 2014, declines during the middle years, and recovers strongly after 2021.

**Table 4.** Annual evolution and sensitivity to observations at 1.3000.

| Year | Mean   | Std. Dev. | Minimum | Maximum | CV     | Theil  | Share at 1.3000 (%) | Mean Excluding 1.3000 |
|------|--------|-----------|---------|---------|--------|--------|---------------------|-----------------------|
| 2012 | 1.076  | 0.0649    | 1.0105  | 1.3     | 0.0603 | 0.0017 | 5.5556              | 1.0629                |
| 2013 | 1.0766 | 0.0645    | 1.0081  | 1.3     | 0.0599 | 0.0017 | 5.5556              | 1.0635                |
| 2014 | 1.0824 | 0.074     | 1.0042  | 1.3     | 0.0683 | 0.0022 | 8.3333              | 1.0626                |
| 2015 | 1.0765 | 0.0681    | 1.0037  | 1.3     | 0.0633 | 0.0019 | 6.4815              | 1.061                 |
| 2016 | 1.0698 | 0.0707    | 1.0134  | 1.3     | 0.0661 | 0.0021 | 7.4074              | 1.0514                |
| 2017 | 1.0597 | 0.0471    | 1.0012  | 1.3     | 0.0445 | 0.0009 | 2.7778              | 1.0528                |
| 2018 | 1.0608 | 0.0518    | 1.0164  | 1.3     | 0.0489 | 0.0011 | 3.7037              | 1.0516                |
| 2019 | 1.0574 | 0.0467    | 1.001   | 1.3     | 0.0442 | 0.0009 | 2.7778              | 1.0505                |
| 2020 | 1.0635 | 0.0608    | 1.0118  | 1.3     | 0.0571 | 0.0015 | 5.5556              | 1.0496                |
| 2021 | 1.0556 | 0.0463    | 1.0063  | 1.3     | 0.0438 | 0.0009 | 2.7778              | 1.0486                |
| 2022 | 1.0648 | 0.0648    | 1.003   | 1.3     | 0.0609 | 0.0017 | 6.4815              | 1.0485                |
| 2023 | 1.099  | 0.1092    | 1.0091  | 1.3     | 0.0994 | 0.0047 | 22.2222             | 1.0416                |

**Table 4** should be read together with **Figure 1**. In 2023, the annual mean rises to 1.0990, the coefficient of variation to 0.0994, and the Theil index to 0.0047, while the share at 1.3000 reaches 22.2222%. The median is 1.0413 and the mean after excluding observations at 1.3000 is 1.0416. The joint movement of the mean and dispersion measures identifies a recent increase concentrated in the upper tail rather than a uniform upward shift of the entire distribution.

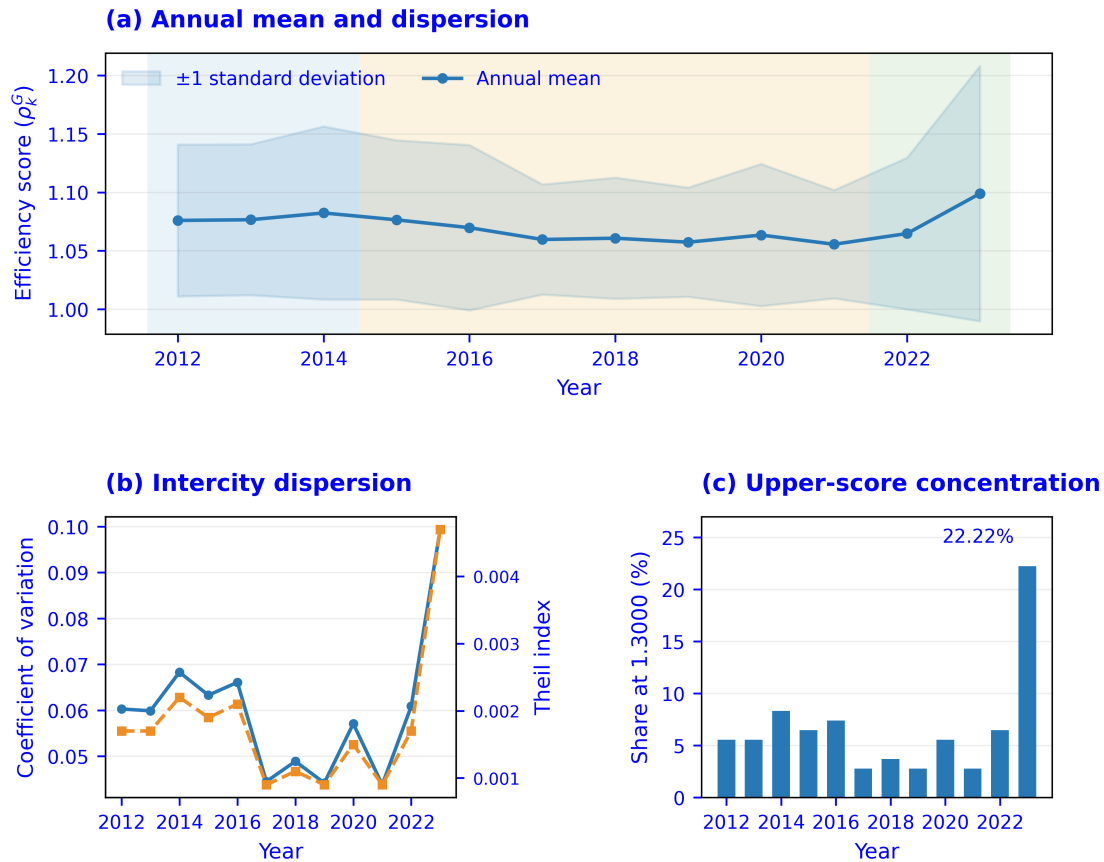


**Figure 1.** Temporal evolution and distributional divergence, 2012–2023. **(a)** Annual mean efficiency with  $\pm 1$  standard deviation; background bands distinguish 2012–2014, 2015–2021, and 2022–2023. **(b)** Coefficient of variation (solid blue) and Theil index (dashed orange). **(c)** Annual share of scores at 1.3000. Values are reported in **Table 4**.

The three-stage pattern is therefore central to the interpretation. During 2012–2014, the mean remains relatively high and fluctuates around 1.08. During 2015–2021, the mean declines and dispersion narrows, indicating that many cities converge toward a lower efficiency interval. During 2022–2023, the mean rises but dispersion expands. The result suggests that a simple statement of efficiency improvement would be incomplete; the distributional structure of the recovery must be emphasized.

## 5.2. Stage Comparison and Transition Interpretation

To make the temporal logic clearer, **Table 5** summarizes the three stages. The recovery stage has the highest mean but also the highest dispersion. This combination indicates that the latest improvement is uneven. It also implies that policy evaluation should monitor not only whether the regional average increases but also whether lagging cities are left behind.

The adjustment stage has the lowest mean and a relatively low Theil value. The recovery stage has a higher mean, a larger standard deviation, and a mean share of 14.3519% at 1.3000. These results show that the recent rise in average efficiency is accompanied by renewed intercity dispersion, so changes in location and distribution should be interpreted together. **Figure 2** shows the corresponding annual trajectories by river reach.

**Table 5.** Stage comparison of efficiency evolution.

| Stage               | Years     | Mean   | Std. Dev. | Theil  | Share at 1.3000 (%) |
|---------------------|-----------|--------|-----------|--------|---------------------|
| Initial fluctuation | 2012–2014 | 1.0784 | 0.0678    | 0.0019 | 6.4815              |
| Adjustment          | 2015–2021 | 1.0633 | 0.057     | 0.0014 | 4.4974              |
| Recovery            | 2022–2023 | 1.0819 | 0.0912    | 0.0034 | 14.3519             |

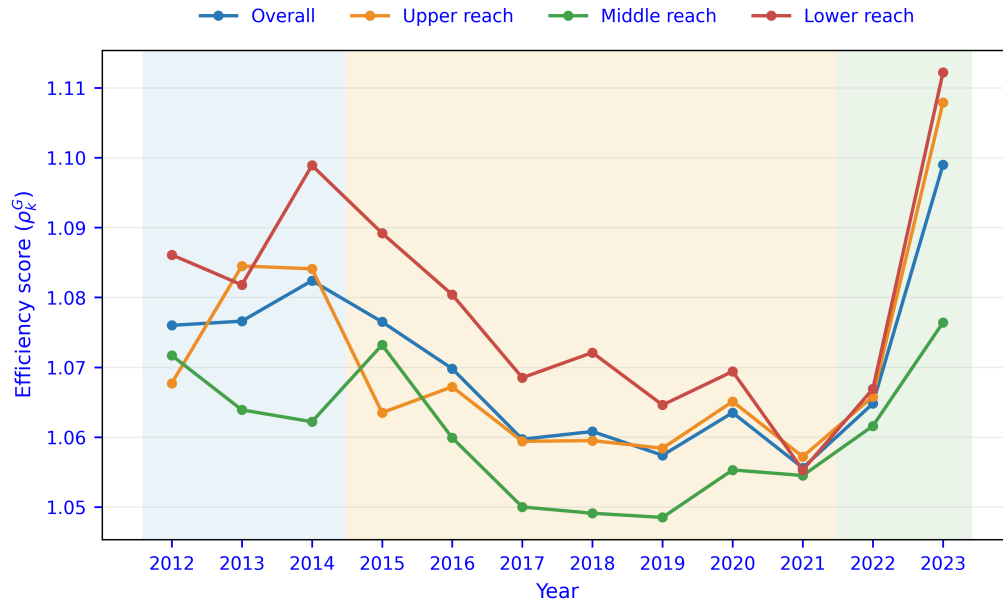


**Figure 2.** Annual mean efficiency by river reach, 2012–2023. Lines distinguish the overall mean and the upper, middle, and lower reaches. Background bands mark the initial-fluctuation, adjustment, and recovery stages.

### 5.3. Temporal Evolution by River Reach

**Figure 2** decomposes the temporal trajectory by upper, middle and lower reaches. The lower reach generally maintains a leading position during most of the sample period, while the middle reach remains weaker. The upper reach shows more volatility and recovers strongly in 2023. This pattern suggests that the river-basin transition is not synchronized across the corridor.

The lower reach advantage is consistent with its stronger innovation system, higher service-sector share and more developed environmental governance capacity. The middle reach weakness is also theoretically plausible because manufacturing-oriented structures and traditional industrial bases can make simultaneous input reduction, output improvement and emission abatement more difficult. The upper reach should not be treated as a homogeneous low-efficiency area; it contains both rapidly improving node cities and cities with weaker industrial and infrastructure foundations.

### 5.4. Distributional Evolution

The annual mean cannot reveal whether city-level efficiency distribution shifts as a whole or becomes more polarized. **Table 6** reports selected quantiles, and **Figure 3** combines kernel density, quantile ribbons and selected-year boxplots. These results show that the median changes more modestly than the upper tail. The 2023 distribution has a more pronounced right tail and wider dispersion, confirming that high-efficiency cities contribute disproportionately to the recent recovery.

The kernel density curves in **Figure 3** show substantially greater upper-tail mass in 2023. The P90 rises to 1.3000, whereas the median is 1.0413, below its 2022 value of 1.0461. The widening quantile band and longer upper tail in the boxplot indicate that the distributional expansion is concentrated above the median.

**Table 6.** Quantile evolution of city-level efficiency scores.

| Year | P10    | P25    | P50    | P75    | P90    |
|------|--------|--------|--------|--------|--------|
| 2012 | 1.0356 | 1.0431 | 1.0551 | 1.0744 | 1.1201 |
| 2013 | 1.0362 | 1.0433 | 1.0566 | 1.0802 | 1.1193 |
| 2014 | 1.0357 | 1.043  | 1.0561 | 1.0838 | 1.1519 |
| 2015 | 1.0346 | 1.0398 | 1.0525 | 1.0827 | 1.1275 |
| 2016 | 1.0287 | 1.0345 | 1.0466 | 1.0685 | 1.1121 |
| 2017 | 1.0326 | 1.0403 | 1.0493 | 1.0595 | 1.088  |
| 2018 | 1.0329 | 1.0386 | 1.0481 | 1.0607 | 1.0905 |
| 2019 | 1.0333 | 1.0381 | 1.0466 | 1.0591 | 1.086  |
| 2020 | 1.0332 | 1.0377 | 1.0471 | 1.0588 | 1.0912 |
| 2021 | 1.0327 | 1.037  | 1.0455 | 1.0592 | 1.0768 |
| 2022 | 1.0331 | 1.0377 | 1.0461 | 1.0593 | 1.093  |
| 2023 | 1.0255 | 1.0328 | 1.0413 | 1.0945 | 1.3    |

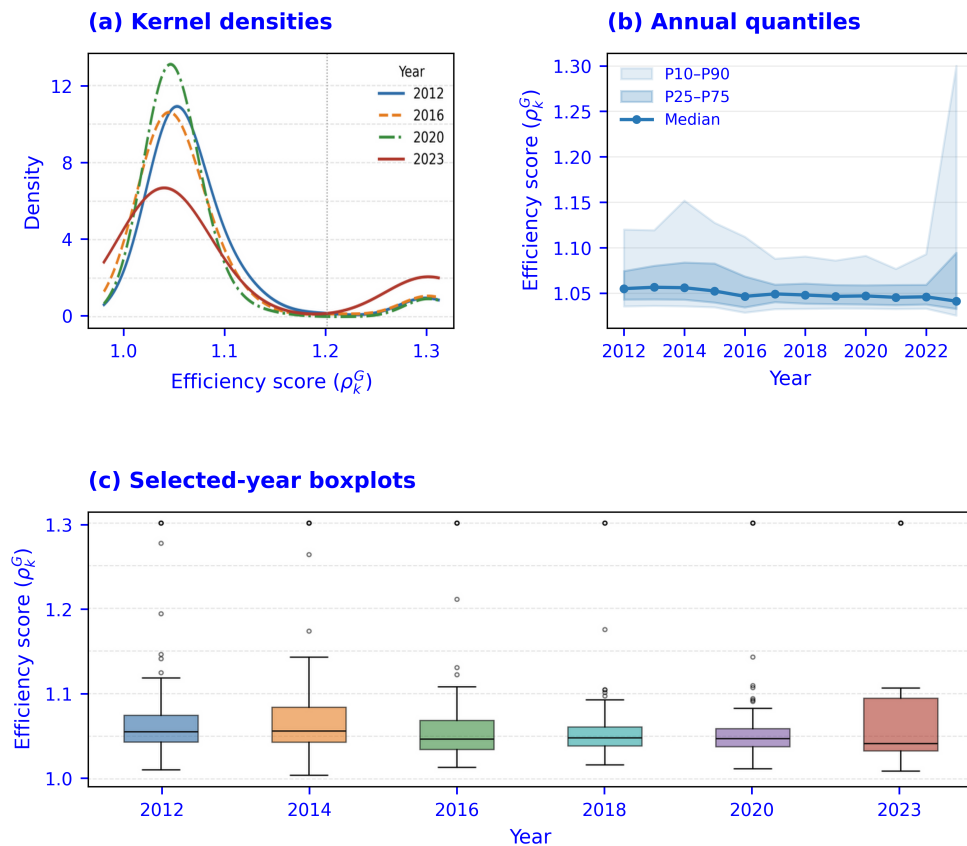


**Figure 3.** Distributional evolution of city-level efficiency. (a) Kernel densities for 2012, 2016, 2020, and 2023. (b) P10–P90 and P25–P75 bands with the median. (c) Selected-year boxplots. All panels use the final efficiency score  $\rho_k^G$ ; annual quantiles are reported in Table 6.

### 5.5. Upper-Score Sensitivity and Distributional Comparison

Figure 4 integrates distributional heterogeneity, regional gradients, and the sensitivity comparison for observations at 1.3000. In 2023, 24 cities, or 22.2222% of the sample, have a score of 1.3000. Excluding these observations reduces the annual mean from 1.0990 to 1.0416, a difference of 0.0574.

From 2012 to 2022, the difference between the full-sample and exclusion means ranges from 0.0069 to 0.0198; it increases to 0.0574 in 2023. The full-sample mean rises from 1.0648 in 2022 to 1.0990 in 2023, whereas the exclusion mean changes from 1.0485 to 1.0416. Thus, the recent increase in the annual mean is associated primarily with the 24 observations at 1.3000.

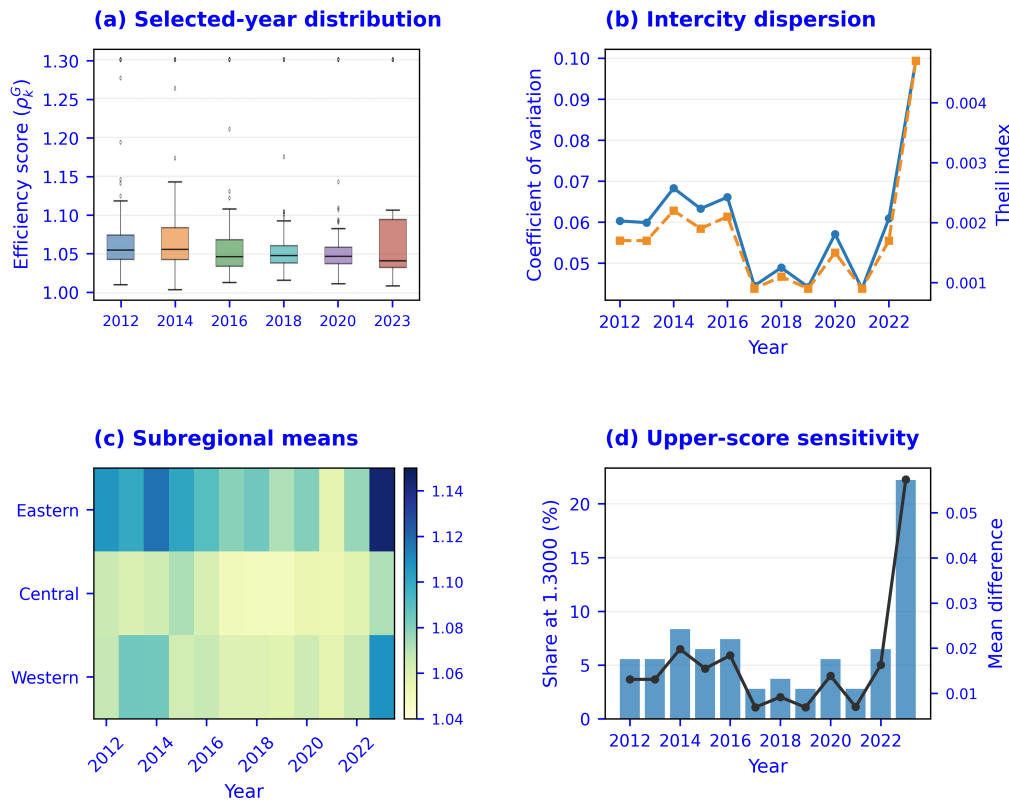


**Figure 4.** Distributional heterogeneity and upper-score sensitivity. (a) Selected-year boxplots. (b) Annual coefficient of variation (solid blue) and Theil index (dashed orange). (c) Eastern, central, and western mean efficiency. (d) Share at 1.3000 (bars, left axis) and the difference between the full-sample mean and the mean excluding scores at 1.3000 (line, right axis).

The combined evidence indicates efficiency recovery accompanied by renewed city-level differentiation. Aggregate improvement and distributional inequality therefore require separate attention in performance monitoring and policy design.

## 6. Regional Gradient, Spatial Pattern and Spatial Dependence

### 6.1. Regional Gradient by River Reach and Subregion

Section 5 shows that temporal improvement is uneven. This section further examines where the differences occur. **Table 7** reports the upper-middle-lower reach means, and **Table 8** reports the eastern-central-western means. The two grouping schemes provide complementary evidence.

**Table 7.** Regional mean efficiency by river reach.

| Year | Upper Reach | Middle Reach | Lower Reach |
|------|-------------|--------------|-------------|
| 2012 | 1.0677      | 1.0717       | 1.0861      |
| 2013 | 1.0845      | 1.0639       | 1.0818      |
| 2014 | 1.0841      | 1.0622       | 1.0989      |
| 2015 | 1.0635      | 1.0732       | 1.0892      |
| 2016 | 1.0672      | 1.0599       | 1.0804      |
| 2017 | 1.0594      | 1.05         | 1.0685      |
| 2018 | 1.0595      | 1.0491       | 1.0721      |
| 2019 | 1.0584      | 1.0485       | 1.0646      |
| 2020 | 1.0651      | 1.0553       | 1.0694      |
| 2021 | 1.0572      | 1.0545       | 1.0553      |
| 2022 | 1.0658      | 1.0616       | 1.0669      |
| 2023 | 1.1079      | 1.0764       | 1.1122      |

**Table 8.** Regional mean efficiency by subregion.

| Year | Eastern | Central | Western |
|------|---------|---------|---------|
| 2012 | 1.1068  | 1.0662  | 1.0677  |
| 2013 | 1.0993  | 1.061   | 1.0845  |
| 2014 | 1.117   | 1.0648  | 1.0841  |
| 2015 | 1.1013  | 1.0723  | 1.0635  |
| 2016 | 1.0902  | 1.0615  | 1.0672  |
| 2017 | 1.0794  | 1.0504  | 1.0594  |
| 2018 | 1.0845  | 1.0502  | 1.0595  |
| 2019 | 1.0721  | 1.0498  | 1.0584  |
| 2020 | 1.0803  | 1.0544  | 1.0651  |
| 2021 | 1.0573  | 1.0538  | 1.0572  |
| 2022 | 1.0769  | 1.0584  | 1.0658  |
| 2023 | 1.1447  | 1.0718  | 1.1079  |

**Figure 5** synthesizes the two regional classifications. The line charts and heatmaps show persistent lower-reach and eastern advantages, while the middle-reach and central groups remain comparatively weak. Reading the two schemes together distinguishes river-basin position from the broader economic-geographic gradient and demonstrates that the main regional ordering is consistent across classifications.

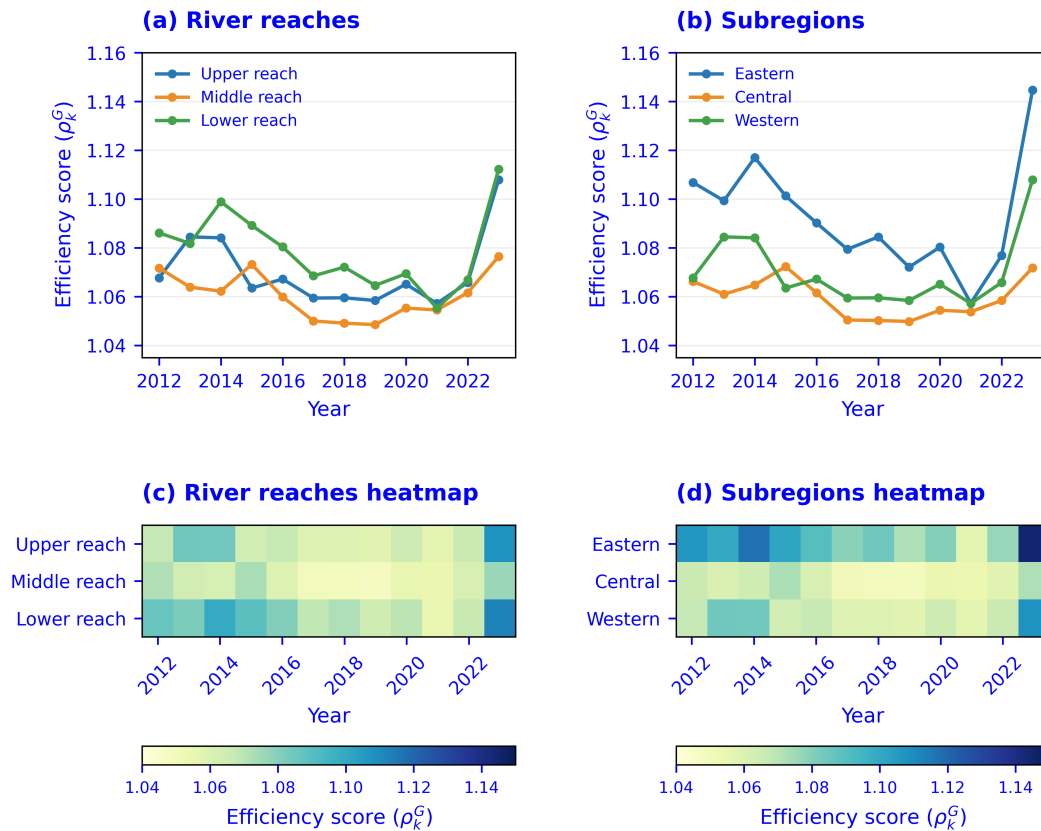


**Figure 5.** Regional gradient of green low-carbon transition efficiency, 2012–2023. **(a,c)** River-reach means as lines and a heatmap. **(b,d)** Eastern, central, and western means. Both heatmaps use the same color scale. Exact values are reported in **Tables 7** and **8**.

The regional-gradient evidence in **Figure 5** does not form a simple upstream-to-downstream ladder. The lower reaches retain a comparatively strong position for most years, a pattern aligned with differences in innovation resources, market integration, producer services, and environmental-governance capacity. The upper reaches rebound in 2023, while the middle reaches remain weaker. The parallel subregional comparison also highlights substantial heterogeneity among upper-reach and western cities.

The subregional comparison strengthens this interpretation. The eastern subregion has the clearest long-run advantage, especially in 2023, while the central subregion remains near the lower part of the distribution. This pattern suggests that the east-central-west classification captures an administrative-economic gradient that is not fully identical to the river-reach classification. In other words, the efficiency gap is shaped not only by location along the river basin, but also by differences in industrial upgrading, fiscal capacity, environmental regulation, green-technology absorption and urban service functions.

The heatmap panels in **Figure 5** are particularly useful because they reveal both persistence and turning points. The persistence lies in the repeated weakness of the middle reach and central subregion across many years. The turning point lies in 2023, when several groups experience a visible recovery but the magnitude of recovery is unequal. Therefore, the regional analysis supports the central argument of the paper: the recent rebound should not be interpreted as uniform regional convergence. It is better understood as a differentiated recovery in which leading regions recover faster, some inland nodes catch up selectively and structurally weaker areas remain under pressure.

## 6.2. Spatiotemporal Distribution of City-Level Efficiency

**Figure 6** presents the spatiotemporal distribution of city-level efficiency scores. The spatial pattern is uneven throughout the sample period. High-efficiency cities appear sporadically in the early years, become less prominent during the adjustment period and increase again in 2023. The distribution does not show a smooth basin-wide diffusion process.

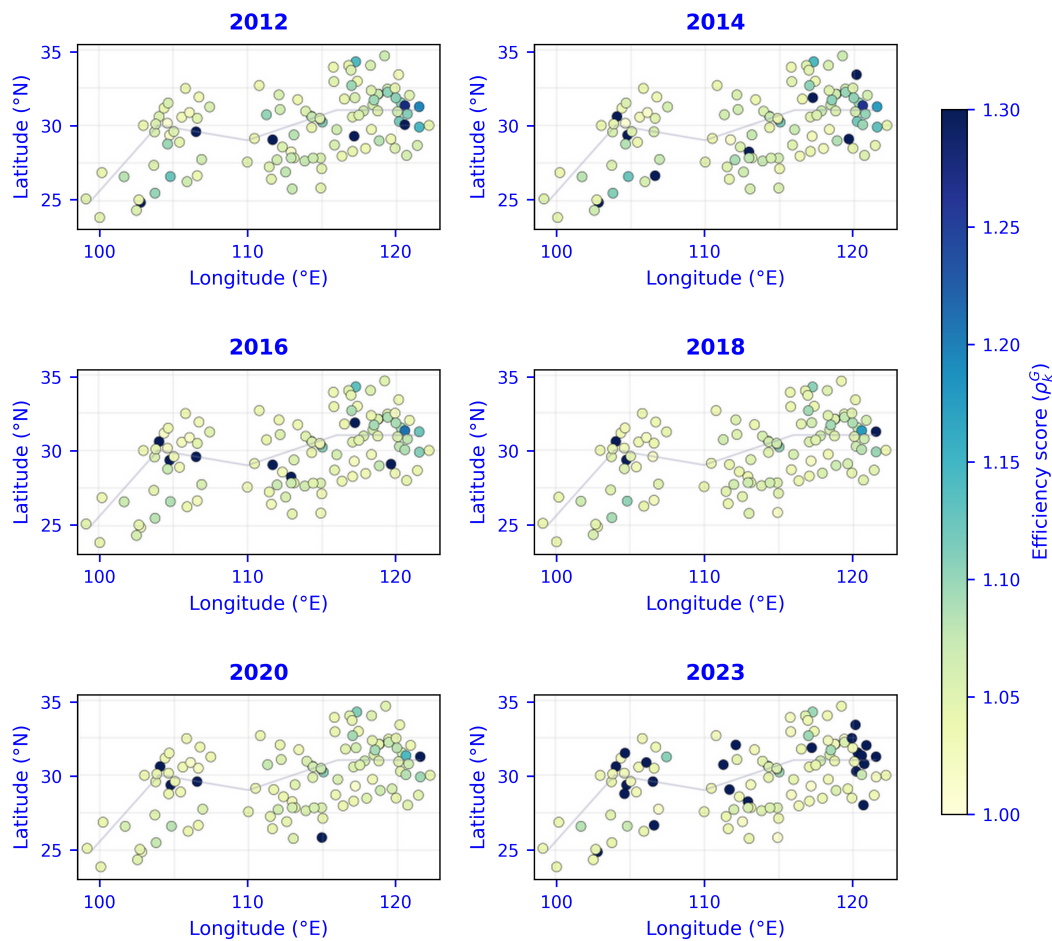


**Figure 6.** Coordinate-based distribution of city-level efficiency in 2012, 2014, 2016, 2018, 2020, and 2023. Each point represents a city, and color encodes  $\rho_k^G$  from 1.00 to 1.30. Coordinates provide an analytical display rather than administrative boundaries or watershed delineations.

**Figure 7** provides a richer four-period atlas and makes the spatial evolution clearer. In 2012 and 2016, high values are scattered rather than clustered. In 2020, most cities remain in the low-to-medium efficiency range. In 2023, high-efficiency points become more visible, especially in selected downstream and node-city areas. This supports the interpretation that the recent recovery is spatially uneven.

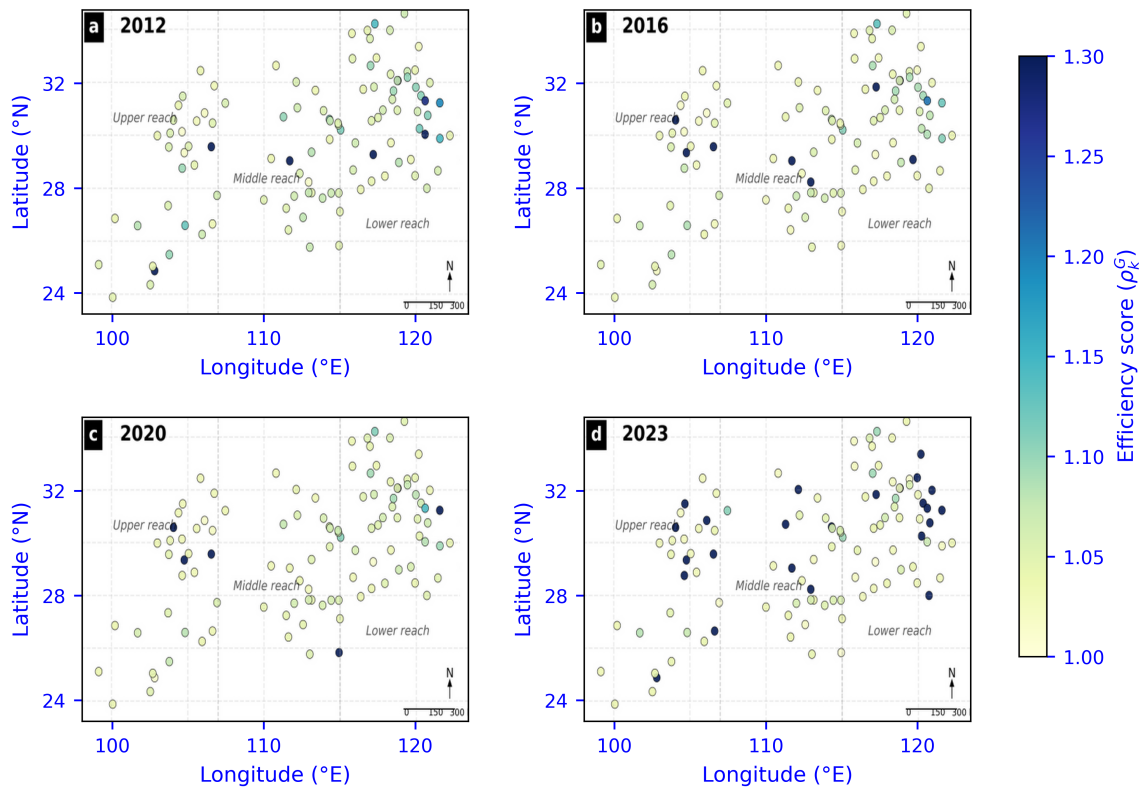


**Figure 7.** Four-period coordinate atlas of urban green low-carbon transition efficiency. (a–d) show 2012, 2016, 2020, and 2023; point color encodes  $\rho_k^G$ . Reach labels and separators are schematic and do not represent official administrative, watershed, or ecological protection boundaries.

The spatial evidence is consistent with the distributional evidence in Section 5. Both indicate that the recovery is not universal. Some cities move toward the frontier, but many cities remain far from it. This finding is important because a river-basin strategy often assumes that leading areas can diffuse standards and technologies to lagging areas. The empirical pattern suggests that such diffusion cannot be taken for granted.

### 6.3. Global Spatial Autocorrelation

**Table 9** reports Global Moran's I under the baseline K6 matrix. Most values are small and statistically insignificant. The only year that approaches marginal significance is 2023, with Moran's I equal to 0.0976 and a pseudo  $p$ -value of 0.0625. This result should be interpreted as weak and emerging spatial association, not as evidence of a mature spillover structure.

**Table 9.** Global Moran's I based on the six-nearest-neighbor matrix.

| Year | Moran's I | Pseudo $p$ -Value |
|------|-----------|-------------------|
| 2012 | 0.0278    | 0.5775            |
| 2013 | 0.0571    | 0.2375            |
| 2014 | −0.032    | 0.5175            |
| 2015 | −0.0181   | 0.7625            |

**Table 9. Cont.**

| Year | Moran's I | Pseudo p-Value |
|------|-----------|----------------|
| 2016 | -0.0497   | 0.37           |
| 2017 | -0.0288   | 0.5925         |
| 2018 | 0.0089    | 0.87           |
| 2019 | 0.0096    | 0.85           |
| 2020 | -0.0297   | 0.58           |
| 2021 | -0.0352   | 0.5075         |
| 2022 | -0.0063   | 0.91           |
| 2023 | 0.0976    | 0.0625         |

The sensitivity to alternative spatial matrices is reported in **Table 10**. The sign and magnitude of Moran's I change across K4, K6, K8 and inverse-distance matrices, especially in the middle years. This sensitivity reinforces a cautious interpretation.

**Table 10.** Robustness of Moran's I to alternative spatial weight matrices.

| Year | Inverse Distance | K4      | K6      | K8      |
|------|------------------|---------|---------|---------|
| 2012 | 0.0011           | 0.004   | 0.0278  | 0.0406  |
| 2013 | -0.0111          | 0.0085  | 0.0571  | 0.0371  |
| 2014 | -0.0246          | -0.0371 | -0.032  | -0.0133 |
| 2015 | -0.0125          | -0.0648 | -0.0181 | -0.0303 |
| 2016 | -0.0322          | -0.1041 | -0.0497 | -0.0339 |
| 2017 | -0.0227          | -0.0367 | -0.0288 | -0.0374 |
| 2018 | -0.0094          | -0.005  | 0.0089  | 0.0538  |
| 2019 | -0.0084          | -0.0261 | 0.0096  | -0.0064 |
| 2020 | -0.0295          | -0.0843 | -0.0297 | -0.0009 |
| 2021 | -0.0132          | -0.0493 | -0.0352 | 0.0264  |
| 2022 | -0.0346          | -0.0082 | -0.0063 | -0.0384 |
| 2023 | -0.0123          | 0.0235  | 0.0976  | 0.0713  |

**Figure 8** shows the annual trends under alternative matrices. The figure confirms that spatial dependence is weak and unstable in most years. A stable spatial spillover system would be expected to produce consistently positive and significant Moran's I values across matrices. The results do not show such a pattern.

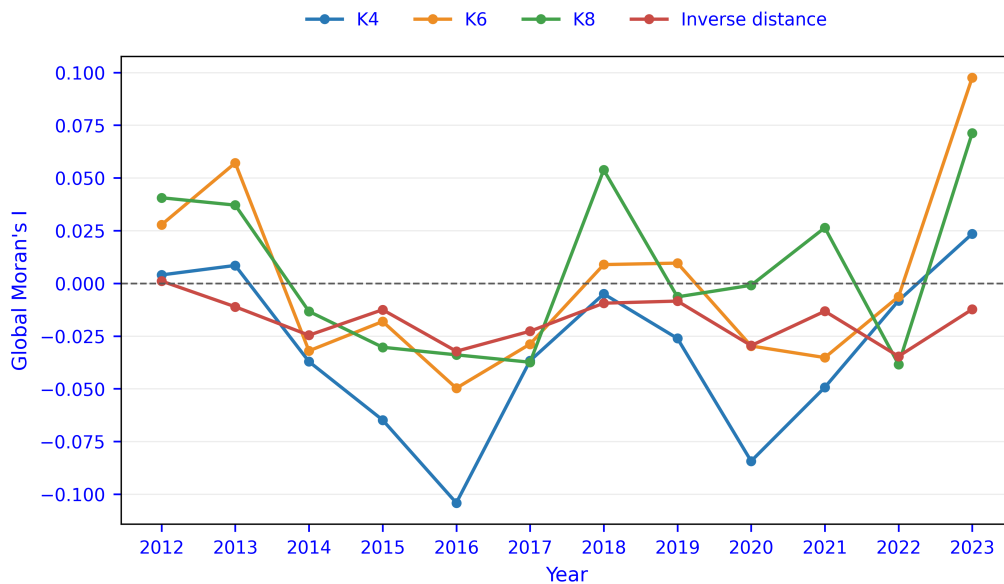


**Figure 8.** Annual Global Moran's I under K4, K6, K8, and inverse-distance spatial-weight matrices. The horizontal dashed line marks zero spatial association. Values are reported in **Table 10**.

**Figure 9** integrates the numerical and graphical spatial-dependence diagnostics. The heatmap, K6 time path with pseudo  $p$ -values, and Moran scatterplots show that spatial association is weak in most years, varies with the weight matrix, and becomes only modestly more positive in 2023. The evidence therefore does not support a mature basin-wide spillover mechanism.

**Figure 9** shows three layers of evidence. First, the heatmap of alternative spatial matrices demonstrates that the sign and magnitude of Global Moran's  $I$  vary across K4, K6, K8 and inverse-distance specifications. If the Yangtze River Economic Belt had already formed a mature basin-wide spillover mechanism, the Moran's  $I$  values would be expected to remain positive and relatively stable under different spatial structures. The observed instability therefore suggests that green low-carbon transition efficiency is still dominated by city-specific and subregional conditions rather than by a robust neighborhood diffusion process.

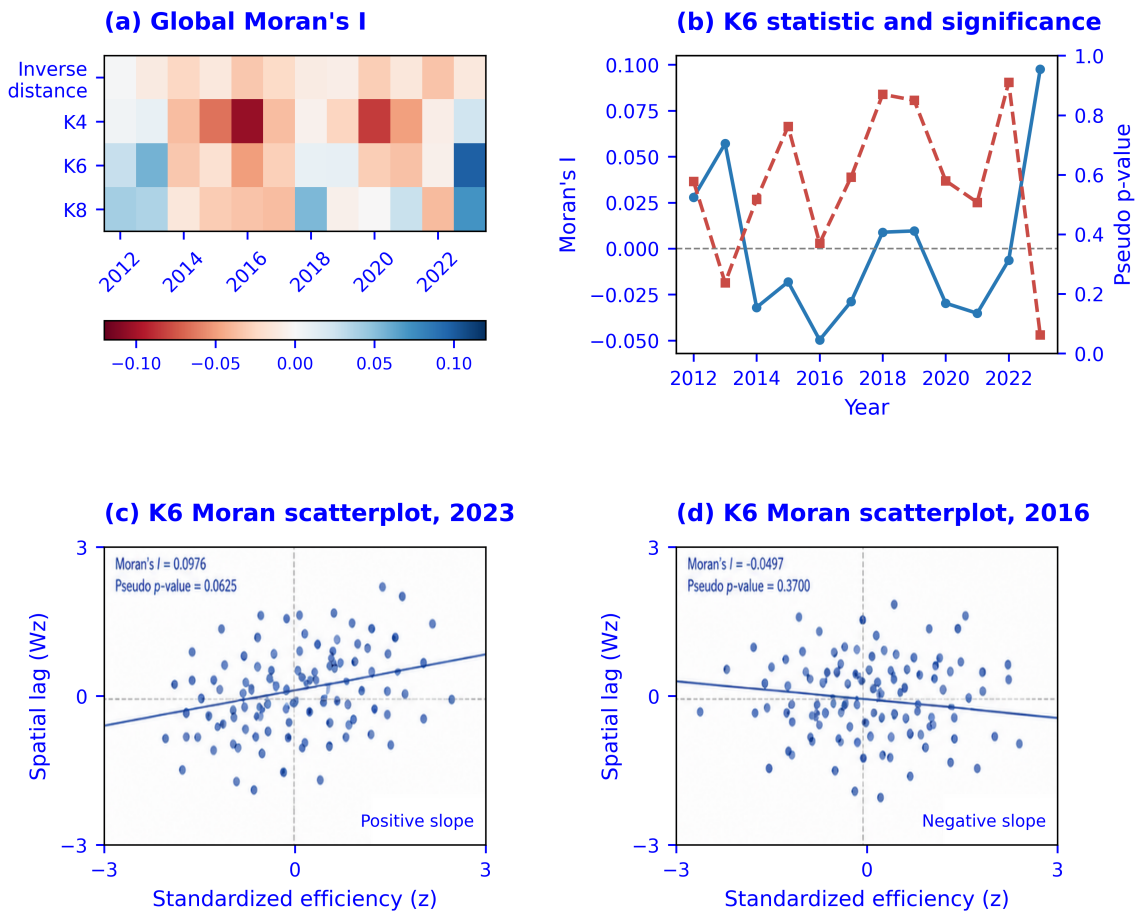


**Figure 9.** Spatial-dependence diagnostics. **(a)** Moran's  $I$  under four matrices. **(b)** K6 Moran's  $I$  (solid blue, left axis) and pseudo  $p$ -values (dashed red, right axis). **(c,d)** K6 Moran scatterplots for 2023 and 2016. The manuscript's reported pseudo  $p$ -values use 999 permutations; numerical summaries are given in **Tables 9** and **10**.

Second, the K6 time path makes the 2023 result more precise. The positive value in 2023 is meaningful because it appears at the same time as the efficiency recovery and the rise in dispersion. However, the pseudo  $p$ -value is close to, but does not pass, the conventional 5% significance threshold. The correct interpretation is therefore 'weak and marginal global spatial association' rather than 'strong and mature spatial dependence'. This wording is important because the policy conclusion should not assume that leading cities automatically transmit low-carbon efficiency gains to surrounding cities.

Third, the comparison between the 2016 and 2023 Moran scatter plots illustrates a structural difference between the adjustment period and the recovery period. The 2016 scatter plot has a weak negative slope, indicating that high- and low-efficiency cities were not organized into a stable positive-neighborhood structure. The 2023 scat-

ter plot has a modest positive slope, implying that some local similarity begins to appear. Nevertheless, the point cloud remains widely dispersed, which means that local association is still fragile. This justifies the subsequent LISA analysis, which examines whether the emerging signal is concentrated in a limited number of local high-high or low-low clusters rather than spread across the entire belt.

#### 6.4. Local Spatial Association and LISA-Type Transition

Global Moran's I provides an overall measure, but it cannot identify local configurations. **Figure 10** reports exploratory LISA categories for selected years. High-high and low-low configurations are present but not dominant. Many cities remain unclear or unstable in local spatial association, which is consistent with the weak global spatial dependence.

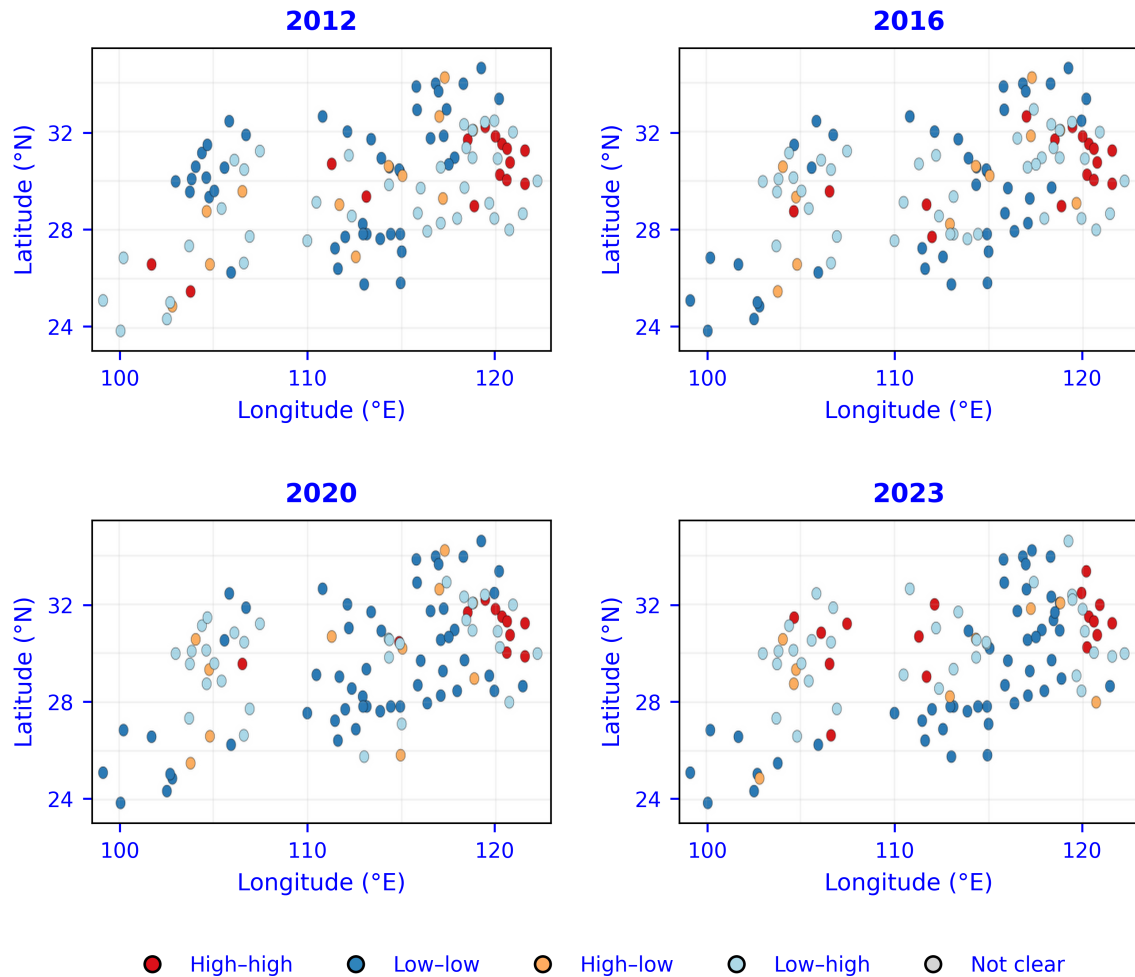


**Figure 10.** Exploratory local spatial-association categories under the K6 matrix for 2012, 2016, 2020, and 2023. Colors identify high–high, low–low, high–low, low–high, and not-clear categories. The coordinate displays represent sign-based exploratory categories rather than confirmed significant local clusters.

**Figure 11** deepens the LISA analysis by combining the 2023 LISA map, category composition and type transition. The figure suggests that local association structures become somewhat more visible by 2023, but the dominance of unclear or weakly structured categories remains. This again supports a cautious interpretation of spatial clustering.

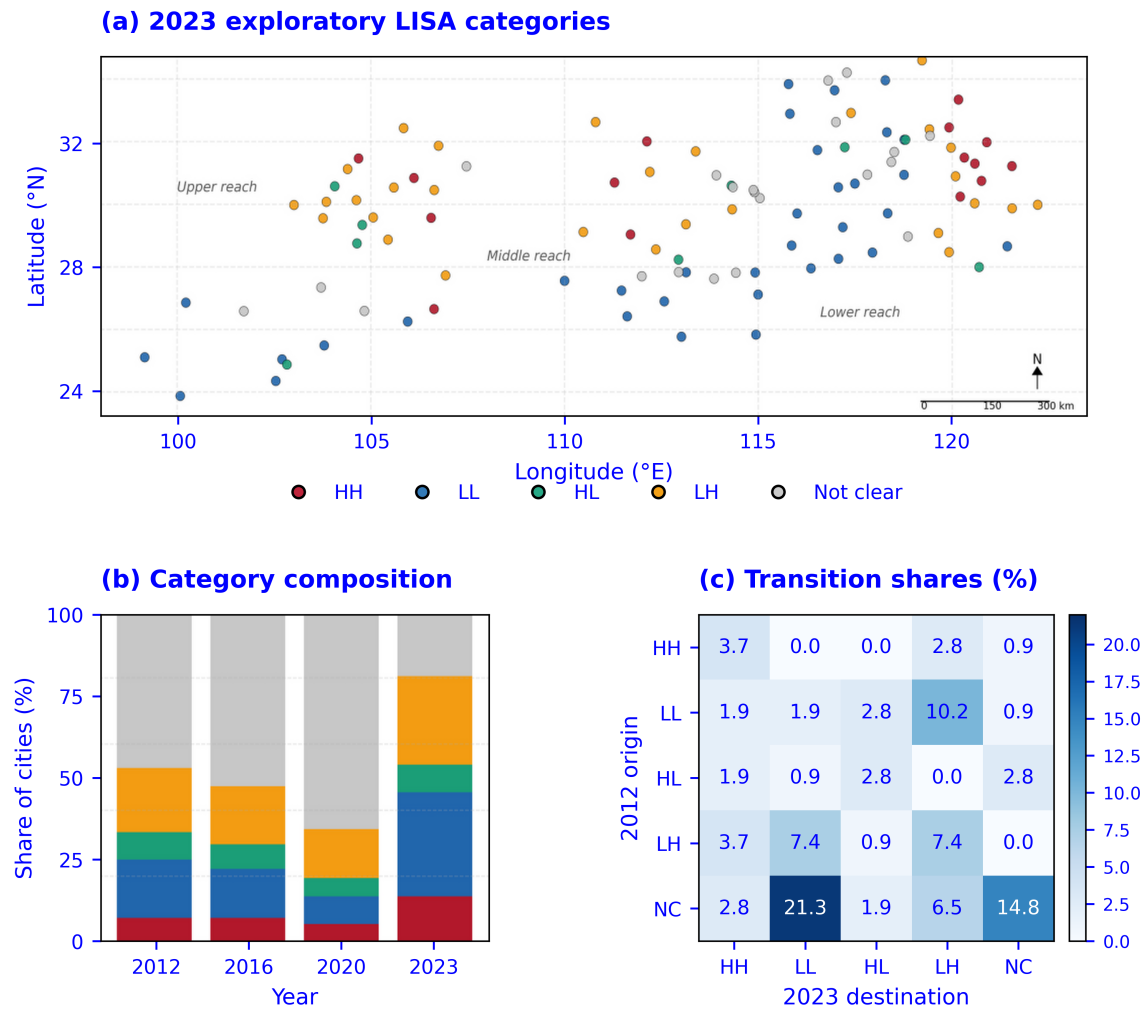


**Figure 11.** Exploratory LISA structure and transition. **(a)** City categories in 2023. **(b)** Category composition in 2012, 2016, 2020, and 2023. **(c)** Transition shares from 2012 origins to 2023 destinations, expressed as percentages of all cities. HH, LL, HL, LH, and NC denote high-high, low-low, high-low, low-high, and not clear. Minor total discrepancies reflect rounding; local significance requires permutation testing.

The local evidence has direct policy implications. A high-high cluster can serve as a diffusion hub only if institutional channels allow technology, standards and governance experience to move outward. A low-low cluster requires coordinated intervention because isolated city-level policies may not be sufficient. High-low and low-high cities deserve special attention because they reveal spatial mismatches: either a leading city surrounded by weaker neighbors or a lagging city located near stronger neighbors. These mismatch cases may be especially useful for designing targeted cooperation mechanisms.

## 7. City Typology, Robustness and Policy-Relevant Classification

### 7.1. Frontier and Lagging Cities in 2023

The preceding sections show that the 2023 recovery is uneven. **Figure 12** and **Table 11** examine the two tails of the distribution, and **Table 11** reports City IDs to avoid transliteration ambiguity. Twenty-four cities have a score of 1.3000 in 2023; the figure and table present a representative subset of ten cities from this group. The bottom-tail observations are ordered by their recorded scores.

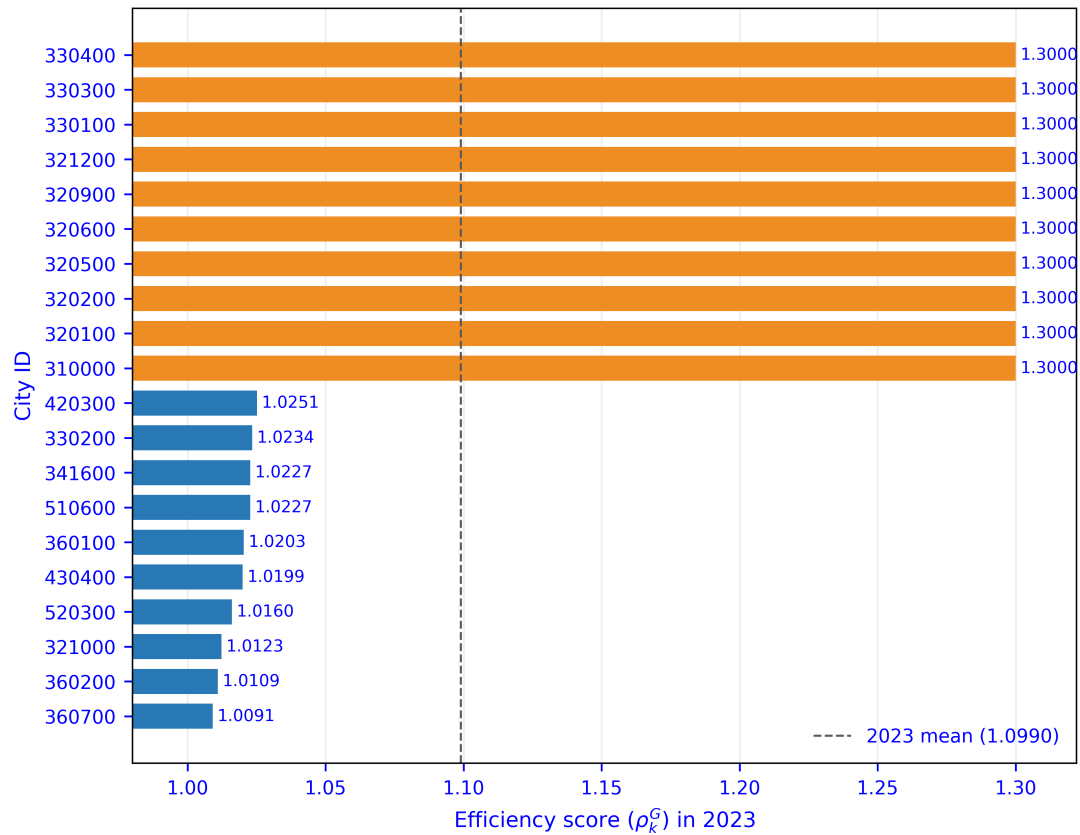


**Figure 12.** City IDs at the lower and upper ends of the 2023 efficiency distribution. Blue bars represent the ten lowest-score cities; orange bars represent ten illustrative cities among the 24 scoring 1.3000. The dashed line marks the 2023 mean of 1.0990. IDs and scores correspond to **Table 11**.

**Table 11.** Cities at the upper and lower ends of the 2023 efficiency distribution.

| Position  | City_ID | Efficiency in 2023 | Reach        | Subregion |
|-----------|---------|--------------------|--------------|-----------|
| Bottom 10 | 360700  | 1.0091             | Middle reach | Central   |
| Bottom 10 | 360200  | 1.0109             | Middle reach | Central   |
| Bottom 10 | 321000  | 1.0123             | Lower reach  | Eastern   |
| Bottom 10 | 520300  | 1.016              | Upper reach  | Western   |
| Bottom 10 | 430400  | 1.0199             | Middle reach | Central   |
| Bottom 10 | 360100  | 1.0203             | Middle reach | Central   |
| Bottom 10 | 510600  | 1.0227             | Upper reach  | Western   |
| Bottom 10 | 341600  | 1.0227             | Lower reach  | Central   |
| Bottom 10 | 330200  | 1.0234             | Lower reach  | Eastern   |
| Bottom 10 | 420300  | 1.0251             | Middle reach | Central   |
| Top 10    | 310000  | 1.3                | Lower reach  | Eastern   |
| Top 10    | 320100  | 1.3                | Lower reach  | Eastern   |
| Top 10    | 320200  | 1.3                | Lower reach  | Eastern   |
| Top 10    | 320500  | 1.3                | Lower reach  | Eastern   |
| Top 10    | 320600  | 1.3                | Lower reach  | Eastern   |
| Top 10    | 320900  | 1.3                | Lower reach  | Eastern   |
| Top 10    | 321200  | 1.3                | Lower reach  | Eastern   |
| Top 10    | 330100  | 1.3                | Lower reach  | Eastern   |
| Top 10    | 330300  | 1.3                | Lower reach  | Eastern   |
| Top 10    | 330400  | 1.3                | Lower reach  | Eastern   |

The tail comparison confirms that 2023 contains a distinct upper group. Twenty-four cities have a score of 1.3000, while the bottom ten range from approximately 1.01 to 1.03. The gap between the two tails reflects substantial differences in relative input-output performance under the common global frontier.

The tail analysis complements the long-run city typology by identifying the score range and city composition of the 2023 distribution. The efficiency score represents relative input-output performance under the common global frontier, while the typology combines long-run level, change, and volatility.

## 7.2. Multidimensional City Typology

A single-year ranking cannot capture long-term transition patterns. Therefore, cities are further classified by long-run average efficiency, efficiency change from 2012 to 2023 and intertemporal volatility. **Figure 13** shows the typology, and **Table 12** reports the number of cities in each group.

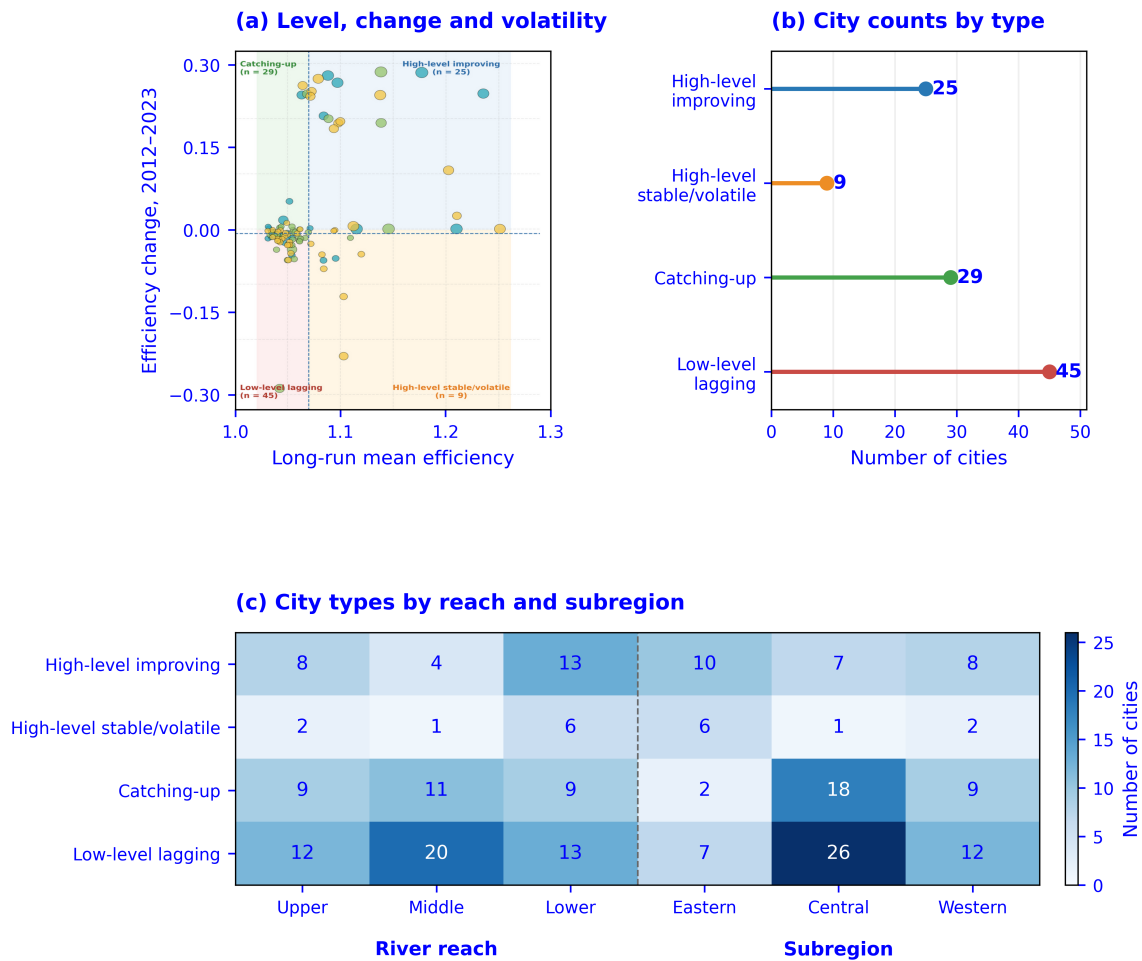


**Figure 13.** Multidimensional city typology. (a) Long-run mean efficiency versus 2012–2023 change; bubble size represents intertemporal volatility. Teal, green, and gold identify the upper, middle, and lower reaches, respectively. (b) Counts by city type. (c) Type counts under two separate classifications: river reach and subregion. Thresholds in panel (a) are the sample mean of long-run efficiency and the median 2012–2023 change. Each classification in panel (c) covers the same 108 cities.

**Table 12.** Number of cities in each typology.

| Type                       | Number of Cities |
|----------------------------|------------------|
| High-level improving       | 25               |
| High-level stable/volatile | 9                |
| Catching-up                | 29               |
| Low-level lagging          | 45               |

The typology provides more policy value than a simple mean comparison. High-level improving cities can be treated as potential demonstration areas. Their role is not only to maintain local efficiency but also to export standards, technology and management experience. High-level stable or volatile cities already have relatively strong performance, but they require mechanisms that reduce fluctuation and prevent regression. Catching-up cities deserve policy support because they show improvement potential. Low-level lagging cities require the most targeted intervention, especially in industrial upgrading, pollution-control infrastructure, carbon accounting and green finance access.

This classification also helps explain why the regional mean can improve while inequality rises. If high-level improving cities and frontier cities move rapidly upward, the regional mean increases. If low-level lagging cities improve slowly, dispersion also increases. The typology therefore connects the statistical result with a differentiated governance strategy.

### 7.3. Robustness and Sensitivity Analyses

**Table 13** evaluates whether the main temporal, distributional, regional, and spatial patterns persist across alternative spatial matrices, upper-score treatment, high-Lab observation exclusion, indicator construction, and score-consistency checks. Sections 7.3.1–7.3.2 add an analytical coefficient check and a comparison that excludes 2023 from the reported summary window.

**Table 13.** Robustness checks and interpretation.

| Robustness Dimension                    | Implementation                                                                        | Implication                                                                                          |
|-----------------------------------------|---------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------|
| Alternative K-nearest-neighbor matrices | K4, K6, and K8                                                                        | Global Moran signals remain weak in most years; 2023 is the clearest positive K6 result.             |
| Inverse-distance spatial matrix         | Continuous distance decay                                                             | Results remain mostly close to zero or negative; mature basin-wide dependence is not supported.      |
| Upper-score sensitivity                 | Full-sample mean versus mean excluding observations at 1.3000                         | The 2023 means are 1.0990 and 1.0416; the difference identifies pronounced upper-tail concentration. |
| Distributional diagnostics              | CV, Theil, quantiles, densities, and boxplots                                         | Mean recovery coexists with renewed dispersion, especially in 2023.                                  |
| Regional grouping comparison            | River reach and eastern-central-western schemes                                       | Lower-reach/eastern advantages and middle-reach/central weakness remain visible under both schemes.  |
| High-Lab sensitivity                    | Exclude 13 observations above the Lab P99 threshold of 890.244                        | Annual means change by at most 0.0023, and the regional ordering remains unchanged.                  |
| Indicator-construction audit            | Gre retained only as the construction variable for UCS                                | The same ecological information is not entered twice as separate desirable outputs.                  |
| Score-consistency check                 | Use $\rho_k^G$ across descriptive, temporal, regional, spatial, and typology analyses | All reported results refer to the same final efficiency-score series.                                |

The existing comparisons describe the staged trajectory, regional differences, upper-tail concentration, and generally weak spatial association. They address different sources of variation and should not be interpreted as interchangeable tests. In particular, excluding high-Lab observations or scores at 1.3000 does not isolate the effect of extrapolated construction-land inputs on the global frontier.

The high-Lab sensitivity comparison changes annual means by no more than 0.0023 and preserves the regional ordering. The upper-score comparison reduces the 2023 mean from 1.0990 to 1.0416, confirming that upper-tail concentration is a central feature of the recent change. Results from K4, K6, K8, and inverse-distance matrices consistently indicate weak basin-wide spatial association. These comparisons describe stability with respect to the specified summary exclusions and spatial matrices; they do not establish that the 2023 rebound is insensitive to land-data extrapolation.

#### 7.3.1. Analytical Sensitivity to the Common Carbon Conversion Coefficient

The scaling argument in Section 4.2 gives an exact model-level sensitivity result. Replacing  $c = 0.0021156$  by  $0.5c = 0.0010578$  or  $2c = 0.0042312$  for every city-year multiplies the reported UCS values by 0.5 or 2, respectively, while leaving the normalized output terms and efficiency values unchanged. This is an algebraic result for the stated SBM specification, not a new empirical model run. It addresses the level of the common conversion factor; it does not test heterogeneous biological uptake rates or the suitability of green-space area as an ecological-output proxy.

### 7.3.2. Comparison of Reported Results through 2022

To examine how strongly the descriptive conclusions depend on including the extrapolation year, **Table 14** compares summaries for 2012–2022 with those for 2012–2023. The shorter window contains 1,188 city-year scores and excludes all 108 scores from 2023. The calculation uses the reported annual summaries in **Tables 4** and **7–9** and retains the original 2012–2023 global reference frontier. Thus, it is a reporting-window comparison, not a re-estimation of the SBM frontier using only pre-2023 inputs. Regional averages are unweighted means of the annual regional means, appropriate to the balanced panel; values calculated from the rounded tables are approximate.

**Table 14.** Reporting-window comparison with the original global frontier held fixed.

| Summary Indicator                   | 2012–2022         | 2012–2023         |
|-------------------------------------|-------------------|-------------------|
| City-year scores summarized         | 1,188             | 1,296             |
| Pooled mean efficiency              | 1.0676            | 1.0702            |
| Upper-reach mean                    | 1.0666            | 1.0700            |
| Middle-reach mean                   | 1.0591            | 1.0605            |
| Lower-reach mean                    | 1.0757            | 1.0788            |
| Eastern-subregion mean              | 1.0877            | 1.0925            |
| Central-subregion mean              | 1.0584            | 1.0596            |
| Western-subregion mean              | 1.0666            | 1.0700            |
| K6 Moran's I range                  | –0.0497 to 0.0571 | –0.0497 to 0.0976 |
| Smallest reported K6 pseudo p-value | 0.2375            | 0.0625            |

Note: Calculations use rounded annual values from **Tables 4** and **7–9**. Both columns retain scores estimated against the 2012–2023 global frontier; the 2012–2022 column excludes 2023 only from the summary window. These are not results from a re-estimated pre-2023 frontier.

The pooled mean is approximately 1.0676 through 2022, compared with 1.0702 through 2023. Within the shorter window, annual mean efficiency increases from 1.0556 in 2021 to 1.0648 in 2022, a rise of 0.0092 (0.87%). The recovery in the reported trajectory therefore begins before the extrapolation year. Average efficiency still follows lower > upper > middle reaches and eastern > western > central subregions. For 2012–2022, K6 Moran's I ranges from –0.0497 to 0.0571 and all reported pseudo p-values exceed 0.10, so the characterization of weak spatial association does not depend on including the positive 2023 observation.

The magnitude and breadth of the 2023 increase require a narrower interpretation. The full mean rises by 0.0342 (3.21%) from 2022 to 2023, whereas the mean excluding scores equal to 1.3000 decreases from 1.0485 to 1.0416. Moreover, the common frontier used for the earlier scores still contains the 2023 input-output observations. The shorter-window comparison therefore cannot rule out an effect of the 106 extrapolated land values on either the 2023 scores or their reference frontier. A direct land-input sensitivity test would re-estimate the model after omitting 2023 from the reference set, or replace only the 106 extrapolated values with their 2022 levels while retaining the two observed 2023 values and all other inputs and outputs. No numerical result from either re-estimation is claimed here. The 2023 rebound is consequently treated as conditional on the baseline land-data treatment.

## 8. Discussion

### 8.1. Discussion of Main Findings

The results reveal a compound evolution pattern of urban green low-carbon transition efficiency in the Yangtze River Economic Belt. The first feature is staged temporal change. Efficiency does not rise smoothly from 2012 to 2023. Instead, it shows initial fluctuation, mid-period adjustment and recent recovery. This non-linear trajectory is consistent with the theoretical expectation that green low-carbon transition involves both short-term restructuring pressure and longer-term capability building. The reported annual mean already rises in 2022, whereas the magnitude of the additional 2023 increase remains conditional on the treatment of extrapolated construction-land inputs (Section 7.3.2).

The second feature is distributional divergence. The 2023 increase is accompanied by a higher CV, a higher Theil index, and a rise in the share of observations at 1.3000 to 22.2222%. A higher regional average can therefore

coexist with wider intercity dispersion. Performance monitoring should report the mean together with distributional indicators and the transition status of lower-efficiency cities.

The third feature is a regional gradient. The lower reaches and eastern subregion generally perform better, while the middle reaches and central subregion remain weaker. This pattern aligns with differences in industrial structure, market integration, fiscal capacity, and environmental-governance resources. The upper and western areas are also heterogeneous, with rapidly improving node cities alongside cities facing stronger constraints.

The fourth feature is weak spatial dependence. Moran's  $I$  is small and statistically insignificant in most years, and the 2023 signal is only marginal under the baseline K6 matrix. These results provide limited evidence of basin-wide clustering of the measured efficiency scores. Spatial autocorrelation does not identify technology diffusion or other causal spillovers; the policy implication is that effective coordination cannot be inferred from geographic proximity alone.

## 8.2. Theoretical Implications

The study contributes to the literature by showing that urban green low-carbon transition efficiency should be interpreted through both frontier performance and distributional structure. A global super-efficiency SBM model can identify relative performance under multiple inputs, desirable outputs and undesirable outputs, but the score becomes more meaningful when combined with temporal stages, regional gradients, dispersion measures and spatial diagnostics.

The findings also distinguish geographical association from governance mechanisms. Hydrological, transport, and industrial connections may be relevant to the diffusion of green practices, but Moran's  $I$  alone cannot establish whether those channels operate. For river-basin land management, coordination requires compatible spatial plans, shared monitoring information, and explicit arrangements to manage effects across administrative boundaries.

A further implication is that regional transition should be evaluated from both mean and inequality perspectives. The 2023 results demonstrate that a higher regional average can coexist with stronger intercity polarization. Future studies of green development should therefore avoid using a single average indicator as the only criterion of success.

## 8.3. Implications for Land Use Planning and Ecological Protection

The inclusion of construction land places development intensity within the resource-use side of the efficiency assessment. The persistent regional gradient is consistent with the need to examine how existing industrial and urban land is used before expanding its area. In lower-reach and eastern cities, comparatively high scores can support closer examination of redevelopment and technology-upgrading practices. In middle-reach and central cities, lower scores motivate diagnostics of industrial land utilization, environmental infrastructure, and pollution-control capacity. These interpretations are compatible with existing evidence on urban construction-land efficiency [2,14], but the present model does not isolate the contribution of any single land-use mechanism.

The 2023 rebound also cautions against allocating additional construction land solely on the basis of an annual mean or a city ranking. The full-sample mean is 1.0990, but it falls to 1.0416 when observations at 1.3000 are excluded, while the median is 1.0413. A reward rule based only on the upper tail could reinforce existing advantages without improving the land-use performance of the wider basin. Planning appraisal should therefore examine persistent performance, improvement relative to a city's starting conditions, and the use of already developed land.

Ecological protection serves a different purpose from relative production efficiency. A city can achieve a high score while still facing absolute emission pressure or site-specific ecological risks. The built-up green-space proxy does not capture the full benefits of upstream forests, wetlands, or riparian habitats. Efficiency gains should therefore inform choices among development options that already meet spatial-planning and ecological requirements, while conservation outcomes receive their own monitoring and support.

## 8.4. Limitations and Further Research

The analysis is descriptive and comparative. It does not estimate the causal effects of construction-land quotas, ecological red line designation, or urban development boundaries, and it does not calculate an optimal quota allocation. The city-level land stock cannot identify idle parcels, redevelopment potential, land-conversion flows, or within-city differences in ecological sensitivity. River-reach categories also cannot replace catchment boundaries.

Future research could link land parcels and observed conversion records to hydrological units and planning-control maps, and evaluate policy effects using an explicit identification design.

The most recent results warrant particular care in a land-policy application. As reported in Section 4.2, 106 construction-land observations for 2023 were extrapolated from their 2021–2022 changes. The comparison through 2022 in Section 7.3.2 shows that the reported pre-2023 trajectory, regional averages, and weak spatial association are not descriptions of 2023 alone. Because this comparison retains the original global frontier, it does not quantify the effect of replacing the extrapolated land inputs. The size of the 2023 rebound remains conditional on that input treatment and should not independently determine land allocations. For UCS, uniform positive rescaling leaves the specified SBM scores unchanged, but this invariance does not establish the accuracy of the proxy's absolute carbon quantities or account for city-specific uptake rates. These distinctions, together with the concentration of scores at 1.3000, support diagnostic use of the index alongside verification of recent land records and ecological conditions.

## **9. Policy Implications**

### **9.1. Link Construction-Land Quotas to Verified Performance**

A green and low-carbon efficiency mechanism should be linked to the allocation of additional construction-land indicators (administrative land quotas). The proposed mechanism would guide the discretionary component of annual allocations within approved planning limits. It would operate through three steps: ecological and planning eligibility screening, verification of land-use and environmental performance, and assessment of project need. This is a policy proposal informed by the observed heterogeneity; the present estimates do not determine the size of any quota adjustment.

Provincial natural-resources departments, working with ecological-environment and development authorities, should first screen proposed allocations against approved ecological protection red lines, permanent basic farmland protection, urban development boundaries, and applicable environmental requirements. A high efficiency score should not substitute for these checks. Among eligible projects, priority could be given to redevelopment of underused land and to projects demonstrating a credible need for additional land after feasible reuse options have been assessed.

Performance appraisal should combine a rolling multi-year efficiency record with independently verified indicators such as output per unit of construction land, reuse of idle or inefficient land, absolute and intensity-based emissions, and protection of urban green space. Both efficiency levels and improvements should be considered, with comparison among cities facing similar functional and industrial conditions. The full-sample and upper-score-exclusion summaries should be reviewed together. The findings do not support a fixed numerical reward coefficient or automatic quota expansion for cities scoring 1.3000.

Annual review should connect approved land allocations to project implementation and verified land-use outcomes. Persistent underuse or deterioration should trigger a diagnostic review and corrective measures before further discretionary allocations. Basic public-service needs and the development requirements of ecological conservation areas should remain part of the assessment, so that the mechanism does not mechanically penalize cities with lower economic output. Conservation responsibilities should be supported through ecological compensation and appropriate public investment.

### **9.2. Apply Differentiated Controls across the Basin**

In the upper reaches, land-use control should prioritize water-source conservation, riparian continuity, and protection of ecologically sensitive areas. New industrial and infrastructure sites should be screened against catchment vulnerability and approved protection boundaries, with preference for suitable existing construction land. Clean-energy or tourism projects should undergo the same ecological and site-suitability assessment as other projects. Compensation for conservation functions can support local development without making additional land conversion the default source of revenue.

In the middle reaches, the priority should be to improve the use of existing manufacturing and industrial-park land. Land supply, pollution permits, and environmental-infrastructure capacity should be examined together. Redevelopment of inefficient industrial sites should include contamination assessment and remediation where necessary, while new projects should be evaluated for cumulative pressures on receiving waters and nearby settlements.

The objective is to support industrial upgrading without transferring pollution-intensive land uses to adjacent jurisdictions.

In the lower reaches, land management should emphasize redevelopment of built-up areas, compact urban growth, and retention of connected blue-green spaces. Comparatively strong efficiency performance should encourage better use of existing urban and industrial land, rather than justify continued outward expansion. Joint review of cross-boundary industrial relocation and associated emissions would help distinguish genuine efficiency improvement from the transfer of environmental burdens upstream or inland.

These reach-level priorities should be refined for tributary watersheds and ecological functional zones. Neighboring cities sharing a catchment should compare proposed construction-land changes with water-resource constraints, downstream environmental pressures, floodplain functions, and habitat connectivity. The city typology can guide the intensity of technical support, while parcel eligibility and permitted uses remain governed by the applicable territorial-spatial plan. This two-level approach connects basin coordination with site-specific control.

### **9.3. Coordinate Monitoring and Targeted Assistance**

Basin and provincial coordination bodies should connect land-supply records, redevelopment inventories, ecological protection maps, and pollution-carbon monitoring through a shared data dictionary and joint verification procedures. Monitoring should report both land-use outcomes and the distribution of efficiency, including the mean, coefficient of variation, Theil index, and upper-score concentration. A rise in the mean accompanied by wider dispersion should prompt review of lagging cities and of the composition of gains before land-allocation rules are adjusted.

Support should reflect the four city types. High-level improving cities can share independently verified redevelopment and environmental-management practices. High-level stable or volatile cities need review of fluctuating land and emission outcomes. Catching-up cities can receive technical and infrastructure support linked to verifiable implementation milestones. Low-level lagging cities require coordinated assistance with inefficient-land redevelopment, pollution-control facilities, and land and carbon accounting. These interventions would establish channels for cooperation that cannot be assumed from spatial proximity alone.

## **10. Conclusions**

This study evaluates urban green low-carbon transition efficiency in 108 cities of the Yangtze River Economic Belt from 2012 to 2023. Using a global super-efficiency SBM framework with undesirable outputs and a set of spatiotemporal diagnostic tools, the paper reaches four conclusions. First, efficiency follows a staged path of initial fluctuation, mid-period adjustment, and recent recovery. Second, the lower reach and eastern subregion generally lead, while the middle reach and central subregion remain relatively weak. Third, spatial dependence is weak in most years, with the clearest positive signal occurring in 2023 under the K6 matrix. Fourth, under the baseline land-data treatment, the 2023 increase is accompanied by widening intercity dispersion and a sharp rise in observations at 1.3000, indicating pronounced upper-tail concentration. The comparison through 2022 retains the broad regional ordering and records a 2021–2022 recovery; because it holds the original global frontier fixed, it does not establish that the 2023 increase is independent of the land extrapolation. The land-management implication is to combine verified green low-carbon performance with construction-land allocation and redevelopment priorities, while maintaining ecological protection as an independent condition. Differentiated controls should reflect both river-reach functions and local watershed sensitivity. The composite efficiency results offer a basis for screening and coordination; they do not replace parcel-level assessment or establish the causal effectiveness of the proposed controls.

## **Author Contributions**

Conceptualization, J.Z.; methodology, J.Z. and L.S.; software, J.Z.; validation, J.Z., L.S. and M.C.; formal analysis, J.Z. and L.S.; investigation, L.S. and M.C.; resources, J.Z. and M.C.; data curation, L.S. and M.C.; writing—original draft preparation, J.Z.; writing—review and editing, J.Z., L.S. and M.C.; visualization, L.S. and M.C.; supervision, J.Z.; project administration, J.Z. All authors have read and agreed to the published version of the manuscript.

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## Institutional Review Board Statement

Not applicable.

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Not applicable.

## Data Availability Statement

This study uses secondary city-level statistics and emissions data. Source-data access points include the National Bureau of Statistics of China's statistical yearbooks (<https://www.stats.gov.cn/sj/ndsj/2024/indexch.htm>), the China Urban Construction Statistical Yearbook issued by the Ministry of Housing and Urban-Rural Development (<https://www.mohurd.gov.cn/>), provincial and municipal statistical yearbooks and communiqués, and China Emission Accounts and Datasets (CEADs; <https://www.ceads.net/>). Indicator definitions, data treatment, and the extrapolation of 2023 construction-land observations are described in Section 4.2. The derived summary statistics and efficiency diagnostics are reported in **Tables 3–14**. Access to source records is subject to the respective providers' terms. Requests concerning the compiled city-year panel may be directed to the corresponding author at [zj916sy@swut.edu.cn](mailto:zj916sy@swut.edu.cn).

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## Conflicts of Interest

The authors declare no conflict of interest.

## AI Use Statement

ChatGPT (OpenAI) was used to assist with language editing, organization of the revision, reference-metadata checks, drafting of explanatory land-management text, and preparation of plotting code. Figures were prepared with conventional plotting tools using numerical results and existing graphical data from the manuscript; no synthetic research observations were generated. The authors are responsible for reviewing and approving the revised text, references, and figures and for the accuracy and integrity of the manuscript.

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