EXPLORING THE ROLE OF DIGITAL ECONOMY AND ENVIRONMENTAL REGULATION IN URBAN GREEN LOGISTICS EFFICIENCY IN THE CONTEXT OF ENERGY TRANSITION: EMPIRICAL EVIDENCE FROM 30 CHINESE PROVINCES FROM 2013-2022

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Abstract. With the severe challenge of global climate change and the urgent need for sustainable development goals, the new energy industry is expanding at an unprecedented speed. Energy transition not only profoundly affects the energy production and consumption patterns, but also initiates green transition in the logistics supply chain industry. Enhancing the efficiency of green logistics is crucial for ensuring the sustainable and normal operation of society. This study examines China's urban green logistics efficiency (UGLE) from 2013-2022 using the Super-SBM (Super-Slack-Based Measure) model. Results indicate rising UGLE nationwide, with eastern cities leading and western cities lagging. The decomposition of the GML index reveals regional differences in contributions from technological progress and efficiency changes. Spatial analysis shows the positive spatial correlation of UGLE, particularly in central China. The SDM (Spatial Durbin Model) model further demonstrates that environmental regulation and the digital economy both directly and indirectly affect UGLE. Notably, environmental regulation's direct impact varies regionally, while the digital economy exhibits a negative nationwide effect. The study identifies an inverted U-shaped relationship between these factors and UGLE, suggesting that moderate improvements in digital economy quality and environmental regulation can enhance urban green economic efficiency, but excessive strictness may produce adverse outcomes.
Keywords: *green logistics, efficiency measurement, super-SBM, GML index, spatial measurement*

Introduction

With the development of urbanization and the increasing expansion of the needs of production and life, the impact and contribution of traditional logistics rough operation to economic growth and industrial development have gradually declined, and there has been a growing focus on streamlining logistics processes and enhancing the efficiency of traditional logistics. However, a logistics development mode that only focuses on economic benefits and process efficiency and ignores the overall ecological balance has led to environmental pollution, wasteful energy consumption, and even inefficient land use and fragmentation of the urban fabric, which has seriously hindered the process of sustainable urban development. Therefore, developing green logistics is a significant way to realize sustainable urban development under the constraint of ecological balance (Abbasi and Nilsson, 2016). The study of green logistics efficiency can help promote sustainable development in the field of international logistics, reduce global carbon emissions, alleviate the pressure of climate change, and promote the synergistic progress of countries in the mode of environmentally friendly logistics. Improving green logistics efficiency can also optimize the cross-border cargo transportation process, enhance the

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environmental-friendly level of the supply chain, strengthen the green competitiveness of industries in various countries in the global market, and lay the foundation for building a green international economic order. The greening of transportation, packaging, warehousing, and distribution of each link is essential to complete the renewal of urban green logistics. Recycling, waste, and information management are also vital to building a unified large-scale green supply chain. Currently, developing urban green logistics is at an intermediate level, with most regions falling within the middle and lower tiers. There remains significant potential for optimization and improvement (Jin et al., 2024). Comprehensively enhancing the efficiency of green logistics has become a critical practical challenge that must be addressed.

Environmental regulation plays a crucial role in developing urban green logistics. Both China's environmental regulation intensity and urban green economic efficiency have been steadily increasing, with environmental regulation significantly promoting UGLE (Mikhno et al., 2021). environmental regulation fosters green technological innovation, supporting the verification of Porter's hypothesis (Yu and Chen, 2015). Additionally, environmental regulation enhances UGLE through the promotion of economic agglomeration, reflecting the positive impact of such clustering. Hence, the thoughtful design and implementation of environmental regulation policies are vital for boosting urban green logistics efficiency and ensuring the sustainable development of the logistics industry (Mazzarino and Rubini, 2019). There is a positive U-shaped relationship between environmental regulation and urban green innovation efficiency, and increasing investment in educational resources, optimizing industrial structure, and improving the level of economic development can strengthen the impact of environmental regulation on urban green innovation efficiency (Fan et al., 2021). Wang and Song (2023) argue that environmental regulation, designed to protect the ecological environment, can promote both environmental and economic benefits when applied moderately. Xu and Xu (2022) employed a quantile regression model to analyze the effects of environmental regulation on carbon dioxide emissions and energy efficiency in the logistics industry, concluding that incentivized and mandatory environmental regulation impact industry efficiency differently across quartiles. Furthermore, Wang et al. (2023) identified significant regional variations in China's logistics industry's GTFP (Green Total Factor Productivity), with regional innovation capacity acting as an intermediary in the transmission of environmental regulation's effects. Specifically, regional innovation capacity mediates the effects of environmental regulation on cumulative technical efficiency change (AEC) and cumulative technical change (ATC), often masking their direct impact.

The digital economy promotes the development of green logistics by strengthening technological innovation ability and improving the efficiency of green distribution (Huang and Lei, 2024). The digital economy empowers the high-quality development of green logistics, and the digital governance environment, digital financial inclusion, and digital industry development are important driving forces. Dzwigode et al. (2021) argue that the digital economy makes it possible for the risks in the process of logistics activities to be better identified and managed, and at the same time, improves the efficiency of logistics activities through an integrated information system. Huang and Lei (2024) also suggest that the digital economy can provide the impetus for carbon emission reduction, which in turn can stimulate the demand for digital upgrading of enterprises and promote the digital economy to improve the efficiency of green logistics, while Akram et al. (2024) elaborated that the digital economy has a positive guiding significance for the

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green supply chain. Technological innovation is an important way for the digital economy to enhance the efficiency level of the green economy (Li et al., 2022). Therefore, the digital economy has an important relationship to the UGLE.

This paper investigates the impact of environmental regulation and the digital economy on the UGLE, highlighting regional differences and examining the spatial and temporal evolution of green logistics. Using the Super-SBM model, the study measures UGLE from the perspectives of environmental regulation and the digital economy and analyzes its trends from 2013 to 2022. The GML index decomposition assesses the dynamic contributions of technological progress and efficiency changes to UGLE. Additionally, SDM is employed to explore the distinct roles and influences of environmental regulation and digital economy across regions. The findings offer valuable insights for advancing urban green logistics, narrowing regional disparities in logistics development, and fostering sustainable, high-quality growth. By promoting the integration of effective environmental regulation and digital transformation, this study contributes to the green transformation and circular development of urban logistics, enabling a balanced approach to economic growth and environmental protection (Seroka-Stolka and Ociepa-Kubicka, 2019). Moreover, the results provide empirical evidence on the spatial and temporal evolution of UGLE in Chinese cities and offer guidance for shaping regional green logistics policies, optimizing resource allocation, and encouraging technological innovation and industrial upgrades. These efforts can help bridge regional gaps in green logistics development and support the sustainable, high-quality progress of cities.

Methodology

Assessment of UGLE

Of the commonly employed UGLE evaluation methods, the DEA (Difference Exponential Average) model is among the most widely utilized (Zhou et al., 2020). The DEA model can simultaneously handle multiple inputs and outputs for analyzing total factor efficiency, without pre-setting functions or parameter weights, avoiding the defects of subjectivity and information compression. At the same time, DEA has a set of mature measurement processes, the detailed information is presented in *Figure 1*.

The fundamental principle of DEA is to evaluate whether a decision-making unit is on the production frontier and achieves DEA efficiency. The traditional radial DEA model makes inefficient adjustments by simultaneous downsizing adjustments to input indicators or simultaneous expansion adjustments to output indicators, but it cannot make effective adjustments to specific indicators, resulting in inefficiencies that could result in biased outcomes. In 2001, Tone (2001) introduced the SBM model, which accounts for shortages in desirable outputs and redundancies in undesirable outputs. This model surpasses traditional DEA models by effectively addressing their limitations and providing a more accurate representation of efficiency evaluation. It enables inputs and outputs to be adjusted at varying rates, with efficiency measured through improvements in the average ratio. Building on the SBM model, Tone (2002) introduced the super-efficient SBM model in 2002, which allows the DEA methodology to compare and rank the efficiencies of multiple efficient decision-making units, which takes into account the relationship between the different input and output variables and allows for the presence in the evaluation of certain cases of exceeding the optimal level of output. In 2020, Tone (2020) refined the SBM model by introducing a super-efficient

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version that incorporates undesirable outputs, breaking away from the previous problem of considering only positive outputs and not negative ones. This model allows for the presence of some non-desired outputs in the assessment that are beyond the optimal level of outputs but still contribute to the efficiency of the production unit.

To solve the problem of multiple decision-making units generating an efficiency value of 1 during the analysis process, this paper adopts the Super-SBM model that takes into account non-desired outputs. This model extends the traditional SBM framework by estimating efficiency non-linearly and accounting for annual changes in production technology throughout the study period. The Super-SBM model offers several advantages: it resolves biases in efficiency values caused by traditional radial and angle-based DEA models that overlook slack variables; it expands the range of efficiency values beyond (0,1], enabling effective ranking of multiple efficient frontiers; and it accommodates undesirable outputs, allowing for more precise efficiency measurement.

The Super-SBM model is frequently employed to assess the efficiency of a DMU (Decision-making Units) (x_0,y_0,b_0) with m inputs, n_1 desired outputs and n_2 undesired outputs:

$$\min \rho = \frac{1 + \frac{\sum_{i=1}^{m} s_i^-}{m x_{i0}}}{1 - \frac{1}{n_1 + n_2}\left(\frac{\sum_{r=1}^{n_1} s_r^+}{y_{r0}} + \frac{\sum_{t=1}^{n_1} s_r^{b-}}{b_{t0}} \right)} \tag{Eq.1}$$

$$s.t. \begin{cases} \sum_{j=1}^{n} x_j \lambda_j - s^- \le x_0 \left(i = 1,2,\ldots,m \right) \\ \sum_{r=1}^{n} x_r \lambda_r - s^+ \le y_0 \left(r = 1,2,\ldots,n_1 \right) \\ \sum_{t=1}^{n} x_t \lambda_t - s^{b-} \le x_0 \left(t = 1,2,\ldots,n_2 \right) \\ 1 - \frac{1}{n_1 + n_2}\left(\frac{\sum_{r=1}^{n_1} s_r^+}{y_{r0}} + \frac{\sum_{t=1}^{n_1} s_r^{b-}}{b_{t0}} \right) > 0 \\ \lambda_j, s_i^-, s_r^+, s_t^{b-} \ge 0 \left(j = 1,2,\ldots,q, j \ne j_0 \right) \end{cases} \tag{Eq.2}$$

In *Equations 1* and *2*, ρ is the efficiency value, λ is the weight vector, j is each DMU, q is the number of DMUs, and m, n_1 and n_2 represent the inputs, desired outputs, and non-desired outputs. s_i^- , s_r^+, and s_r^{b-} denote the relaxation variables of inputs, desired outputs, and non-desired outputs. In this paper, provincial panel data from 30 provinces in China (excluding Tibet) are utilized and calculated using MATLAB software, and then the UGLE of each province in China is estimated.

Choice of input and output variables

Input indicators: This study incorporates capital, labor, infrastructure, and energy inputs into the indicator system. Capital input is measured by fixed asset investment in the logistics industry; labor input is represented by the number of employees in the

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logistics sector; infrastructure input is assessed by the number of operating cargo vehicles, postal network points, and the mileage of transport routes; and energy input is quantified by the total energy consumed in the logistics industry. In calculating the energy inputs, this study adopts the methodology of Chen et al. (2024), which uses standard coal consumption (million tons) as the unit of measurement and discounts the nine main energy sources typically consumed by the logistics industry through conversion factors.

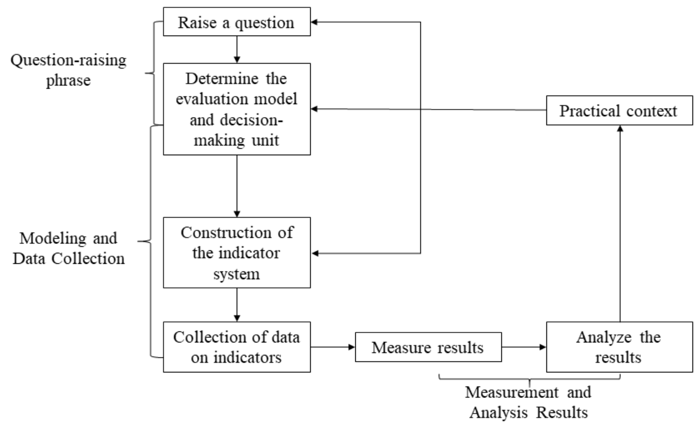

Figure 1. *DEA (difference exponential average) measurement flowchart*

Expected output: Expressed in terms of value added to the logistics industry and social cargo turnover.

Undesired outputs: Referring to the data from the Ministry of Ecology and Environment of the People's Republic of China, the total amount of carbon dioxide emitted by the logistics industry was converted by the carbon dioxide emission factors provided (Chen et al., 2024; Cui et al., 2024). The indicator system is shown in *Table 1*.

Table 1. *System of input and output indicators*

	Level 1 indicators	Secondary indicators
Input	Capital investment	Investment in fixed assets in the logistics industry (billions of dollars)
	Labor input	Number of employees in the logistics industry (10,000)
	Infrastructure inputs	Miles of transport routes (10,000 km) Number of goods vehicles in operation (10,000) Number of postal network points (Branch)
	Energy inputs	Energy consumption in the logistics industry (tons of standard coal)
Output	Desirable outputs	Value added to the logistics industry (billions of dollars) Social cargo turnover (billion tons kilometers)
	Undesirable outputs	Carbon emissions from logistics (tons)

Methodology for the analysis of regional changes

Using the GML (Global Malmquist Luenberger) index model, it is possible to make comparisons of regional UGLE across time and analyze the dynamic changes in regional UGLE, and the basic form of its decomposition model is as follows:

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$$GML(t-1,t)=\frac{E_g(x_t,y_t)}{E_{g-1}(x_{t-1},y_{t-1})} \quad \text{(Eq.3)}$$

$$EC(t-1,t)=\frac{E_t(x_t,y_t)}{E_{t-1}(x_{t-1},y_{t-1})} \quad \text{(Eq.4)}$$

$$TC(t-1,t)=\frac{GML(t-1,t)}{EC(t-1,t)}=\frac{\dfrac{E_g(x_t,y_t)}{E_t(x_t,y_t)}}{\dfrac{E_{g-1}(x_{t-1},y_{t-1})}{E_{t-1}(x_{t-1},y_{t-1})}} \quad \text{(Eq.5)}$$

In *Equations 3*, *4* and *5* $GML(t-1,t)$ represents the GML index in period t. $E_g(x_t,y_t)$ and $E_t(x_t,y_t)$ are the efficiency values obtained in period t under the super-efficient SBM model that incorporates undesired outputs, using the global optimal point and the period t optimal point as references, respectively. $EC(t-1,t)$ and $\mathrm{TC(t-1,t)}$ respectively represent the change in technical efficiency from period $t-1$ to period t and the technical change.

Spatial correlation analysis

The spatial correlation of UGLE is evaluated using the Moran index, which measures both the spatial correlation of UGLE and its temporal evolution across city clusters. In *Equation 6*, n is the total number of spatial units, x_i and x_j are the attribute values of the i-th and j-th spatial units, x is the average UGLE value across all provinces, and w_{ij} is the spatial weight value. The Moran's I ranges from -1 to 1. If Moran's I is greater than 0, it will indicate a positive spatial correlation of UGLE within the city cluster. If Moran's I is less than 0, it will signify a negative spatial correlation. When Moran's I approaches 0, it suggests no spatial correlation (Chen, 2013).

Global spatial autocorrelation measures spatial dependence within an overall spatial context, and Moran's I is a common measure of this autocorrelation. Using Moran's scatterplot, we can classify regions into four categories: the first category is "high high", i.e., both the region and its neighboring areas have high attribute levels with little spatial variation; the second category is "high low", i.e., the region has high attribute levels but its neighboring areas have low attribute levels with high spatial variation; the third category is "Low-Low", and the fourth category is "Low-High". By observing whether the "high-high" and "low-low" types are dominant, it can be judged whether a region has obvious spatial autocorrelation, i.e., whether there is a spatial aggregation phenomenon (Chen, 2013).

Local spatial autocorrelation, on the other hand, focuses on the similarity between individual spatial units and their neighbors, which reflects the consistency of the local unit with the overall trend, including the direction and strength of the trend, and reveals spatial heterogeneity, i.e., how spatial dependence varies according to location. Local Moran's I classifies patterns of spatial correlation into four types: positive spatial correlation includes "high-high correlation" (regions with above-average attribute values are surrounded by neighboring regions that are also above-average) and "low-

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low correlation"; negative spatial correlation includes Negative spatial correlations include "high low correlations" and "low high correlations".

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(x_i-\bar{x})^2} \tag{Eq.6}$$

In this study, the spatial weight matrix is constructed based on the neighbor weight matrix. In *Equation 7*, the distance between region i and region j is denoted as d_{ij}, and d represents the pre-determined distance threshold value. The spatial weights can be defined as follows:

$$w_{ij} = \begin{cases} 1 \ \ if \ \ d_{ij} < d \\ 0 \ \ if \ \ d_{ij} \geqslant d \end{cases} \tag{Eq.7}$$

Spatial metrology analysis methods

When spatial dependence exists between variables, traditional statistical models may not be able to adequately address the problems posed by such dependence, which could result in biased research outcomes. To avoid this situation, researchers need to consider using spatial econometric models (Mur and Angulo, 2006). This study aims to explore the "local neighborhood" effect of UGLE, where spatial dependence between variables is an important consideration in the analysis. Hence, this section aims to develop a suitable spatial econometric model.

Currently, three commonly used spatial econometric models are the Spatial Lag Model (SLM), the Spatial Error Model (SEM), and the Spatial Durbin Model (SDM) (Mur and Angulo, 2006). The Spatial Lag Model (SLM) is typically preferred when the dependent variable exhibits spatial correlation. The specific form of the spatial lag model is:

$$\ln UGLE_{it} = \rho \sum_{j=1}^{N} w_{ij} UGLE_{it} + \beta_i X_{it} + \gamma_i + \mu_t + \varepsilon_{it} \tag{Eq.8}$$

In the model, ρ denotes the spatial lag coefficient; N refers to the number of spatial units; X_{it} represents the vector of explanatory variables, which constitute the explanatory variable matrix; β_i is the estimated parameter for the explanatory variables; and γ_i and μ_t capture the spatial and temporal fixed effects, respectively.

When spatial dependence is present in the residuals, the Spatial Error Model (SEM) is used to account for this spatial correlation. The mathematical formulation of this model is as follows:

$$\ln UGLE_{it} = \tau \sum_{j=1}^{N} w_{ij} \varphi_{ij} + \beta_i X_{it} + \gamma_i + \mu_t + \varepsilon_{it} \tag{Eq.9}$$

In the spatial econometric model, φ_{ij} represents the spatial autocorrelation error term, and τ indicates the spatial autocorrelation coefficient of the error term. The other variables maintain the same definitions as in *Equation 8*.

The Spatial Durbin Model (SDM) is suitable when spatial dependence is present in both the dependent and independent variables. The SDM model is:

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$$\ln UGLE_{it} = \rho \sum_{j=1}^{N} w_{ij} UGLE_{it} + \sum_{j=1}^{N} w_{ij} x_{jt} + \beta_i X_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad \text{(Eq.10)}$$

In this paper, to identify the most appropriate model to analyze the correlation and interaction of spatial data, a specific spatial econometric model will be selected based on tests such as the LM (Lagrange Multiplier) test, Wald test, Hausman test, and LR (Likelihood Ratio) test.

Selection of variables and model formulation

Explanatory variable

Urban green logistics efficiency (UGLE): The UGLE results were evaluated using the Super-SBM model.

Core explanatory variables

Digital Economy (DE): By empowering the logistics industry, the digital economy enhances the depth of digital integration, gives rise to intelligent logistics and digital logistics, realizes the precision and intelligence of logistics services as well as the real-time availability of logistics information, and thus enhances the efficiency of developing logistics industry. The application of digital technology optimizes the whole logistics process and reduces carbon emissions and energy consumption. In addition, the digital economy also optimizes the cargo transportation path and warehouse layout through the construction of a data-driven logistics management and logistics information platform, improving transportation efficiency and reducing costs. The application of Internet of Things (IoT) technology has improved the safety and reliability of logistics and transportation, and the digitalization and collaborative development of the supply chain has strengthened the transparency and flexibility of the logistics supply chain. The digital economy also promotes the green development of the logistics industry, realizes real-time tracking and sharing of logistics information through information technology, optimizes the logistics path and distribution scheme, and reduces the idling rate and inefficiency in logistics transportation. Referring to the conclusion of Zhao et al. (2020) this paper measured the digital economy through the construction of the indicator system, using the global entropy weight-Topsis method, as shown in *Table 2*.

Environmental regulation (ER): Environmental regulation probably influences the efficiency of the logistics industry by curbing polluting activities of businesses and safeguarding the ecological environment during regional development. First, environmental regulation may depress corporate profits, resulting in lower logistics efficiency, that is, the “cost of compliance” effect; Second, environmental regulation incentives for environmental protection and technological innovation, improve productivity levels, and logistics efficiency is therefore affected. The formula is as follows (McKinnon, 2010):

$$ER = \frac{\text{Completed investment in industrial pollution control (million yuan)}}{\text{Value added of industry (billions of dollars)}} \quad \text{(Eq.11)}$$

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Table 2. *Digital economy indicator system*

Level 1 indicators	Secondary indicators	Tertiary indicators	Indicator properties
Comprehensive development index for the digital economy	Internet penetration	Internet per 100 population	+
	Number of Internet-related workers	Percentage of employees in computer services and software	+
	Internet-related outputs	Total telecommunication services per capita	+
	Number of mobile Internet users	Cell phone subscribers per 100 population	+
	Digital finance for inclusive development	China digital inclusive finance index	+

Control variable

Gross Domestic Product per capita (RGDP): Regions with a high level of economic development have more frequent production, circulation, and consumption processes of internal economic activities, and also have a large amount of goods and commodities coming and going with neighboring regions, which greatly promotes the demand for logistics, thus expanding the scale of the logistics industry. On the supply side, a strong economic base can provide abundant material conditions for developing the logistics industry, which is conducive to supporting the construction of the logistics system and improving the transportation infrastructure, thus reducing the cost of logistics operation and improving logistics efficiency. In addition, the growth of per capita GDP also indicates an increase in residents' income levels, which will enhance the consumption ability of residents, which in turn will boost the demand for commodity circulation and logistics, and increase the demand for logistics such as express delivery and cargo distribution. Therefore, GDP per capita has a non-negligible impact on urban logistics efficiency and is a key factor in controlling the impact of other variables in the study of logistics efficiency.

Advanced Industrial Structure (AIS): An advanced industrial structure reflects a higher proportion of high-tech and value-added industries, which not only drives the transformation of the economic growth model but also guides the logistics industry toward greater sustainability, efficiency, and intelligence. As the industrial structure optimizes, the logistics industry gains access to more technological inputs and innovation support, enhancing operational efficiency while reducing environmental pollution and resource consumption. Furthermore, the advanced industrial structure indirectly fosters green development in logistics by promoting efficient resource allocation and improving the utilization of production factors. For instance, a rationalized industrial structure can absorb surplus urban labor, alleviate employment pressures, narrow development gaps, and enhance overall development quality, thereby impacting UGLE. Consequently, the advanced industrial structure is a critical factor in determining UGLE and should be considered as a control variable in examining its specific effects.

Tax burden level (TBL): The tax burden level is used as a control variable because it directly affects the costs and profit margins of logistics enterprises, which in turn affects their green transformation and operational efficiency. A high tax burden may increase the operating costs of logistics enterprises and compress their capital investment in green technology investment and environmentally friendly logistics solutions, thus

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affecting the improvement of UGLE. At the same time, changes in the level of tax burden also reflect the government's policy orientation and support for the logistics industry. Tax incentives can motivate enterprises to implement more eco-friendly logistics practices and promote the improvement of UGLE. Therefore, the level of tax burden needs to be used as a control variable to study its specific impact on UGLE. *Table 3* shows the statistics and description of the above variables.

Table 3. *Descriptive statistics for core explanatory and control variables*

Variable	Obs	Mean	Std. dev.	Min	Max
UGLE	300	0.3323	0.2567	0.0750	1.0820
DE	300	0.3639	0.1454	0.1107	0.8709
ER	300	31.7291	36.1490	0.7929	309.8377
RGDP	300	62662.8800	31082.5900	22089.1000	189988.0000
AIS	300	1.4216	0.7567	0.6653	5.2440
TBL	300	0.0827	0.0286	0.0355	0.1882

Data sources

This study conducts empirical analysis using panel data from 30 Chinese provinces (excluding Tibet) spanning from 2013 to 2022. The selection of the study period is primarily guided by considerations of data availability, methodological appropriateness, and research relevance. Firstly, the year 2013 marks the onset of comprehensive digital economy policies in China, closely aligning with substantial advancements in technologies such as big data analytics, artificial intelligence, and mobile internet proliferation, thus making it a pertinent starting point. Secondly, data availability constraints for essential indicators related to UGLE, digital economy, and environmental regulations further necessitate this temporal scope, ensuring consistency and completeness.

Provincial-level data was selected instead of city-level data due to substantial disparities in statistical reporting capabilities among different cities, particularly within central and western regions of China. Utilizing provincial data mitigates issues of data inconsistency and missing values, thereby improving the accuracy and reliability of analytical outcomes.

The primary data utilized in this research were meticulously sourced from authoritative statistical databases and official publications, including the China Statistical Yearbook, China High-Tech Industry Statistical Yearbook, and China Environmental Statistics Yearbook. Supplementary data were collected from respective provincial statistical yearbooks, providing detailed regional insights and enhancing the robustness of the analysis.

The indicator system for assessing UGLE was specifically derived from these comprehensive sources. Input indicators such as capital investment, labor input, infrastructure inputs, and energy inputs were collected from industry-specific data reported in the China Statistical Yearbook and the China High-Tech Industry Statistical Yearbook. Output indicators, including desirable outputs like the value added to the logistics industry and social cargo turnover, as well as undesirable outputs such as carbon emissions from logistics activities, were obtained from the China Statistical Yearbook and China Environmental Statistics Yearbook.

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Moreover, to capture digital economy developments comprehensively, this study constructed an indicator system employing the entropy-weight TOPSIS method, based on indicators such as internet penetration, number of internet-related workers, and digital inclusive finance. Similarly, environmental regulation intensity was measured following the method by McKinnon (2010), utilizing relevant data extracted from the China Statistical Yearbook and China Environmental Statistics Yearbook.

Overall, the dataset encompassing 300 observations (30 provinces × 10 years) provides a robust empirical basis for analyzing the spatial-temporal impacts of digital economy and environmental regulation on urban green logistics efficiency across China's diverse regions.

Results

Measurement results of UGLE

In this study, the Super-SBM model was employed to calculate the efficiency of 30 regions from 2013 to 2022, with the results presented in *Table 4*.

Table 4. *UGLE (urban green logistics efficiency) measured in 30 Chinese provinces, 2013-2022*

Region	Province	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Mean	Sort by mean
Eastern Region	Beijing	0.1058	0.0978	0.0830	0.1147	0.3362	1.0015	1.0820	0.2552	0.3072	0.2268	0.3610	10
	Tianjin	1.0273	1.0161	0.7010	0.7032	1.0093	1.0051	1.0314	0.8055	0.8033	1.0487	0.9151	1
	Hebei	1.0520	1.0045	0.8927	0.7924	0.8845	0.6533	0.5902	0.6500	1.0656	0.8925	0.8478	2
	Liaoning	0.2251	0.2293	0.2273	0.2821	0.3014	0.3063	0.3430	0.2314	0.1687	0.1550	0.2470	17
	Shanghai	0.4769	0.5953	0.5166	0.5488	0.5956	1.0216	0.9310	1.0368	1.0415	0.9471	0.7711	3
	Jiangsu	0.3451	0.3143	0.2448	0.2078	0.2088	0.1997	0.2086	0.2334	0.5592	0.4129	0.2935	14
	Zhejiang	0.2992	0.3020	0.2788	0.2969	0.2733	0.3043	0.3407	0.2937	0.4466	0.4563	0.3292	11
	Fujian	0.3791	0.4074	0.3706	0.4046	0.4163	0.4444	0.4617	0.4424	0.6156	0.6260	0.4568	7
	Shandong	0.2193	0.2696	0.2540	0.2542	0.2900	0.2944	0.2748	0.2361	0.5241	1.0203	0.3637	9
	Guangdong	0.2006	0.2757	0.2657	0.3371	0.3758	0.3788	0.4233	0.3466	1.0136	0.9511	0.4568	6
	Hainan	0.1540	0.2223	0.1939	0.1849	0.1575	0.1795	0.5934	0.6074	0.8867	1.0682	0.4248	8
Central Region	Shanxi	0.1735	0.1644	0.1572	0.1561	0.1905	0.1883	0.1960	0.1967	0.2730	0.2553	0.1951	22
	Inner Mongolia	0.2213	0.2506	0.2609	0.2565	0.3310	0.3666	0.3320	0.2755	0.3616	0.3765	0.3033	13
	Jilin	0.1494	0.1434	0.1089	0.1081	0.0968	0.1017	0.1102	0.1114	0.1267	0.1054	0.1162	29
	Heilongjiang	0.1115	0.1050	0.0940	0.0909	0.0916	0.0800	0.0783	0.0750	0.0854	0.0889	0.0901	30
	Anhui	1.0084	1.0108	0.5772	0.5469	0.4543	0.5549	0.4763	0.4298	0.5394	0.5531	0.6151	4
	Jiangxi	0.2357	0.2272	0.2112	0.2095	0.2224	0.2775	0.2667	0.2384	0.3639	0.3900	0.2643	16
	Henan	0.4233	0.4817	0.4576	0.4411	0.4673	0.6076	0.6489	0.4297	0.7956	1.0388	0.5792	5
	Hubei	0.2083	0.2305	0.2144	0.2319	0.2654	0.2524	0.2735	0.1826	0.3905	0.4025	0.2652	15
	Hunan	0.3036	0.3604	0.3280	0.3984	0.3879	0.3683	0.2314	0.2111	0.3098	0.3142	0.3213	12
	Guangxi	0.2098	0.2074	0.2070	0.2092	0.2038	0.2052	0.1725	0.1768	0.2406	0.2421	0.2074	19
Western Region	Chongqing	0.1899	0.1925	0.1952	0.1970	0.1978	0.2180	0.2173	0.2001	0.2458	0.2201	0.2074	20
	Sichuan	0.0844	0.0992	0.0975	0.1031	0.1234	0.1397	0.1311	0.1278	0.1878	0.1982	0.1292	28
	Guizhou	0.1236	0.1388	0.1319	0.1353	0.1490	0.1350	0.1176	0.1200	0.1532	0.1393	0.1344	26
	Yunnan	0.1141	0.1179	0.1407	0.1458	0.1584	0.1796	0.1415	0.1304	0.2567	0.3294	0.1715	24
	Shaanxi	0.2003	0.2153	0.2003	0.2020	0.1824	0.1601	0.1692	0.1988	0.2515	0.2700	0.2050	21
	Gansu	0.2270	0.1953	0.1668	0.1541	0.1657	0.1723	0.1767	0.1779	0.1925	0.2449	0.1873	23
	Qinghai	0.1394	0.1647	0.1470	0.1424	0.1239	0.1263	0.1028	0.1046	0.1301	0.1470	0.1328	27
	Ningxia	0.3642	0.3022	0.2574	0.2384	0.2078	0.1782	0.1722	0.1987	0.1574	0.1640	0.2241	18
	Xinjiang	0.1243	0.1337	0.1232	0.1285	0.1537	0.2226	0.1916	0.1157	0.1455	0.1967	0.1535	25
National average		0.3032	0.3158	0.2702	0.2741	0.3007	0.3441	0.3495	0.2947	0.4213	0.4494	0.3323	

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Looking at the national trend over time, the national average efficiency increases from 0.3032 in 2013 to 0.3323 in 2022, indicating a fluctuating upward trajectory of the value during the study period. Among the 30 regions, Tianjin has the best performance, with an average value of 0.9151 in ten years, and the value is greater than 1 in as many as six years, which proves that the development of Tianjin is characterized by long-term stability and continuous leadership.

The 30th-ranked region is Heilongjiang, whose urban green logistics value has not exceeded 0.2 in ten years, and the average value is only 0.0901, which is almost a gap with other cities. Proof that China's cities have different levels of UGLE development and serious polarization.

As illustrated in *Figure 2*, there are significant regional differences in efficiency across the east, central, and west. The east has an average value of about 0.5, the central around 0.3, and the west at approximately 0.15. Taking into account the temporal evolution of efficiency values at the provincial, city, and municipal levels, the regional patterns can be summarized as follows: the east consistently has the highest average, followed by the central, while the west ranks the lowest.

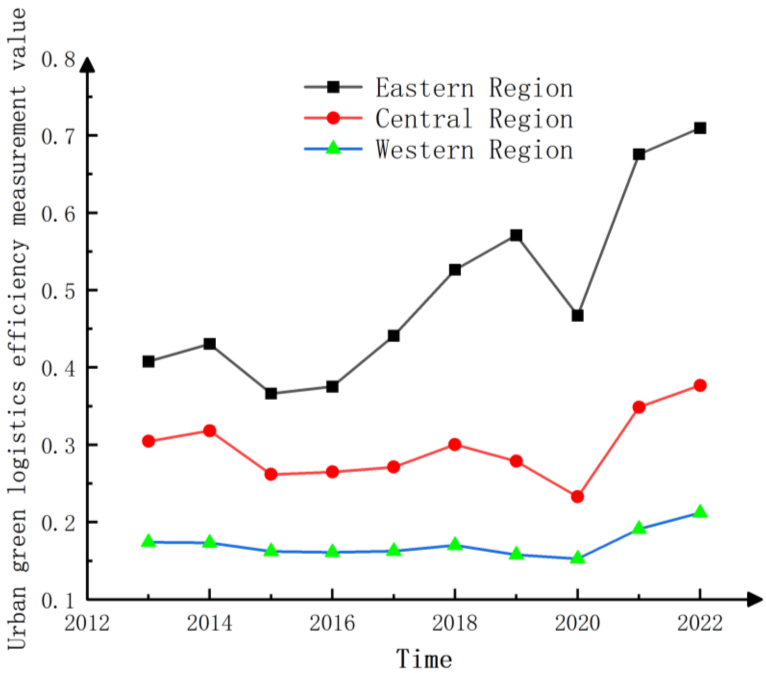

Figure 2. *Distribution of UGLE (urban green logistics efficiency) in eastern, central, and western China from 2013 to 2022*

The east shows a fluctuating upward trend of "falling-rising-falling-rising" during the study period; the central shows a slow decline and then a rising trend; and the west is relatively stable, showing a slowly rising trend in general, with smaller progress. It can be concluded that the level of economic development is closely related to UGLE, the greater the economic development level, the more complete the supporting infrastructure, and the more cutting-edge green logistics technology and policies in place, on the contrary, all the shortcomings of economically backward areas will become the "short board factors" affecting the development of urban green logistics.

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UGLE GML index decomposition

The study adopts the GML index to comprehensively assess the UGLE, and at the same time considers the changes in desired output and non-desired output, measures the distance between the desired output of decision-making units and the efficiency maximization frontier, and improves the problem of unsolvability and non-transferability of linear programming that cannot be avoided by the traditional ML (Malmquist Luenberger) index. Among them, EC (Efficiency Change) stands for technical efficiency change, reflecting the change in production efficiency of decision-making units (e.g. enterprises, regions, etc.) under the current technology level. TC (Technological Change) stands for technical progress change, reflecting the movement of the technological frontier surface, i.e. the contribution of technological progress to production efficiency. Meanwhile, the GML index can analyze the technical progress, technical efficiency change, and technical bias through decomposition, revealing the specific contribution of technical progress and efficiency change to UGLE, and helping to identify potential ways to improve UGLE. The GML index and decomposition of the three regions are presented in *Table 5*.

Table 5. *GML (Global Malmquist Luenberger) index and its EC (efficiency change) and TC (technological change) decompositions in eastern, central, and western China from 2013 to 2022*

Region	Eastern region			Central region			Western region		
Year \ Type	GML	EC	TC	GML	EC	TC	GML	EC	TC
13-14	1.0648	0.9525	1.1270	1.0043	0.9064	1.2011	1.0005	1.0009	1.0069
14-15	1.0369	1.3998	0.8205	1.0766	1.2188	0.9026	0.9795	1.3414	1.0373
15-16	1.0255	0.8215	1.3377	0.9894	0.8055	1.2797	1.0187	0.7720	1.4744
16-17	1.0176	1.4065	0.7804	0.9994	1.4791	0.7954	1.1868	2.3769	0.6119
17-18	1.1867	1.0030	1.4530	1.3702	1.2450	1.5024	1.0605	0.7447	1.7473
18-19	1.0102	0.9598	1.2978	1.1678	1.1406	1.2863	1.1561	1.1666	1.3595
19-20	1.2420	1.3214	1.1244	1.5643	1.3732	1.4418	1.4090	0.9328	1.4984
20-21	1.1442	1.0132	1.3559	1.0124	0.8200	1.3781	0.9426	0.9606	0.9843
21-22	1.0799	0.9453	1.2438	1.1699	1.2482	1.0927	0.9792	0.7864	1.5898
Mean	1.0897	1.0915	1.1712	1.1505	1.1374	1.2089	1.0814	1.1202	1.2566

The average values of the GML, TC, and EC indices of UGLE in China’s three major regions consistently exceed 1 from 2013 to 2022, signaling a positive overall trend in UGLE. The mean values of these indices in each region are generally above 1, indicating that growth is achieved through the combined effects of green technology advancement and technological transformation efficiency. The central has the highest mean value for the GML index, reaching 1.1505, while the west has the lowest, at only 1.0814. The GML index values in the east and west range from 0.94 to 1.4, with the difference between the beginning and end years of the study period being less than 0.1. This suggests that the growth rate of UGLE in cities within these regions is relatively slow.

The decomposition of the GML index reveals a partial convergence effect among the east, central, and west. The central ranks the highest in the EC index, while the east

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exhibits the lowest value. This is likely because the central has a stronger policy inclination, gradually improved its industrial base, and has a sufficient talent pool one after another. The East has encountered development bottlenecks in recent years, and forward-looking technology research has favored the field of high-precision science and technology, so the growth of logistics technology efficiency is relatively weak. According to the TC index, the West ranks highest, while the East ranks lowest, suggesting that green logistics technology has advanced more rapidly in Western cities. This is likely linked to policies such as regional development initiatives and talent retention strategies. In contrast, the high energy consumption and environmental pollution in the East's logistics industry contribute to its lower technological progress. Despite the East's advanced economic development, its energy-saving and emission-reduction efficiency remains relatively low, with approximately 50% of potential energy-saving and emission-reduction capacity untapped. This suggests that the East's logistics industry has considerable potential for improvement in terms of energy consumption and environmental impact. Moreover, the logistics industry's informatization level does not significantly affect its green logistics performance. This could indicate that the East has insufficient investment in logistics informatization and its application, which limits the advancement of green logistics technology. Meanwhile, green technology innovation in the east is mainly concentrated on the southeast coast, but the level of innovation is not high, and the benefits generated have not yet offset the input of factor costs, which may also lead to a lower TC index.

Regional spatial and temporal distribution and evolution of UGLE analysis

In this paper, 3 years as a development stage can be more clearly seen in the spatial and temporal evolution of UGLE features, *Figures 3* and *4* present the spatial and temporal distribution of UGLE.

In 2013, China's Beijing-Tianjin-Tangshan, Yangtze River Delta, and Pearl River Delta regions had higher UGLE. It has gradually shown a regional cluster distribution. In 2016, two major clusters were formed: Beijing-Tianjin-Hebei and six southern provinces. By 2019 the development trend is more decentralized, the level of development in Hebei Province has dropped to the second echelon, and the southern provinces and cities have concentrated and outstanding development to present a chain development trend. In 2022, Shandong, Guangdong, Fujian, and Hainan will enter the first echelon of development, and other provinces and cities across the country will have different degrees of progress. Roughly, the Hu Huanyong line is the dividing line, and the geographical mountain range on the right side of the line, where the level of development is ahead of the second and third echelons, is the axis running through the north and south. Provinces and cities on the axis have higher levels of development. Overall, the decade shows a spatial development pattern that decreases from the southeast coast to the northwest interior, with the southern region being better than the northern region. This trend is mainly due to the economic development of the eastern region, which has a clear advantage in logistics infrastructure and green emission reduction technology innovation. These factors have attracted more investment and accelerated the development of green logistics. In addition, the industrial structure and layout are more rational, and the agglomeration effect is more obvious, which helps reduce carbon emissions and technology costs. The integration and development of industrial agglomeration and green supply chains have also begun to bear fruit, which contributes to the improvement of urban UGLE. In contrast, the progress of UGLE in central and western cities is slower. This is mainly due to the poor regional

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economic and investment environment, insufficient urban infrastructure, low level of technological progress, and irrational industrial structure. This in turn leads to the failure to form an effective agglomeration effect to reduce logistics costs, which is not conducive to the development of green logistics technology and ultimately leads to the low UGLE.

Figure 3. *Distribution of average UGLE (urban green logistics efficiency) across 30 provinces in China over 10 years from 2013-2022*

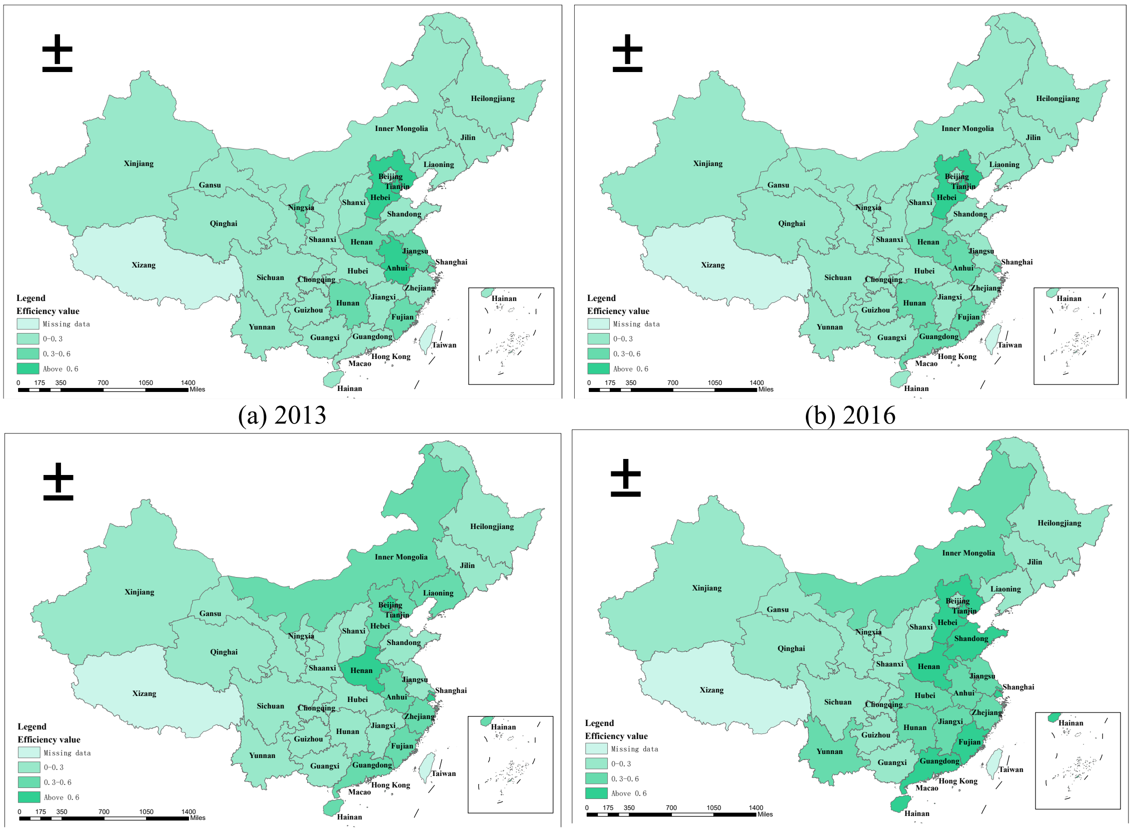

Figure 4. *Distribution of UGLE (urban green logistics efficiency) across 30 provinces in China, in 2013, 2016, 2019, and 2022*

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As shown in *Figure 5*, the level of development is uneven among provinces and cities within the east and central, and more evenly distributed in the west. In the east, Tianjin, Hebei, and Shanghai are the best performers, Tianjin and Hebei are located in the Beijing-Tianjin-Tangshan industrial zone with strong infrastructure strength, Shanghai is located at the periphery of the Yangtze River Delta, there are good industrial and technological advantages, so the two places are in a better position to develop; in the central, Anhui and Henan respond to the strategy of the rise of the Central Plains to take the lead in the industrial structural adjustment for green logistics to provide a good economic environment and investment environment, so the two areas UGLE is significantly ahead of the west, the development of a more average, concentrated development performance in Chengdu-Chongqing and Shaanxi-Gansu-Ningxia region, but limited by the geographic situation and industrial support is not sound, the average level of development of the level of 0.2 or less, the level is low.

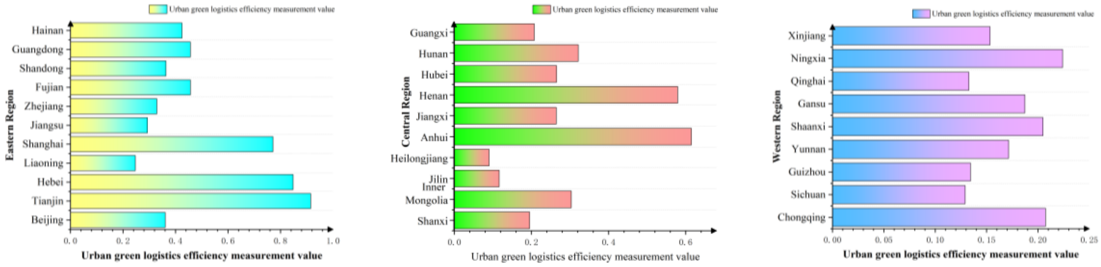

Figure 5. *Histogram of the mean value of UGLE (urban green logistics efficiency) in the eastern, central, and western regions*

Spatial measurement regression results

Spatial correlation test

Using Stata to calculate the Moran's I value of UGLE for each city in China in 2013-2022, all of them have significant positive spatial autocorrelation test results, showing obvious spatial autocorrelation characteristics, as shown in *Table 6*.

Table 6. *Spatial autocorrelation test results*

Years	Moran'I	P-value	Years	Moran'I	P-value
2013	0.1190	0.1810	2018	0.4070	0.0000
2014	0.1060	0.2270	2019	0.4740	0.0000
2015	0.1180	0.1860	2020	0.1890	0.0520
2016	0.1270	0.1730	2021	0.4110	0.0000
2017	0.3190	0.0020	2022	0.3700	0.0010

Using the neighbor weight matrix, this study calculated the Moran's I of 30 provinces (cities and districts) in China from 2013 to 2022 and conducted a significance test. The Moran indexes of 30 provinces (cities and districts) in China are all positive from 2013 to 2022. The Moran indexes of 2013-2016 are insignificant, while the Moran indexes of 2017-2022 show different degrees of significance, which indicates that there

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is a significant positive spatial correlation of the UGLE in different regions of China (Zhao et al., 2014), and the spatial econometric model can be utilized to analyze the effects of digital economy and environmental regulation.

After understanding the relevance of UGLE at the provincial level in China, this paper further applies the Moran scatterplot study to intercept the scatterplot of the Moran index for four years in 2013, 2016, 2019, and 2022 (*Fig. 6*). From a macro point of view, the provinces (cities and districts) across the country have been characterized by more areas of “low-low” and “low-high” types than “high-low” and “low-high” types in the past ten years. Provinces (cities and districts) with a lower level of development are more likely to be spatially aggregated. From the perspective of difference, if the number of “low-low” and “high-high” type districts and counties is large, it means that the spatial difference is small at this time. By the theory of technology diffusion, the study focuses on the high-high type and low-low type regions of the Moran scatter plot. From *Figure 6*, it can be seen that there is indeed a significant agglomeration and positive spatial correlation in the spatial geographic distribution of UGLE in Chinese cities.

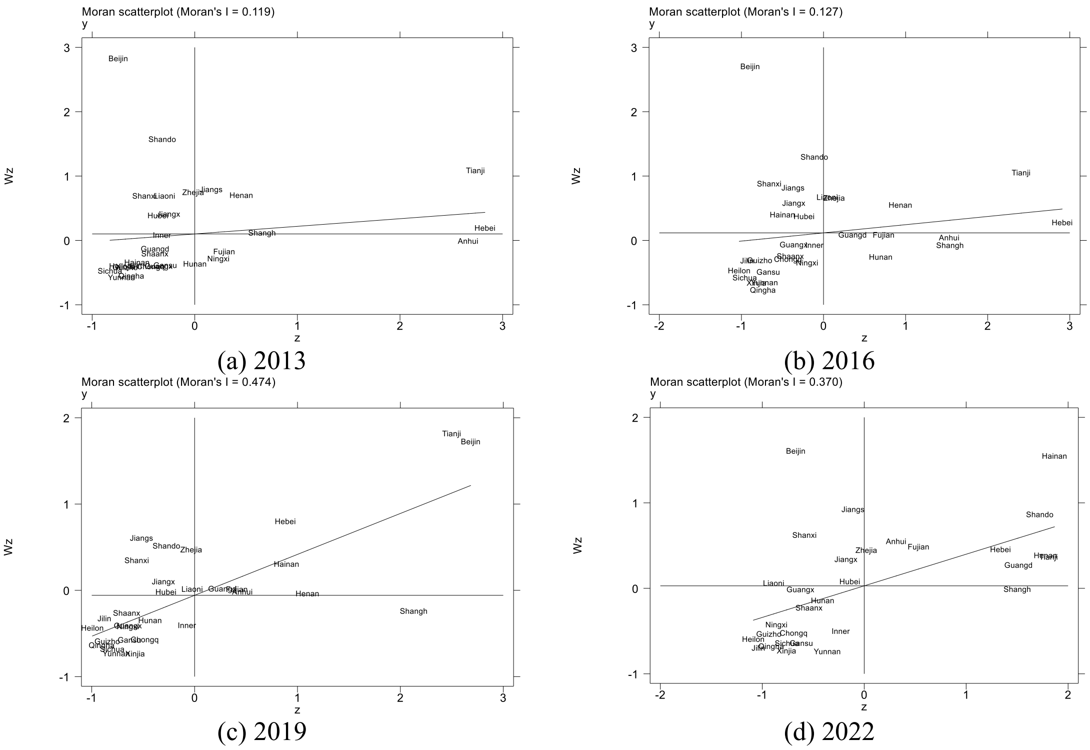

Figure 6. *13, 16, 19, 22 Localized Moran’s Index at various locations*

The eastern part of China is mainly concentrated in the “High-High” quadrant, while the central provinces (cities and districts) bordering the western part are mainly concentrated in the “Low-Low” quadrant. It can be seen that most of the cities with high UGLE in the “low-low” quadrant (LL) are located in the western inland economic activity cluster and the core of the central and western urban network system, not only their own infrastructure and logistics technology is low, and the radiation driving capacity of the surrounding areas is also limited. Gradually formed to the Taihang Mountains - Central Plains - the two regions as the main axis of the development trend:

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the axis of the region and through the region of the city's UGLE development is better, and the distribution of the phenomenon of obvious agglomeration. After preliminary analysis of the spatial data, the study reveals that as a whole shows an obvious upward trend, and shows significant positive spatial correlation and agglomeration characteristics. However, the development of UGLE is largely affected by the stage of economic development and agglomeration effect.

Selection of spatial models

This study uses the LM, Wald, LR, and Hausman tests to determine the appropriate model specification. The LM statistic in *Table 7* passes the significance test, indicating spatial autocorrelation in the model's residuals, suggesting spatial autocorrelation in the model's residuals. Consequently, the model is further evaluated using the Wald and LR tests. The Wald and LR statistics for both the spatial lag and spatial error models reject the null hypothesis, suggesting that the Spatial Durbin Model (SDM) is more appropriate. This suggests that the selected model cannot be simplified directly into either the spatial lag model or the spatial error model. Moreover, the negative Hausman test value presents a more complex situation. Through simulation analysis, it was found that this was mainly because the asymptotic assumption of the basic assumptions of the RE (Random Effect) model could not be satisfied, and the selection of fixed effects was preferable. Therefore, this study finally chose the SDM with time and spatial fixed effects to explore the spatial spillover effects.

Table 7. *Model test results on spatial measurement model selection*

Testing method	Statistic	Testing method	Statistic
LM (lag) test	19.667***	lr_both_ind	31.42***
Robust LM (lag) test	17.893***	lr_both_time	314.23***
LM (error) Moran	0.777	Wald_spatial_lag	20.73***
LM (error) test	5.320**	LR_spatial_lag	21.31***
Robust LM (error) test	3.545***	Wald_spatial_error	22.29***
Hausman test	-152.07	LR_spatial_error	21.48***

*** Denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.1$

Collinearity analysis

Before conducting the regression analysis, it is important to check whether the explanatory variables are highly correlated with each other, i.e., multicollinearity. Multicollinearity occurs when the explanatory variables in a linear regression model are highly or perfectly correlated, potentially causing inaccuracies in the model's estimations. To address this issue, this paper employs the Variance Inflation Factor (VIF) to evaluate multicollinearity among the variables, with higher VIF values indicating greater covariance.

Usually, a VIF value of more than 5 implies the existence of severe multicollinearity, at which point it is not appropriate to proceed with the regression analysis. In *Table 8*, the highest VIF value among all explanatory variables is 3.58, which is below 5. This indicates that the model has no significant multicollinearity, ensuring the reliability of the regression results.

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Table 8. *Multicollinearity test results*

Variable	DE	ER	RGDP	AIS	TBL
VIF	3.58	1.38	3.45	2.28	2.21
1/VIF	0.2793	0.7253	0.2900	0.4378	0.4528

Spatial Durbin model results

In summary, the SDM model with double fixed effects is used for spatial econometric analysis in this paper.

The higher Log-likelihood value shown in *Table 9* indicates that the model has high explanatory power. The spatial regression coefficient is 0.1890, which indicates that the spatial spillover effect exerts a significant positive influence on UGLE. The improvement of local UGLE will positively affect the UGLE of neighboring cities, promoting its growth in those areas. In addition, the model findings indicate that in Main, the coefficients of both digital economy and environmental regulation are more significant, and both of them have a negative impact on UGLE. Furthermore, the Wx term more effectively reflects the spatial transmission effect than the coefficient of Main. From the W ER, it is evident that environmental regulation has a positive spatial spillover effect, with neighboring areas exerting a positive influence on local UGLE. This reinforces the idea that neglecting spatial effects may result in biased empirical results.

Table 9. *Spatial measurement regression results*

Variable	Two-way fixed effects
DE	-1.1040**
ER	-0.0007**
RGDP	4.22e-06***
AIS	0.4621***
TBL	-0.8809
W DE	1.2501
W ER	0.0014**
W RGDP	-5.86e-06**
W AIS	0.2160*
W TBL	5.8171***
R-square	0.0919
rho	0.1890**
Log-likelihood	242.8718

*** Denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.1$

Decomposition effects of spillovers

LeSage and Pace (2009) in their study proposed a spatial econometric model with special emphasis on the concepts of direct and indirect impacts. Direct impacts represent the effect of a change in a region’s independent variable affecting its dependent variable, while indirect impacts represent the effect of such a change on the dependent variable in neighboring regions. Such indirect effects reflect spatial

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spillovers, i.e. how changes in one region affect other regions through spatial correlations. To measure this impact, they suggest using averages to measure direct, indirect, and aggregate impacts. Subsequently, Elhorst and Fréret (2009) further developed this theory by providing corresponding statistical tests to validate these effects. When analyzing spatial spillovers, the direct and indirect effects are decomposed through a matrix of partial derivatives. This allows one to observe and analyze the effects of different variables on complex phenomena such as geographic coverage in more detail, and to understand more accurately how key economic indicators such as the digital economy and environmental regulation interact and influence each other spatially, thus providing a more precise basis for policymaking and economic strategy, as shown in *Table 10*.

Table 10. *Decomposition results for spillover effects*

Region	Variable	Direct effect	Indirect effect	Total effect
Nationwide	DE	-1.0377**	1.2432	0.2055
	ER	-0.0007**	0.0014*	0.0007
Eastern	DE	-1.7331*	1.3878	-0.3453
	ER	-0.0022*	0.0009	-0.0013
Central	DE	-3.5695***	-0.5173	-4.0871***
	ER	-0.0011*	-0.0003	-0.0014*
Western	DE	-0.8454***	-0.2842	-1.1296
	ER	0.00004	-0.0003	-0.0002

*** Denotes $p < 0.01$, ** denotes $p < 0.05$, and * denotes $p < 0.1$

Statistical analysis reveals that the digital economy and environmental regulation may inhibit UGLE at the national level. Specifically, the direct effect of the digital economy on UGLE is significant, with a coefficient of -1.0377, while the indirect effect is insignificant, with a coefficient of 1.2432. This suggests that the development of the digital economy has yet to align with the current green logistics technology environment, rendering the overall effect insignificant, likely due to the offset of the direct effect by the insignificant indirect effect. For environmental regulation, the direct effect has a coefficient of -0.0007, while the indirect effect has a coefficient of 0.0014. From a national perspective, environmental regulation appears to hinder UGLE within its region but promotes development in other regions through spillover effects. However, excessive environmental regulation negatively impacts UGLE, acting as a deterrent. The generally low significance of the total effect may stem from the offsetting of positive and negative effects influenced by spatial heterogeneity.

In the eastern region, the digital economy demonstrates a negative direct effect and a generally significant positive indirect effect. While the digital economy may initially cause a decline in UGLE due to challenges such as technological transformation, resource reallocation friction, and disruptions to traditional logistics models, these short-term obstacles impede UGLE. However, in the long term, the digital economy fosters technological innovation, upgrades industrial structures, and enhances green distribution efficiency. These improvements, achieved through indirect pathways, provide robust technical support and efficiency gains, creating spillover effects that positively influence surrounding cities. This interplay between short-term negative

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impacts and long-term positive outcomes makes the relationship between the digital economy and environmental regulation in the East complex and dynamic. Similarly, environmental regulation is negatively correlated with direct effects and positively correlated with indirect effects. In the short term, environmental regulation may increase production costs and transformation pressures on enterprises, compelling inefficient businesses to relocate or restructure, which can negatively impact UGLE. In the long run, however, environmental regulation drives the green transformation and upgrading of the logistics industry by promoting technological innovation, advancing industrial structures, and optimizing the greening of the entire logistics supply chain. This enhances carbon emission efficiency, generating a positive indirect effect on UGLE. Furthermore, strong adaptive environmental regulation within a region spills over to surrounding areas, amplifying its positive impact.

The results in the central and west are more similar, the difference is that only the direct effect of environmental regulation in the west is positive, indicating that environmental regulation development in the underdeveloped central and west will drive the growth of urban green logistics in these areas, and therefore has a positive driving effect, and the appropriate environmental regulation in the region will benignly lead to the advancement of UGLE in the neighboring regions. The various effects of the remaining variables are all negative. This is likely due to the imperfect digital economy infrastructure and relatively low economic development in the region, resulting in a low level of digital economy development, which fails to become one of the mechanisms of the local digital economy to foster the growth of green logistics. In addition, the relatively limited logistics demand in the central and west restricts the market size and development potential of green logistics. The relatively insufficient digital economy infrastructure, talent pool, and technological innovation in the West further hinder the R&D (Research and development) and application capabilities of logistics companies in digital technology. Together, these factors make the direct promotion of the digital economy in the central and west on UGLE is not obvious, and may even be negatively correlated because of the increased pressure and cost of enterprises to adapt to new technologies. At the same time, the positive effects of indirect effects such as technological innovation, industrial structure upgrading, and green distribution efficiency enhancement are not fully utilized in the central and west, which may result in the indirect effects also showing a negative correlation. Under the total effect, both the digital economy and environmental regulation are more obvious in the Central, while they are not obvious in the West, which may be because under the strategy of the rise of the Central Plains, the development of the Central has a better inherent environment, and they can adapt to the development trend well, form a strong development reasonably, and promote the development of UGLE together. On the other hand, the west is geographically isolated, the transportation and other infrastructures are less sound than those in the east coastal region, and the industrial structure is not reasonable, so the economic environment does not support the benign development of both.

Discussion

This study comprehensively examines the impact of the digital economy and environmental regulations on UGLE in China from 2013 to 2022. At the level of efficiency measurement, this paper concludes that “the UGLE of Chinese cities is generally on the rise, but there are obvious regional differences, and the UGLE

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decreases from the southeast coast to the northwest inland". This point of view is consistent with the research results of Chen et al. (2024) and Bi et al. (2019), indicating that this conclusion has a certain degree of reliability and scientific validity. However, the two previous researchers utilized a single indicator system and hierarchical analysis to conduct a more superficial study. This paper utilizes the Super-SBM model for a more comprehensive measurement. From the perspective of connotation interpretation and indicator selection, this paper is more scientific in the selection of explanatory variables and control variables. The digital economy is an emerging mode of economic development, while environmental regulation takes into account the influence of external factors on UGLE. This paper also creatively utilizes the decomposition of the GML index to show the dynamics of the contribution of technological progress and efficiency changes to UGLE. It is concluded that the central region has the highest average GML index and the most significant efficiency improvement, while the east and west regions lag behind the central region in terms of technological progress and efficiency shift. Given that there is no academic research on the GML decomposition of UGLE, this paper refers to Deng and Zhang (2019) GML decomposition of industrial water efficiency and analyzes the UGLE in a related way as well.

This paper also examines the impact of environmental regulation and the digital economy on UGLE using the SDM model. The results show positive spatial correlations, with the national as well as the eastern and western parts of the country being non-significant while the central part is significant under the total effect. The conclusion is consistent with the study of Fan et al. (2022). However, this paper takes the perspective of the East, Central, and West, unlike its choice of using the overall perspective.

In addition, the paper concludes that in the East and the Center, environmental regulation hinders efficiency, while in the West, it positively contributes to efficiency. The UGLE is negatively affected by the digital economy in all regions. Indirect effects show positive spillover effects in the national and eastern regions and negative spillover effects in the central and western regions. Among them, the conclusion of this paper on the impact of the digital economy on green logistics efficiency is different from Guo et al. (2024). The reason is that this paper builds the digital economy indicator system are positive indicators, the selection of indicators is biased towards the Internet-driven economic development to interpret the development of the digital economy. Guo et al. (2024) favor digital industry and industrial digitization to interpret the digital economy. Therefore, the regression results are not the same.

Finally, this paper concludes that there is a significant inverted U-shaped relationship between environmental regulation, digital economy, and urban green economy efficiency in China from a macro perspective. It is consistent with the conclusions of Zhou et al. (2024) and Cai et al. (2025) and is therefore generalizable and rigorous.

In conclusion, the research perspective of this paper is detailed from global research to regional research, which is consistent with the conclusions of previous studies on the whole, there are also innovative points and different insights, but they are all based on the differences in research perspectives and methods used. Although the study maintains a certain degree of completeness and scientificity, there is still much room for optimization. For example, if China's trend can be assessed based on international trends, the scientific quality of the study can be significantly improved. Adding the analysis of mediating effects can support the scientificity of the conclusions together with the spillover effects, making this study more comprehensive and scientific.

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Conclusions and recommendations

Conclusion

This study uses the Super-SBM model to assess the UGLE of Chinese cities from 2013 to 2022, examining its spatial and temporal trends. The findings indicate an overall increase in UGLE across Chinese cities, though significant regional differences exist. The east demonstrates the highest efficiency, whereas the west shows the lowest, with UGLE decreasing from the southeast coast to the northwest inland. The decomposition of the GML index reveals dynamic changes in the contributions of technological progress and efficiency to UGLE. The central demonstrates the highest mean GML index and the most notable efficiency improvements, while technological progress and efficiency transformation in the east lag behind those of the central. The research also examines the impact of environmental regulation and the digital economy on UGLE using the SDM model. Spatial autocorrelation analysis reveals positive spatial correlation in China, and the spatial econometric model results indicate that, under the total effect, the entire country, as well as the east and west, are not significant, whereas the central is significant. Both environmental regulation and the digital economy exhibit direct and indirect effects on UGLE. The direct effect of environmental regulation varies by region: it hinders efficiency improvement in the east and central, while positively promoting it in the west. UGLE is negatively impacted by the digital economy in all regions, with the effect being more significant in the east, central, and west. The indirect effect reveals a positive spillover effect for the entire country and the east, whereas the central and west exhibit a negative spillover effect. From a macro perspective, there is a significant inverted U-shaped relationship between environmental regulation, digital economy, and urban green economy efficiency in China, indicating that increasing the intensity of environmental regulation within a certain range can improve, but after exceeding a certain inflection point value, overly stringent environmental regulation may have a negative impact on efficiency.

Recommendations

Developing regionally differentiated green logistics policies

When formulating regionally differentiated green logistics policies, alongside considering regional economic development and the current state of logistics development, other factors should also be taken into account. It is also necessary to support the greening and upgrading of logistics hubs and stations, warehousing facilities, and means of transport, in conjunction with the catalog for the promotion of key technologies and equipment for green logistics referred to in the Action Plan for Effectively Reducing the Costs of Logistics for the Whole of Society. For example, the East can leverage its mature economic foundation and technological innovation capacity to advance the use of new energy logistics vehicles in urban distribution, postal express, and other areas, and study the development path of zero-carbon emission technology for medium and heavy-duty trucks. The central and west should focus on strengthening infrastructure construction, such as promoting the construction of green railroads, green highways, green ports, green airports, etc., as well as planning to build a charging and switching network system.

Strengthening synergies between environmental regulation and the digital economy

In implementing environmental regulatory policies, the Government should combine them with the digital economy and utilize digital technology to improve the

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efficiency and effectiveness of environmental regulation. For example, through the establishment of an environmental information platform, real-time monitoring and sharing of environmental data can be realized, and green technology innovation and application can be promoted. At the same time, enterprises are encouraged to use digital technology to optimize the logistics process. In summary, we can utilize new technologies such as big data, remote sensing, and cloud computing platforms to make a good foundation for the digital industry and establish and improve the environmental monitoring service system to carry out scientific and accurate monitoring of environmental quality.

Spatial correlation study for enhancing the efficiency of green logistics

Relevant departments should strengthen research on the spatial correlation of UGLE and explore the interaction and influence mechanism between different regions. Through regional cooperation and policy coordination, they should promote the balanced regional development of UGLE, realize resource sharing and complementary advantages among regions, and jointly promote the sustainable development of green logistics. The study shows that the region of high efficiency of green logistics development moves gradually from north to south, showing the trend of balanced development in each region. Therefore, relevant suggestions should be put forward from the perspective of regional cooperation in light of the actual development status of each region, to promote the harmonious development of regional green logistics. Meanwhile, the spatial evolution of UGLE is related to a variety of factors, such as regional macroeconomic development, logistics industry environment, policy environment, environmental regulation, etc., which are important aspects to be considered in the study of spatial correlation.

Conduct research on the spatial correlation of green logistics efficiency through international cooperation

Relevant departments should strengthen the research on the spatial correlation of UGLE, actively carry out international cooperation and exchanges, share the experience and data on the development of green logistics with other countries, and explore the interaction and influence mechanism between different regions. Through regional cooperation and policy coordination, promote the balanced regional development of UGLE, realize resource sharing and complementary advantages among regions, and jointly promote the sustainable development of green logistics.

Establish a scientific research system and an international talent exchange mechanism

To improve the scientificity of the research, it is necessary to establish a scientific research system covering data collection, model construction, and result analysis, and strengthen the cultivation and introduction of interdisciplinary talents in green logistics, digital economy, and environmental regulation. Meanwhile, international talent exchange activities are actively carried out to enable researchers to understand international cutting-edge research, bring back advanced research methods and concepts, and improve the scientific level of green logistics research in China.

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