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China's New-Style Urbanization and Its Impact on the Green Efficiency of Urban Land Use

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Abstract: Improving the green efficiency of urban land use (GEULU) is essential for optimizing resource utilization while minimizing waste and pollution, making it a critical factor influencing the sustainability of urban development. However, the spatiotemporal heterogeneity of the impact of China's New-Style Urbanization (NU) policy on the GEULU, particularly at the urban agglomeration scale, remains understudied. This study employed a super SBM-DDF-GML model and spatial data analysis to examine the characteristics and spatiotemporal dynamics of the GEULU and its interactions with varying implementations of NU at the regional, urban agglomeration, and city levels. The results show that China's GEULU followed a "U-shaped" tendency from 2006 to 2020. Cities in western China exhibit higher levels of green efficiency but slower growth, compared with lower absolute levels and faster development rates amongst the eastern cities. The GEULU displays a significant positive spatial autocorrelation, with "high-high clusters" shifting from west to east and "low-low clusters" moving in the opposite direction. The impact of NU on the GEULU is divergent: positive in eastern and central regions but negative in the western areas. Economic urbanization, urban population growth, and the clustering of research and education facilitate green efficiency, while urban sprawl significantly hinders its improvement. Social urbanization and digitalization exert adverse effects on green efficiency across many cities. Ecological and environmental protections promote the GEULU in southwestern cities but obstruct it in northeastern cities. The negative effect of NU on the green efficiency has diminished over time, while its positive effects have grown stronger. These findings provide insightful information for urban planners and politicians in crafting region-contextualized adaptive strategies to enhance sustainable urbanization and efficient land use in China.

Keywords: urban land use; green efficiency; new-style urbanization; super SBM-DDF-GML model; China

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1. Introduction

Urbanization in China has developed rapidly since sweeping economic and social reforms were instigated in the late 1970s. Between 1978 and 2023, the population of permanent urban residents grew significantly, rising from 172 million to 933 million. Concurrently, the urbanization rate experienced a substantial increase, advancing from 17.92% to 66.16%, reflecting an average annual growth rate of 1.07% points. Rapid urban expansion promoted economic growth, improved the flow of goods and services, and brought much convenience to people's lives [1]. Nevertheless, the swift expansion of urban areas and the high concentration of inhabitants have intensified the imbalance between the soaring demand for land and its constrained availability. This has created substantial pressures on the ecological capacity of land resources [2,3]. Certain cities have grown mainly through urban sprawl, leading to environmental problems such as rising pollution and excessive energy usage [4–6]. Consequently, promoting efficient and environmentally friendly urban land utilization has become essential to China's sustainable urban growth [7].

The green efficiency of urban land use (GEULU) denotes the rise in productivity per unit of land area linked to socio-economic activities, all while preserving a balanced ecological environment [8]. It aligns with the social expansion trend of greening transformation and offers three advantages. First, it is multidimensional, considering not only the economic benefits brought by production activities but also potential effects on various aspects, especially society, the economy, and the environment [9]. Second, it is in accordance with the United Nations Sustainable Development Goals (SDGs), which stress the need to preserve resources and safeguard the environment, maintain the ecological balance, and ensure the sustainable development of society while meeting current needs [10]. Third, the GEULU pursues high efficiency, implying a requirement for the rational arrangement and configuration of land use so that it is capable of fulfilling the diverse needs of both natural ecology and socio-economic development, while enhancing the efficiency of resource systems [11].

To address the challenge of balancing population growth with a limited land supply and to foster green and sustainable urban development, the Chinese central government introduced its New-Style Urbanization Plan (hereafter NU, 2014–2020) in March 2014. NU addresses the issues of the intensification, inclusiveness, and sustainability of Chinese urban development [12]. Its adoption coincided with the 2016 UN-HABITAT III Conference, where the New Urban Agenda was introduced, striving to "make cities inclusive, safe, resilient, and sustainable" in line with SDGs [13]. Compared with traditional urbanization, which is characterized by rapid expansion and the centralized development of resources, New-Style Urbanization exhibits new characteristics in its thinking, geographical layout, and development mode [14]. It may have impacted the urban economic structure, industrial development modes, and residents' lifestyles. We cannot help but ask whether a fresh urbanization mode affects the pattern of urban land utilization. Hence, exploring the drivers of the GEULU from the perspective of NU and empirically analyzing how NU affects the GEULU in China have become crucial for addressing land use issues in urbanization and promoting green, high-quality, and sustainable development.

This study contributes to scholarship in four ways. Firstly, we defined the GEULU based on the synergistic relationship of the "economic-fiscal-social-environment", thereby enriching the connotation of the GEULU. Secondly, by employing the super slacks-based measure–directional distance function–global Malmquist–Luenberger (SBM-DDF-GML) model [15], we measured the GEULU level more accurately. Thirdly, by constructing a system of driving factors, measuring the impact of NU on the GEULU, and employing the GTWR model, this paper, for the first time, quantifies the multidimensional effects of the key dimensions of NU (economic, population, land, social, environmental, digitalization, and research and education clustering) on the GEULU. Finally, we investigated the spatiotemporal patterns of the GEULU within urban agglomerations and examined the influence of NU on the GEULU, offering substantial empirical support for this area of research at the urban agglomeration scale.

2. Literature Review

2.1. Definition of GEULU

As global urbanization accelerates, it is essential to manage land resources in a more efficient and logical manner to optimize their functionality and the benefits of the resource system. The urban land use efficiency (ULUE) is regarded as a function that integrates both land utilization (an outcome) and the resources necessary to attain this result, mainly measured from the view of economics [16,17]. However, this understanding is contrary to the concept of SDGs, as it overlooks environmental and societal considerations. It is not conducive to addressing long-term challenges like climatic change, resource exhaustion, and environmental pollution [18–20]. Ou et al. (2019) argue that ULUE-related studies are essential to both consider the economic advantages of urban land utilization and incorporate socio-ecological dimensions [21]. There is a pressing need to include environmental pollution factors as undesired outputs to avoid underestimating the resulting productivity [22]. Introducing the concept of green development, Tan et al. (2021) defined the GEULU as an integrated reflection of diverse urban resource input–output systems, including resources utilized (or squandered) through environmentally friendly (or unsustainable) methods, as well as the intended (or unintended) outcomes of urban land use [23]. Koroso et al. (2020) similarly determined the GEULU from a sustainability perspective [24]. However, prior research has rarely addressed the crucial influence that government fiscal policy plays, which affects economic performance through taxation and expenditure, reflecting the government's capacity to deliver social services and the level of social welfare. Fiscal policy also influences resource utilization and environmental protection behaviors by regulating resource prices [25,26].

2.2. Methodology for Estimating GEULU

To measure the ULUE, some researchers have utilized single indicators such as the proportion of urban land expansion relative to the rate of population growth [17] and the proportion of the GDP to the urban land space [27]. Others have constructed production functions to quantify the ULUE [28,29] or estimate the ULUE by employing a holistic evaluation framework along with techniques like the entropy method and principal component analysis [30,31]. As resource efficiency assessment systems continue to evolve, stochastic frontier analysis (SFA) and data envelopment analysis (DEA) have progressively emerged as widely adopted techniques for evaluating the ULUE [32,33]. For instance, Liu et al. (2020) used SFA to estimate the ULUE in China [9] and Ferreira and Féres (2020) for the Brazilian Amazon [34]. However, SFA requires the setting of a deterministic frontier equation, which may lead to structural bias due to the misspecification of the production function, and it is only applicable when there are multiple inputs but only one output [35,36].

DEA is a nonparametric approach used to assess the relative efficiency of various inputs and outputs, without accounting for the functional relationship between them. It remains unaffected by the dimensions of the input and output indicators, thus mitigating the impact of subjective factors. It can be expanded and simplified according to the research objectives [37]. While DEA overlooks potential measurement errors or statistical noise that could influence the boundary's shape and location and thus cannot be used for research hypothesis testing, it has been recognized as the most appropriate approach for assessing the efficiency of production functions involving multiple inputs and outputs [38,39].

Based on DEA, various advanced models have been proposed and implemented to evaluate the ULUE. Tone (2001) proposed the slack-based measure (SBM) model, which is the most used one [40]. Being non-radial and non-angular, the SBM corrects the measurement error caused by the inability of traditional DEA models to measure how slackness affects efficiency. Song et al. (2022) utilized SBM models containing undesired outputs to estimate the ULUE in China's resource-based cities [41], and Tan et al. (2021) measured the GEULU in the Yangtze River Delta region [23]. Compared with general efficiency, super-efficiency further considers redundant inputs and incomplete outputs, making the evaluation more comprehensive and accurate. By allowing the efficiency values to exceed 1, the super-efficiency model enables the ranking of decision-making units (DMUs) that are deemed efficient in traditional DEA models, thus providing a more refined differentiation among high-performing units [40,42–44]. Within the framework of total factor productivity, Chung et al. (1997) introduced the directional distance function (DDF), expanding upon Shephard's distance function [45], while Färe et al. (1992) proposed the Malmquist–Luenberger (ML) index [46]. These methodologies enhance the accuracy of measuring undesirable outputs within the DEA model, thereby improving the assessment efficiency. The integration of these indices can better capture the essence of sustainable development [15]. Oh (2010) further extended the ML index to the global scale, namely through the global ML (GML) index, to solve limitations such as the infeasibility of linear programming and non-transitivity [47]. So far, researchers have applied a combination of the GML index and SBM-DDF model to evaluate the green total factor productivity field, which can effectively reduce the estimation error resulting from radial and angular issues and achieve the global comparability of production frontiers [48]. Nevertheless, the community has yet to apply similar frontier efficiency measurement models to the estimation of the ULUE or GEULU.

2.3. Driving Forces of GEULU

To identify the factors influencing the GEULU, some scholars have started analyzing the effects of specific aspects, e.g., the urban structure, collaborative innovation, and the digital economy [49,50]. Recent research has examined the factors from the lens of the economy, environment, policy, and social development and used quantitative analysis models to identify significant factors [51]. Analysis from an economic perspective mainly includes the per capita GDP, financial development, industrial upgrading, technological progress, foreign investment introduction, and degree of market openness. Most studies conclude that economic factors can promote the progress of the GEULU [7,52,53]. Environmental factors such as ecosystem services, resource endowment, and natural conditions are found to be significant factors influencing the ULUE [54–56]. Policies play a profound role, resulting in changes in the GEULU. For example, government support has an incentive effect on the GEULU, while environmental regulations have an opposite effect [57]. Land management policies developed by administrative agencies are not conducive to improving the GEULU from a long-term perspective [10]. However, Chen et al. (2024) demonstrated that smart city pilot programs significantly contribute to improving the green economic performance of urban regions [5].

Socio-demographic factors such as urbanization, the population density, the employment structure, and transportation facilities significantly influence the GEULU [58,59]. Uncontrolled urbanization may result in inefficient land use, urban sprawl, and resource depletion, which in turn limits both economic and social progress [60]. With the spread of the "green" philosophy and sustainable development, a New-Style Urbanization (NU) mode emphasizing "people-oriented" approaches has emerged [61]. This is beneficial for improving the intensification, efficiency, and ecological friendliness of land use by promoting green land use due to constraints on land resources [62,63]. This is particularly vital for developing nations like China, where the combination of a high population density and limited land availability makes achieving efficient land use and sustainable resource distribution essential [41]. Cheng et al. (2023) examined China's New-Style Urbanization Plan (2014–2020) as a quasi-experimental framework to assess its effects on the GEULU [11].

They found that the NU policy can promote the GEULU effectively. However, research on policy effects has not addressed the spatiotemporal heterogeneity of policy interventions. Urban agglomerations rely on multiple geographically adjacent and economically linked cities to form a relatively independent regional economic entity. Urbanization serves as the essential foundation and prerequisite for the growth of urban agglomerations, and in turn, the formation of urban agglomerations reinforces urbanization [64,65]. Exploring how policies affect the GEULU at the urban agglomeration level can provide references for urban land resource planning and contribute to regional sustainable development [66]. However, existing works have not yet paid attention to the GEULU at the urban agglomeration scale.

3. Materials and Methods

3.1. Study Area

This paper examines 284 cities at the prefectural or higher level and 18 urban agglomerations in China. However, certain regions, including Hong Kong, Macau, Taiwan, and Xizang and specific cities such as Yanji (Jilin Province), Honghe (Yunnan Province), and Daxinganling (Heilongjiang Province) were excluded due to data unavailability. Figure 1a–c illustrates the urban population, built-up area, and urban population density of the cities, showing significant discrepancies in spatial distributions. Interestingly, some cities, like Baoding (in Hebei Province) and Linyi (in Shandong Province), have a population of 10 million or over (Figure 1a), but their built-up area is small, ranging between 103.9 and 243.33 km^2 (Figure 1b), and their urban population densities exceed 500 persons/km^2 (Figure 1c). Clearly, there is a mismatch between the class of built-up area and such a large urban population, highlighting the need to explore ways to upgrade the GEULU. Geographically, these cities are in three regions: eastern, central, and western (Figure 1d). Specifically, our interest is in the GEULU issues at the urban agglomeration level. Figure 1d displays the distribution of 18 urban agglomerations. Their names, population size, built-up land area, and GDP are presented in Table 1.

Table 1. Description of the 18 urban agglomerations.

Urban Agglomeration	Abbreviation	Area (10,000 km^2)	Population (Million Persons)	GDP (100 Million CNY)
Beijing–Tianjin–Hebei	JJJ	21.80	107	86,000
Yangtze River Delta	YRD	22.50	175	212,000
Guangdong–Hong Kong–Macao Greater Bay Area	GHM	5.50	78	90,000
Chengdu–Chongqing	CC	18.50	103	68,000
Middle Yangtze River	MYR	31.70	130	92,000
Shandong Peninsula	SP	7.40	103	73,000
Central Plains	CP	28.70	160	81,266
Guanzhong Plains	GZP	10.71	38.87	22,000
Guangdong–Fujian–Zhejiang Coastal Area	GFZ	27.00	93.65	69,695
Beibu Gulf	BG	11.66	44	22,000
Harbin–Changchun	HC	26.40	44.09	20,468
Central and Southern Liaoning	CSL	8.15	20	21,000
Central Shanxi	CS	7.41	15.43	8937
Central Guizhou	CG	5.38	11.78	12,600
Central Yunnan	CY	11.14	19.56	12,800
Hohhot–Baotou–Ordos–Yulin	HBEY	17.50	12	13,211
Lanzhou–Xining	LX	9.75	10.61	5198
Ningxia Yellow River	NYR	6.64	6.85	3568

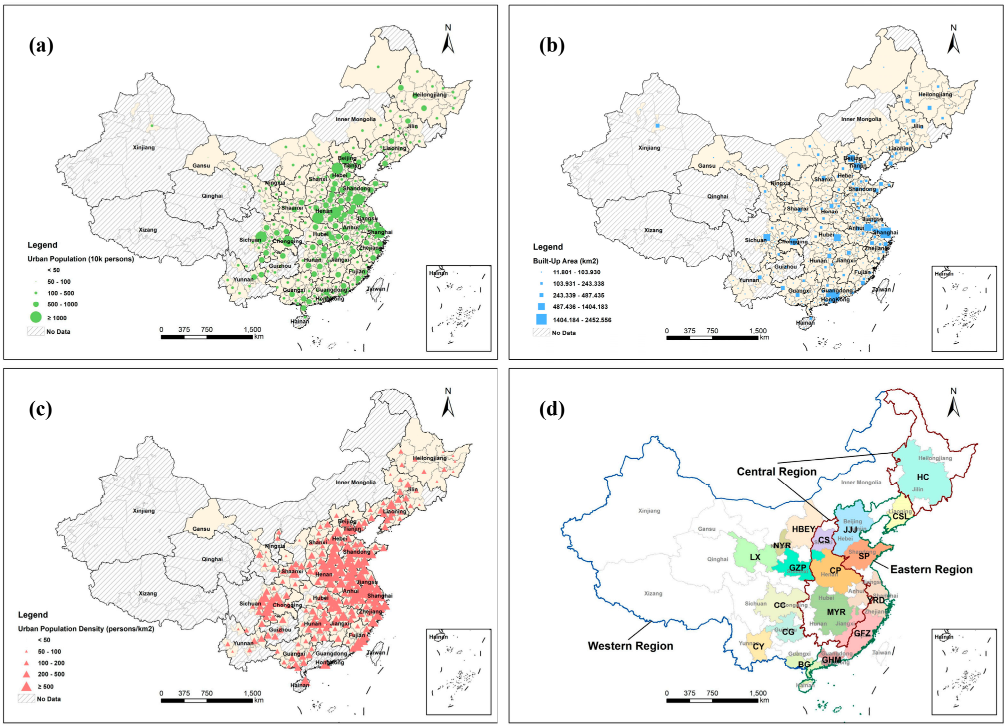

Figure 1. The distribution of the urban population, built-up area, and population–area ratio across 284 cities (**a**–**c**), along with the spatial layout of 18 urban agglomerations and the eastern, central, and western regions (**d**).

3.2. Indicators and Data Sources

3.2.1. Input–Output System for GEULU

We identified the land, capital investment, and labor force as the input indicators, measured by the urban construction land area, total fixed asset investment, and the number of employees in the secondary and tertiary industries [23]. The GEULU differs from the traditional urban land use efficiency by placing more emphasis on sustainability [58]. Therefore, when constructing the input–output index system for the GEULU, we examined output benefits from "economy-revenue-society-environment" perspectives. Specific variables included the value added by secondary and tertiary industries, the public financial revenue, the average salary of on-the-job workers, and the green coverage rate in built-up areas [41]. To capture the negative output of environmental pollution, industrial wastewater, exhaust gas, and smoke and dust emissions were used to measure the potential water, air, and soil pollution [67]. The implementation mechanism to determine the GEULU is depicted in Figure 2.

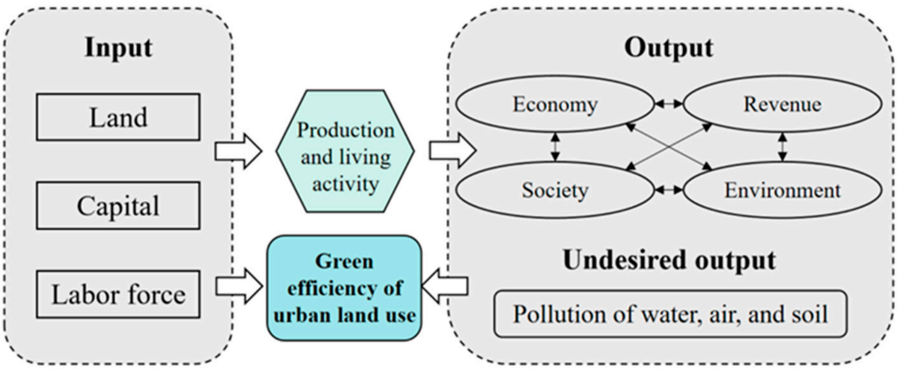

Figure 2. Description of GEULU.

3.2.2. GEULU Under NU

The GEULU was treated as the dependent variable in this study, and seven aspects of NU were used to construct independent variables. First, four variables—economic urbanization (EU), population urbanization (PU), land urbanization (LU), and social urbanization (SU)—were selected based on traditional economic, population, spatial, and social dimensions [68,69]. Referring to the definition, three measurement dimensions of ecological and environmental benefits (EEBs), urban development digitalization (UDD), and research and education clustering (REC) were introduced innovatively. Among them, EEBs refer to practices and activities that minimize harm to the environment and promote sustainability by reducing pollution, conserving resources, and protecting ecosystems. UDD refers to the integration and application of digital technologies in urban governance, infrastructure, and economic activities, aiming to enhance efficiency, connectivity, and digital economic growth. REC represents the aggregation of educational and research institutions, technological investments, and innovation-driven enterprises, facilitating knowledge creation and scientific advancements. These three dimensions reflect the greening degree, intelligence level, and innovation value of urbanization, which are in line with the SDGs of NU. Thus, the GEULU drivers comprised seven dimensions and 32 indicators (Table 2).

Table 2. Factors influencing the GEULU in the context of China's NU.

Dimensions	Indicators	Association
Economic urbanization (EU)	Per capita GDP (CNY)	+
	Percentage of the secondary industry in the GDP (%)	+
	Percentage of the tertiary industry in the GDP (%)	+
	Per capita disposable income of urban residents (CNY)	+
	Per capita retail sales of consumer goods (CNY)	+
Population urbanization (PU)	Urban population proportion (%)	+
	Urban population density (persons/km^2)	+
	Urban registered unemployment rate (%)	–
	Per capita consumption expenditure of urban residents (CNY)	+
Land urbanization (LU)	Proportion of the built-up area to the total administrative area (%)	+
	Park green space area (hectares)	+
	Per capita urban road area (square meters)	+
Social urbanization (SU)	Number of public transport vehicles per ten thousand people	+
	Number of health technical personnel per thousand people (per person)	+
	Number of medical and health institution beds per thousand people (beds/1000 persons)	+
	Per capita public library collection (volumes)	+
	Engel coefficient of urban residents (%)	–
Ecological and environmental benefits (EEBs)	Proportion of environment protection-related words in the government work report (%)	+
	Urban domestic waste harmless treatment rate (%)	+
	Industrial solid waste utilization rate (%)	+
	Urban sewage treatment rate (%)	+
	Green total factor productivity (%)	+
Urban development digitalization (UDD)	Proportion of digital-related words in the government work report (%)	+
	Number of internet broadband access users (10k households)	+
	Proportion of total telecommunications business volume of GDP (%)	+
	Number of mobile phone users (10k households)	+
	Degree of digital transformation of listed companies	+

Table 2. *Cont.*

Dimensions	Indicators	Association
Research and education clustering (REC)	Proportion of education expenditure to fiscal expenditure (%)	+
	Number of faculty members and students in higher education institutions (10k persons)	+
	Proportion of expenditure on science and technology to fiscal expenditure (%)	+
	Number of patent applications	+
	Degree of AI adoption by listed companies	+

Note: "+" indicates a positive association between the indicator and the GEULU, while "−" refers to a negative association.

3.2.3. Data Description

Socio-economic and environmental data were sourced from the China Environmental Statistics Yearbook and China Urban Economic Statistics Yearbook. These data were supplemented by statistical bulletins from each city and its latest available government reports. Data on the green total factor productivity were calculated following Zhang et al. (2021) [70]. The degree of digital transformation of listed companies was measured by applying logarithmic transformation to the frequency of digital transformation-related terms found in government annual reports [71,72]. The degree of AI adoption by listed companies was indicated by the per capita value of enterprises' intelligent robotic hardware and software equipment [73]. Both the degree of digital transformation and AI adoption were aggregated to the city level using the microdata for enterprises from the China Stock Market & Accounting Research (CSMAR, https://data.csmar.com) and Wind databases (https://www.wind.com.cn). Missing values and outliers were supplemented or corrected using interpolation. The spatial data used to produce the base maps were sourced from the Center for Resource and Environmental Science and Data (https://www.resdc.cn).

3.3. Methods

3.3.1. Super SBM-DDF-GML Model Involving Undesired Outputs

This study employed the super SBM-DDF-GML model to estimate China's GEULU using Max DEA 9 software [74,75]. This model incorporated undesired outputs (e.g., pollution) to increase the precision of the results. We constructed the model through three steps.

First, we established a global production possibility set. We set the city K as DMU_K. By adding N factor inputs, $x = (x_1, \cdots, x_n) \in R_N^+$, to DMU_K, we obtained M desired outputs, $y = (y_1, \cdots, y_n) \in R_M^+$, and I undesired outputs, $b = (b_1, \cdots, b_n) \in R_I^+$. The inputs and outputs of DMU_K in period t can be expressed as $\left(x^{kt}, y^{kt}, b^{kt}\right)$. Guided by Färe et al. (2007) [76], the set of production possibilities $P^t(x)$ in period t is denoted in Equation (1) as

$$P^t(x) = \left\{ \begin{array}{c} (y^t, b^t) : \sum_{k=1}^{K} z_k^t y_{km}^t \geqslant y_{km}^t, \forall m; \sum_{k=1}^{K} z_k^t b_{ki}^t = b_{ki}^t, \forall i; \\ \sum_{k=1}^{K} z_k^t x_{kn}^t \leqslant x_{kn}^t, \forall n; \sum_{k=1}^{K} z_k^t = 1, z_k^t \geqslant 0, \forall k \end{array} \right\} \quad (1)$$

where z_k^t denotes the weighting of each cross-section, which indicates constant returns to scale if $z_k^t \geqslant 0$, and the variable returns to scale when $\sum_{k=1}^{K} z_k^t = 1$ is satisfied simultaneously with $z_k^t \geqslant 0$. The GML index requires the replacement of a period-specific $P^t(x)$ with a domain-wide production likelihood set, $P^G(x)$, denoted in Equation (2):

$$P^G(x) = \left\{ \begin{array}{c} (y^t, b^t) : \sum_{t=1}^{T} \sum_{k=1}^{K} z_k^t y_{km}^t \geqslant y_{km}^t, \forall m; \sum_{t=1}^{T} \sum_{k=1}^{K} z_k^t b_{ki}^t = b_{ki}^t, \forall i; \\ \sum_{t=1}^{T} \sum_{k=1}^{K} z_k^t x_{kn}^t \leqslant x_{kn}^t, \forall n; \sum_{t=1}^{T} \sum_{k=1}^{K} z_k^t = 1, z_k^t \geqslant 0, \forall k \end{array} \right\} \quad (2)$$

Second, we developed a super SBM-DDF model that accounted for undesired outputs. Based on the framework introduced by Fukuyama and Weber (2009) [77], the formulation of the super SBM-DDF model is presented in Equation (3):

$$\vec{S}_V^t\left(x^{t,k'}, y^{t,k'}, b^{t,k'}, g^x, g^y, g^b\right) = \max_{s^x,s^y,s^b} \frac{\frac{1}{N}\sum_{n=1}^{N}\frac{S_n^x}{g_n^x} + \frac{1}{M+I}\left(\sum_{m=1}^{M}\frac{S_m^y}{g_m^y} + \sum_{i=1}^{I}\frac{S_i^b}{g_i^b}\right)}{2} \tag{3}$$

The constraints of Equation (3) can be computed using Equation (4).

$$s.t.\begin{cases} \sum_{k=1}^{K} z_k^t x_{kn}^t + s_n^x \leqslant x_{k'n}^t, \forall n; \\ \sum_{k=1}^{K} z_k^t y_{km}^t - s_m^y \geqslant y_{k'm}^t, \forall m; \\ \sum_{k=1}^{K} z_k^t b_{ki}^t + s_i^b \leqslant b_{k'i}^t, \forall i; \\ \sum_{k=1}^{K} z_k^t = 1, z_k^t \geqslant 0, \forall k; \\ s_m^y \geqslant 0, \forall m; s_i^b \geqslant 0, \forall i \end{cases} \tag{4}$$

where $\left(g^x, g^y, g^b\right)$ represents the direction of the vectors of the input reductions, increases in the desired outputs, and decreases in the undesired outputs. S^x denotes the slack in the inputs, indicating excess resource usage that does not contribute to efficiency; S^y represents the slack in the desired outputs, capturing the shortfall in achieving optimal production; and S^b corresponds to the slack in the undesired outputs, reflecting the potential for further reduction in emissions or waste. $\left(x^{t,k'}, y^{t,k'}, b^{t,k'}\right)$ is a slack vector measuring the quantities of redundant inputs, under-delivered desired outputs, and over-delivered undesired outputs, respectively. S^x A value greater than zero signifies that the actual inputs and undesired outputs surpass those at the efficiency boundary, whereas the desired outputs remain below the boundary level. Likewise, the global super SBM-DDF is formulated in Equation (5):

$$\vec{S}_v^G\left(x^{t,k'}, y^{t,k'}, b^{t,k'}, g^x, g^y, g^b\right) = \max_{s^x,s^y,s^b} \frac{\frac{1}{N}\sum_{n=1}^{N}\frac{S_n^x}{g_n^x} + \frac{1}{M+I}\left(\sum_{m=1}^{M}\frac{S_m^y}{g_m^y} + \sum_{i=1}^{I}\frac{S_i^b}{g_i^b}\right)}{2} \tag{5}$$

The constraints of Equation (5) can be estimated using Equation (6).

$$s.t.\begin{cases} \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t x_{kn}^t + s_n^x \leqslant x_{k'n}^t, \forall n; \\ \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t y_{km}^t - s_m^y \geqslant y_{k'm}^t, \forall m; \\ \sum_{t=1}^{T}\sum_{k=1}^{K} z_k^t b_{ki}^t + s_i^b \leqslant b_{k'i}^t, \forall i; \\ \sum_{k=1}^{K} z_k^t = 1, z_k^t \geqslant 0, \forall k; \\ s_m^y \geqslant 0, \forall m; s_i^b \geqslant 0, \forall i \end{cases} \tag{6}$$

Finally, we defined the GML index. The ML index is often non-cyclical and can frequently encounter issues such as unsolvable linear programming. In this study, we adopted Oh's (2010) approach to construct the GML index using the super SBM-DDF model [47].

$$GML_t^{t+1} = \frac{1 + \vec{S}_V^G\left(x^t, y^t, b^t; g^x, g^y, g^b\right)}{1 + \vec{S}_V^G\left(x^{t+1}, y^{t+1}, b^{t+1}; g^x, g^y, g^b\right)} = GEC_t^{t+1} \cdot GTC_t^{t+1} \tag{7}$$

where $\vec{S}_V^G\left(x^t, y^t, b^t; g^x, g^y, g^b\right)$ represents both the current period and global SBM-DDF, formulated using non-radial, non-angular measures. The GML index captures changes between period t and $t+1$. A value greater than 1 signifies an improvement in the GEULU, a value below 1 indicates a decline, and a value of 1 suggests no change.

3.3.2. Entropy Weight Method

The entropy weight was utilized to calculate seven-dimensional indicators which measure NU [78,79]. Firstly, the method standardized the initial value.

$$X_{ij}^{*} = \frac{X_{ij} - min(X_{\cdot j})}{max(X_{\cdot j}) - min(X_{\cdot j})} \tag{8}$$

where X_{ij} represents the degree of city p at time q with indicator j, and $\max(X_{\cdot j})$ and $min(X_{\cdot j})$ separately denote the biggest and smallest values for indicator j. Standardization was applied to smoothen the effects of differing dimensions, ensuring comparability.

The next step was to determine the contribution of each standardized degree.

$$Y_{ij} = \frac{X_{ij}^{*}}{\sum_{i=1}^{m} X_{ij}^{*}} \tag{9}$$

Then, the entropy of each indicator was calculated, and the divergence coefficient was estimated using Equations (10) and (11).

$$e_j = -\frac{1}{\ln(m)} \sum_{i=1}^{m} Y_{ij} \cdot \ln Y_{ij} \tag{10}$$

$$d_j = 1 - e_j \tag{11}$$

where m refers to the sample size. The value ($Y_{ij} = 0$) in indicator j will be eliminated due to $\lim_{z \to 0} z \cdot \ln z = 0$. Consequently, the indicator j plays a more vital role if d_j is bigger.

Finally, the weight of each indicator was calculated, and each dimension of NU was ascertained for each city in various periods.

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{12}$$

$$NU_i = \sum_{j=1}^{n} w_j \cdot x_{ij}^{*} \tag{13}$$

3.3.3. Nonparametric Kernel Density Estimation (KDE)

We depicted the GEULU using KDE curves [80]. The advantage of KDE is that the assumptions of any parametric model do not constrain it. Instead, it captures the distribution patterns and evolutionary characteristics of random variables through continuous 2D density plots. The function formula is

$$f(x) = \frac{1}{Nh} \sum_{i=1}^{n} K\left(\frac{x_i - x}{h}\right) \tag{14}$$

where N is the number of cities, h is the bandwidth, x_i represents the sample observations, and $K(\cdot)$ denotes the stochastic kernel function.

3.3.4. Exploratory Spatial Data Analysis (ESDA)

ESDA was applied to illustrate the correlation and spatial clustering patterns of geographic object attributes [81,82]. To examine the spatial relationships between independent variables potentially affecting the GEULU across 284 cities in China, we utilized ArcGIS 10.8 software. The analysis employed both the global Moran's I [83] and local Moran's I [16], with the global Moran's I computed using Equation (15):

$$Moran'sI_{\text{Global}} = \frac{\sum_{i=1}^{n}\sum_{j\neq i}^{n} w_{ij}(x_i-\overline{x})(x_j-\overline{x})}{\sigma^2\sum_{i=1}^{n}\sum_{j\neq i}^{n} w_{ij}} = \frac{\sum_{i=1}^{n}\sum_{j\neq i}^{n} w_{ij}\left(x_i-\frac{1}{n}\sum_{i=1}^{n}x_i\right)\left(x_j-\frac{1}{n}\sum_{i=1}^{n}x_i\right)}{\frac{1}{n}\sum_{i=1}^{n}\left(x_i-\frac{1}{n}\sum_{i=1}^{n}x_i\right)^2\sum_{i=1}^{n}\sum_{j\neq i}^{n} w_{ij}} \quad (15)$$

In Equation (15), n represents the number of cities. x_i and x_j represent the observed values of the GEULU for spatial units i and j, and $\overline{x}$ represents the mean of the GEULU across cities. The sample variance is denoted by σ^2. The spatial weight matrix, w_{ij}, is assigned a value of 1 if i and j are adjacent; otherwise, it is 0. The decision rule for the global Moran index is that if $I > 0$, it signifies a positive spatial autocorrelation, indicating that similar GEULU values are clustered together. In contrast, if $I < 0$, it reflects a negative spatial autocorrelation, meaning dissimilar values are spatially adjacent. When $I = 0$, it suggests no spatial autocorrelation, implying that GEULU data are randomly distributed across space.

The local spatial autocorrelation primarily captures the spatial correlation and disparities between individual spatial units and their neighboring areas. The local Moran's I index classifies spatial autocorrelation patterns into "high-high (HH) clusters", "low-high (LH) clusters", "low-low clusters (LL) clusters", and "high-low (HL) clusters". The computation formula is provided in Equation (16):

$$Moran'sI_{\text{Local}} = \frac{n(x_i-\overline{x})\sum_{j=i}^{n} w_{ij}(x_j-\overline{x})}{\sum_{i=1}^{n}(x_i-\overline{x})^2} \quad (16)$$

The meanings of the variables in Equation (16) are the same as in Equation (15).

3.3.5. Geographically and Temporally Weighted Regression (GTWR) Model

The GTWR model addresses the limitations of geographically weighted regression (GWR) by incorporating the time factor, overcoming the challenge of limited cross-sectional samples, and capturing the temporal and spatial smoothing of the research subject [8,84,85]. Thus, we employed the GTWR model to explore the spatiotemporal heterogeneity of GEULU drivers from the perspective of NU, with the model formulated as follows:

$$Y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^{p}\beta_k(u_i, v_i, t_i)X_{ik} + \varepsilon_i \quad (17)$$

In Equation (17), Y represents the independent variable GEULU; X is the vector of the dependent variables defining the GEULU, which cover a wide range of factors measuring NU and its seven dimensions: EU, PU, LU, SU, EEBs, UDD and REC. t stands for time; (u_i, v_i, t_i) are the spatiotemporal coordinates of each sample point; p is the total number of explanatory variables; $\beta_0(u_i, v_i, t_i)$ is the intercept term; $\beta_k(u_i, v_i, t_i)$ denotes the estimated coefficients; and ε_i is the random disturbance term.

4. Empirical Results

4.1. Measurement Results of GEULU and Its Characteristics of Spatiotemporal Evolution

The super SBM-DDL-GML model was utilized to evaluate the GEULU from 2006 to 2020 and to characterize spatiotemporal features at the region, urban agglomeration, and city scales.

4.1.1. Measurement Results of GEULU

Figure 3 shows the spatiotemporal evaluation of the GEULU. Regarding the development level and growth rate of the GEULU, the mean efficiency for 284 cities stood at 0.700, ranging from a minimum of 0.605 to a maximum of 0.874. The average growth rate as 0.72%, changing from 0.791 in 2006 to 0.874 in 2020.

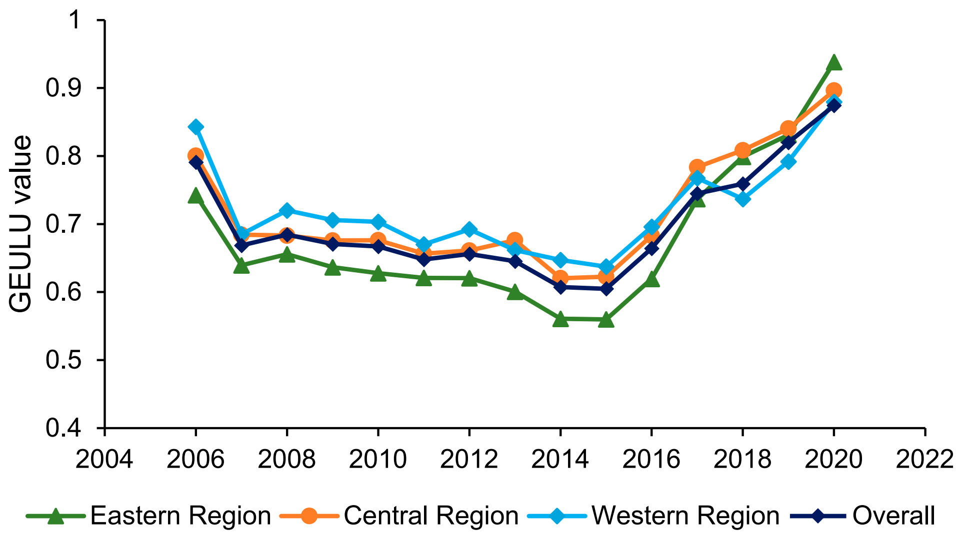

Figure 3. Spatiotemporal evaluation of the GEULU at the overall and regional scales.

On the regional scale, the results exhibited a significant discrepancy across regions. The average GEULU in the eastern region was 0.679, with values ranging from a minimum of 0.560 to a maximum of 0.938. It increased from 0.743 in 2006 to 0.938 in 2020, showing an annual growth rate of 1.69% on average. In the central region of China, the average GEULU was 0.718 (minimum: 0.621; maximum: 0.896), increasing from 0.801 in 2006 to 0.896 in 2020, with an average growth rate of 0.81% per annum. In western China, the average GEULU was 0.723 (minimum: 0.637; maximum: 0.880), rising from 0.843 to 0.880; the average annual growth rate was 0.30%. Comparatively, the western region's GEULU had a greater absolute level but developed more slowly, whereas the eastern region's GEULU had a lower absolute level but grew more rapidly. This discrepancy is due to several aspects. The western region's vast area and abundant natural resources provide a significant advantage in land use, coupled with a relatively lower demand for green efficiency, resulting in slower GEULU development.

The eastern region initially followed a more intensive development model with less emphasis on environmental protection. However, due to rapid urbanization, the eastern region faces a high population density and scarce land resources, causing an urgent need for higher resource allocation efficiency. Additionally, the eastern region's more advanced technology supports the rapid enhancement of the GEULU. Chronologically, the development of the GEULU exhibits a "U-shaped" pattern, marked by an initial decrease followed by a subsequent increase. Before 2014, the GEULU experienced a significant downward trend, which may be attributed to the negative influence of the 2008 global financial crisis, coupled with an insufficient emphasis on green development, leading to a sustained decrease in the GEULU [86,87]. After 2015, the GEULU began to show a fluctuating growth trend, likely linked to the Chinese government's adoption of green development and ecological civilization principles in 2015 [7,49,51], gradually increasing the GEULU. However, from 2017 to 2018, the growth rate of the GEULU slowed down, and there was even a slight decline in the western area, possibly because of the negative impacts of the U.S.–China trade war.

4.1.2. Spatiotemporal Evaluation of GEULU at Urban Agglomeration Scale

As shown in Figure 4, a comparison of the GEULU among the 18 urban agglomerations shows that the BG, GHM, NYR, and CS urban agglomerations had higher levels of GEULU. In contrast, SP had a lower GEULU level. Nearly three-quarters (72.22%) of urban agglomerations had GEULU levels ranging from 0.60 to 0.75, reflecting natural differences among them, such as in renewable resources and land areas. For example, the BG urban agglomeration is in the southern coastal region of China, with abundant port resources and a superior natural endowment due to its geographic location. GHM is economically developed, with a high economic vitality and innovation capacity. The NYR and CS urban agglomerations are situated in the Yellow River Basin, with rich water and agricultural resources. Despite its economic development, SP faces challenges of land scarcity and environmental pressure, which may have contributed to its lower GEULU. In terms of development trends, most urban agglomerations exhibited a "U-shaped" tendency, initially declining before experiencing growth. CSL, YRD, and BG had the highest average growth rates. These have specific natural resources and geographical advantages, coupled with government policies supporting environmental protection, green industry promotion, carbon emission reduction, and energy conservation, leading to favorable development, as reflected by the GEULU. However, the GEULU degrees of HC, CC, and MYR had relatively lower average growth rates, with HC and CC even experiencing negative growth. This could be attributed to their heavy reliance on high-energy-consumption and high-pollution industrial development, coupled with the insufficient utilization of low-emission resources. Therefore, there is a need to strengthen environmental protection, promote green development, transition economic development modes, and enhance the GEULU in these urban agglomerations.

4.1.3. Spatiotemporal Evaluation of GEULU at City Scale

Figure 5 shows the spatial pattern of the GEULU and changes over time. According to the values of the GEULU, the 284 cities can be categorized into five groups. Specifically, using the guiding principle of the super SBM-DDL-DML model, a GEULU ≥ 1 indicates that the inputs and outputs are in a relatively balanced relationship, and a city that meets this condition can be defined as an "Efficient" city. Non-efficient cities with a GEULU < 1 were categorized into four types according to quartiles: "Highly inefficient" ($0 <$ GEULU ≤ 0.25); "Moderately inefficient" ($0.25 <$ GEULU ≤ 0.5); "Slightly inefficient" ($0.5 <$ GEULU ≤ 0.75); and "Nearly efficient" ($0.75 <$ GEULU ≤ 1).

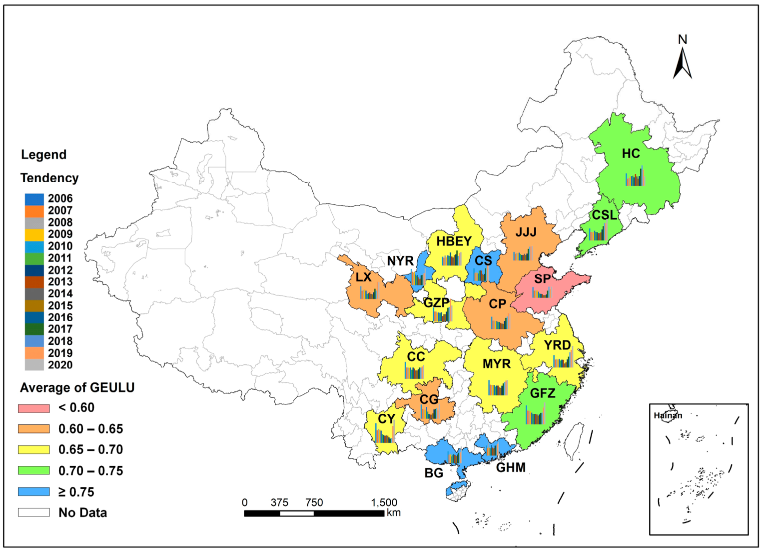

Figure 4. Spatiotemporal evaluation of the GEULU at the urban agglomeration scale.

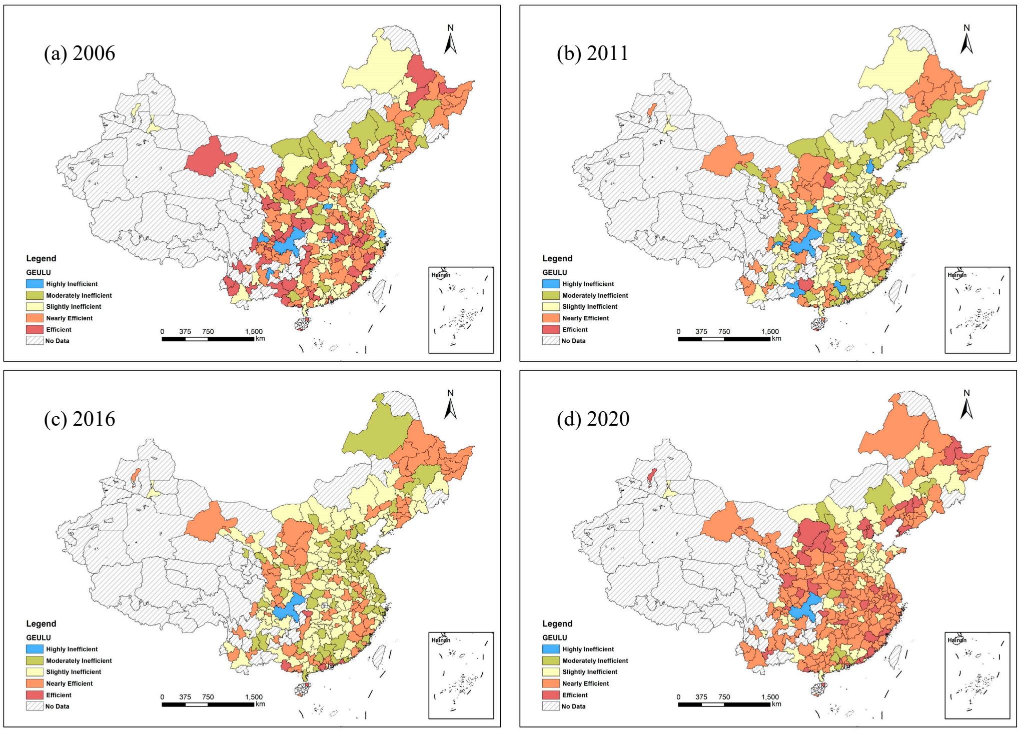

Figure 5. Spatial distribution of the GEULU at the city scale.

The distribution of various types of cities was influenced by the geographical location and exhibited a clustered pattern. “Efficient” cities demonstrated a shift from the western to the eastern areas. In 2006, 19.64% of “Efficient” cities were in the eastern area. In 2020, this had risen to 44.19%. “Highly inefficient” cities were economically developed cities such as Shanghai and Tianjin, which have a significant level of urbanization coupled with a dense population, which may lead to inefficient land use. Alternatively, cities characterized by manufacturing and heavy industries, such as Zhengzhou (in Henan Province) and Harbin (in Heilongjiang Province), face heavy pressure regarding environmental governance and green transformation, resulting in lower levels of the GEULU. It is worth mentioning that the Chongqing municipality was categorized as “Highly inefficient”. The possible reasons include its large population (over 30 million), advanced industrial development, and complex mountainous terrain. Therefore, Chongqing faces significant challenges in urban planning, making it difficult to improve the GEULU due to land constraints.

Figure 6 presents the KDE curve of the GEULU, illustrating its temporal evolution. The peaks of all four curves are located between 0.5 and 1.0, indicating that the GEULU values were generally concentrated within this range. Over time, the KDE curve of the GEULU initially shifts leftward before moving rightward, suggesting a trend of a first decreasing and then increasing GEULU. In terms of the peak height and distribution, the KDE curves from 2006 to 2020 exhibit a unimodal characteristic, with the peak height increasing progressively. This indicates that GEULU values have become more concentrated over time, reflecting an increasing disparity between regions.

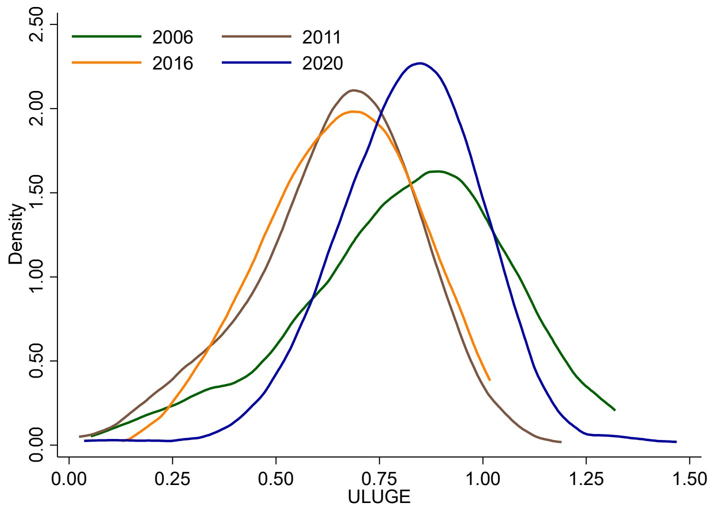

Figure 6. KDE curves of the GEULU at the city scale.

Further analysis was conducted on the spatial correlation pattern of the GEULU. Table 3 shows the estimated global Moran's I index for the GEULU. Each year's Moran's I value was significantly positive, indicating a high degree of spatial autocorrelation among neighboring cities within the study area. This suggests that the GEULU of cities is characterized by spatial clustering, with neighboring cities exhibiting similar GEULU features.

Table 3. Global Moran's index of GEULU.

Years	Moran's I	Z Value	Years	Moran's I	Z Value
2006	0.035 **	2.333	2014	0.078 ***	4.848
2007	0.046 ***	2.984	2015	0.070 ***	4.389
2008	0.027 **	1.999	2016	0.080 ***	4.987
2009	0.055 ***	3.491	2017	0.026 *	1.846
2010	0.040 ***	2.617	2018	0.028 **	2.019
2011	0.029 **	2.019	2019	0.097 ***	6.265
2012	0.055 ***	3.553	2020	0.092 ***	5.855
2013	0.053 ***	3.361	-	-	-

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The local indicators of spatial association (LISA) cluster analysis is reported in Figure 7. As most cities with clustering characteristics were of the HH and LL types over the years, this indicates a positive spatial spillover effect of the GEULU among cities. LH clusters were typically located around HH types, while HL clusters were more commonly found around LL clusters. By comparing the clustering characteristics of the GEULU in the four years (2006, 2011, 2016, 2020), it can be observed that the HH clusters showed a shift from west to east, while the LL clusters exhibited the opposite trend, moving from eastern to western regions. This shift may relate to the varying characteristics and phases of economic progress and urbanization processes in various regions of China. Economic development in the western regions relies more on energy resource extraction, mineral resource extraction and processing, and agriculture. Industrial structures in the eastern regions are more diversified and modernized. Particularly with the emergence of high-tech industries and the promotion of concepts such as "smart cities" and "digital cities", the eastern regions are placing more emphasis on the scientific and sustainable aspects of urban planning and construction, thus having a greater advantage in improving their GEULU.

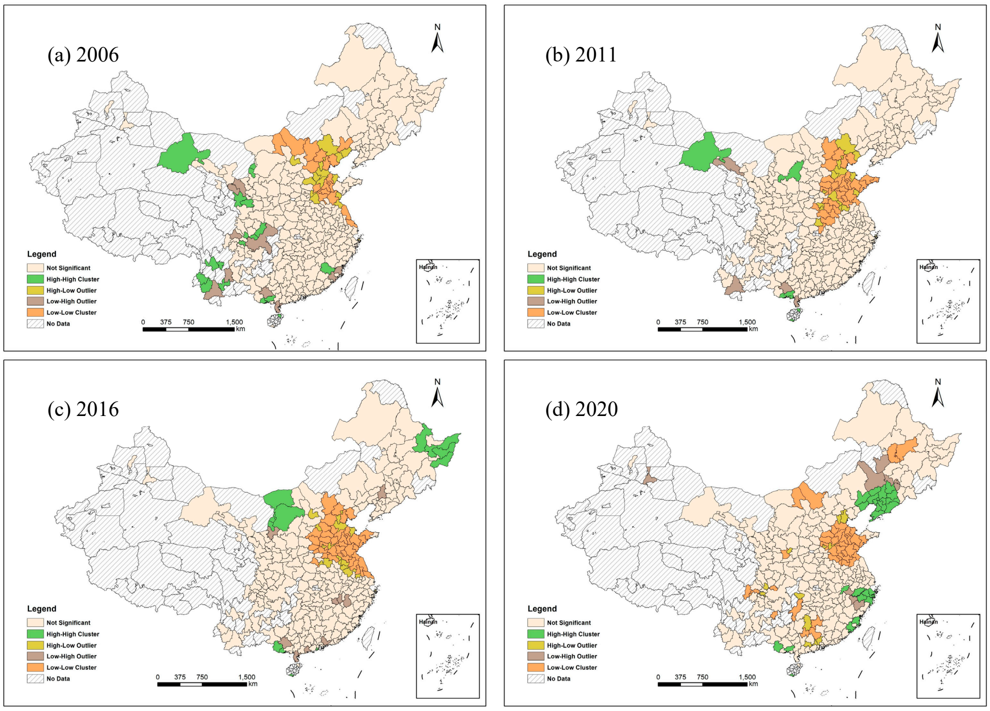

Figure 7. LISA cluster results of the GEULU at the city scale.

4.2. Driving Mechanism of NU on the GEULU

4.2.1. A First Look: Why the GTWR Model?

Firstly, a multicollinearity analysis was performed on the seven driving factors of the GEULU from an NU lens. The findings revealed that the variance inflation factor (VIF) values were all below 10, suggesting the absence of substantial multicollinearity. Following the usual analysis paradigm, the effects of the driving factors on the GEULU were estimated using the ordinary least squares (OLS), geographically weighted regression (GWR), temporally weighted regression (TWR), and GTWR models. Table 4 compares the effectiveness of each model. The results show that the GTWR model has a large R-squared and adjusted R-squared and smaller AICc and Residual Squares, suggesting that the GTWR has analytical advantages as it comprehensively considers both temporal and spatial factors.

Table 4. Parameters of OLS, GWR, TWR, and GTWR models.

Models	Bandwidth	R^2	Adjusted R^2	AICc	Residual Squares
OLS	-	0.004	-	15,821.930	10,193.040
GWR	0.539	0.005	0.004	15,823.300	10,177.400
TWR	0.710	0.006	0.004	15,820.700	10,173.200
GTWR	0.414	0.008	0.006	15,818.500	10,151.600

4.2.2. The General Results of the GTWR

To understand how NU drives the GEULU, built on the driving factors discussed in Section 2.3, this section examines the spatial and temporal heterogeneity of NU's influence. Overall, the influence of NU on the GEULU exhibits notable spatiotemporal variation, as evidenced by the differing directions of the coefficients in the upper and lower quartiles (Table 5). This underscores the necessity for further analysis of the spatiotemporal heterogeneity.

Table 5. Summary of the parameters and coefficients of the GTWR model.

Parameters	Minimum	Lower Quartile	Median	Upper Quartile	Maximum
EU	3.293	4.632	5.172	5.682	7.825
PU	1.451	1.898	2.114	2.289	2.914
LU	−5.491	−3.781	−3.161	−2.389	−1.272
SU	−2.434	−1.208	−0.881	−0.506	0.572
EEBs	−6.269	−1.217	−0.265	0.053	1.221
UDD	−7.664	−2.636	−2.105	−1.639	4.806
REC	0.799	1.951	2.688	3.142	7.091
NU	−0.278	−0.138	0.025	0.163	0.665

Specifically, among NU's seven dimensions, economic urbanization (EU), population urbanization (PU), and research and education clustering (REC) have positive effects on the GEULU. Land urbanization (LU) is notably detrimental to GEULU improvement. EU, PU, and REC signify a concentration in urban resources, talent, and technology, which aids in promoting industrial structural upgrades, fostering knowledge innovation and technological progress, and enhancing the utilization of urban infrastructure, thus incentivizing the GEULU. Conversely, LU may lead to urban spatial expansion and excessive land development (particularly when urbanization lacks proper planning and management), thereby hindering the GEULU. Social urbanization (SU) and urban development digitalization (UDD), with negative coefficients in the upper quartile, indicate slight heterogeneity but generally have an adverse effect on the GEULU. This could be explained by SU potentially increasing urban social issues like traffic congestion and environmental pollution, negatively affecting green land utilization. In the case of UDD, while infrastructure development (e.g., payment clearing, information communication, and network base stations) promotes production scale expansion and increased energy use, overall adverse effects may arise from technological innovation and industrial structural optimization not fully offsetting the costs of the former. Ecological and environmental benefits (EEBs) exhibit notable spatiotemporal heterogeneity in their association with the GEULU, as deduced from the contrasting directions observed in the upper and lower quartiles. This divergence likely stems from varying environmental conditions and policy measures across different regions. These findings confirm that economic growth and innovation enhance the GEULU, while rapid land expansion and social pressures hinder it. The heterogeneous effects of EEBs further highlight regional disparities in environmental policies, underscoring the need for tailored urbanization strategies.

4.2.3. Spatiotemporal Heterogeneity of NU's Impact on GEULU at Regional Scale

Figure 8 illustrates the spatiotemporal heterogeneity of NU's impact on the GEULU at the regional scale. Overall, the impact of NU shows a positive trend in both the eastern and central regions, while in the western area it shows a slight negative trend. Its influence magnitude follows the pattern "Eastern > Central > Western". The variation in development levels across regions may account for this pattern: the eastern region is economically developed and urbanized with well-developed infrastructure systems, improving the GEULU. The central region is in a rapid developmental stage, having a smaller effect on the GEULU than the eastern area. The western region, meanwhile, is more sparsely populated than the central and eastern regions and thus has a low demand for urbanization and insufficient attention to land use efficiency, which may lead to a slightly negative direction and a low degree of influence of NU on the GEULU. NU's impact on the GEULU has shifted from negative to positive over time, with a steady increase in its influence. This shift is due to the growing focus of the government on green development, prompting a transition towards a greener and more sustainable development model coupled with technological advancements.

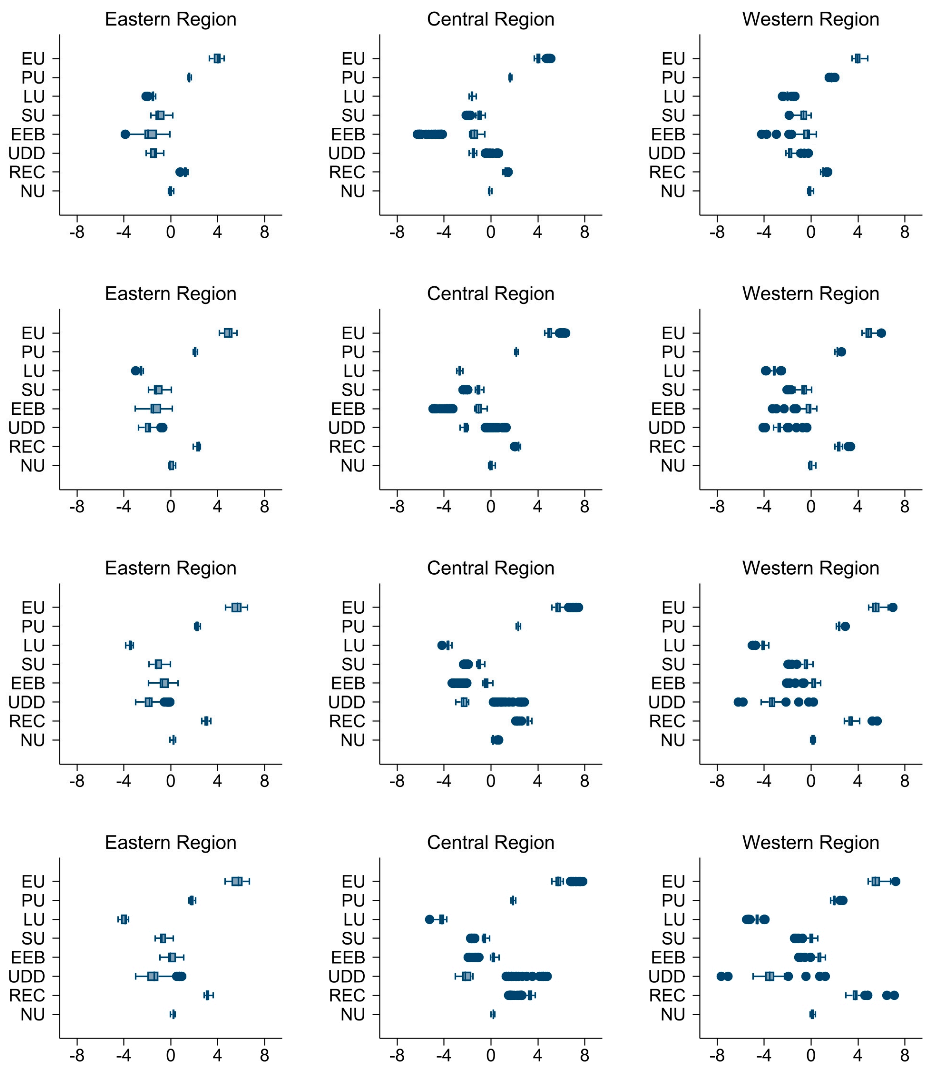

Figure 8. Coefficient distribution of effects of NU on GEULU at regional scale.

The specific analysis revealed notable heterogeneity in SU, EEBs, and UDD. In the western region, SU and EEBs exert the strongest positive influence on the GEULU, with a slightly lesser effect in the eastern area. However, their impact is negative in the central region. In turn, UDD's influence on the GEULU is mostly positive in the central region, slightly weaker in the eastern area, and most strongly negative in the western region. The western region is likely to benefit from richer natural resources and a better ecological environment, including in terms of the air quality, forest coverage, and water resources. The eastern region's advanced green technologies make it relatively easier to achieve the positive impacts of EEBs and SU compared with the central region, which is possibly in a phase of rapidly developing digitalization, leading to a significant impact of UDD on the GEULU. The eastern region, with a higher digitization level and relatively mature digitization system, experiences lower marginal benefits from digital progress compared with the central region, thus resulting in a lesser impact of UDD on the GEULU. In contrast, the western region's reliance on resource-driven industries reduces its dependence on digitalization, resulting in the strongest negative impact of UDD on the GEULU in this region. The temporal trend indicates that the impacts of SU, EEBs, and UDD on the GEULU are evolving towards more favorable directions.

4.2.4. Spatiotemporal Heterogeneity of NU's Impact on GEULU at Urban Agglomeration Scale

Figure 9 illustrates the spatial–temporal heterogeneity of NU's impact on the GEULU at the urban agglomeration scale. In 2006, NU positively affected the GEULU only in the GFZ, CG, CY, BG, and GHM urban agglomerations, all located in southern China. By 2011, the MYR urban agglomeration also showed a positive impact. In 2016, the positive influence of NU on the GEULU extended to 15 urban agglomerations, with only NYR, GZP, and LX—located in the northwest—experiencing negative impacts. By 2020, NU positively impacted the GEULU across all urban agglomerations, indicating a shift from a negative to a positive influence over time. Particularly, NU, EU, PU, and REC significantly enhanced the GEULU for most urban agglomerations, while LU, SU, EEBs, and UDD generally hindered GEULU development. Exceptions include the CY, CG, CC, and BG urban agglomerations, where EEBs promote the GEULU, and the HC urban agglomeration, where UDD positively influences the GEULU. Over time, the impacts of NU and its seven dimensions on the GEULU show a trend of diminishing adverse effects or strengthening positive effects.

4.2.5. Spatiotemporal Heterogeneity of NU's Impact on GEULU at City Scale

Figure 10a,b show that the EU coefficient exhibited an upward trend from 2006 to 2020, with higher values in the northeast compared with the southwest. This implies a greater positive association between EU and the GEULU in northeastern cities, probably due to the economic boost generated by the Northeast Revitalization Strategy, driving high-quality development in these areas [88]. Regarding the PU coefficient (Figure 10c,d), the influence of PU on the GEULU became more positive over time, exhibiting higher values in the northwest and lower ones in the southeast. This trend suggests that northwestern cities have improved their resource allocation efficiency and infrastructure utilization through population concentration. Meanwhile, southeastern cities, facing a high population density and resource pressure, saw limited enhancement in the GEULU from population growth. For LU (Figure 10e,f), in 2005, the negative impact of LU on the GEULU was more pronounced in western cities and relatively weaker in eastern cities, possibly due to weaker infrastructure and management during early urbanization in the west. By 2020, the distribution of its negative impact had shifted from west–east to north–south. Regarding SU (Figure 10g,h), it generally exerted a negative impact on the GEULU for most cities, with more potent adverse effects in northeastern cities and relatively weaker effects in southwestern cities. By 2020, however, SU's impact had shifted from a hindrance to promotion in some cities, like Lijiang (in Yunnan Province), Yibin (in Sichuan Province), Nanning (in Guangxi Province), Dingxi (in Gansu Province), and Zunyi (in Guizhou Province). For EEBs (Figure 11a,b), in 2006, EEBs only positively impacted a few southwestern cities while hindering the GEULU in northeastern cities. By 2020, its influence had become more positive, promoting the GEULU in most southwestern cities.

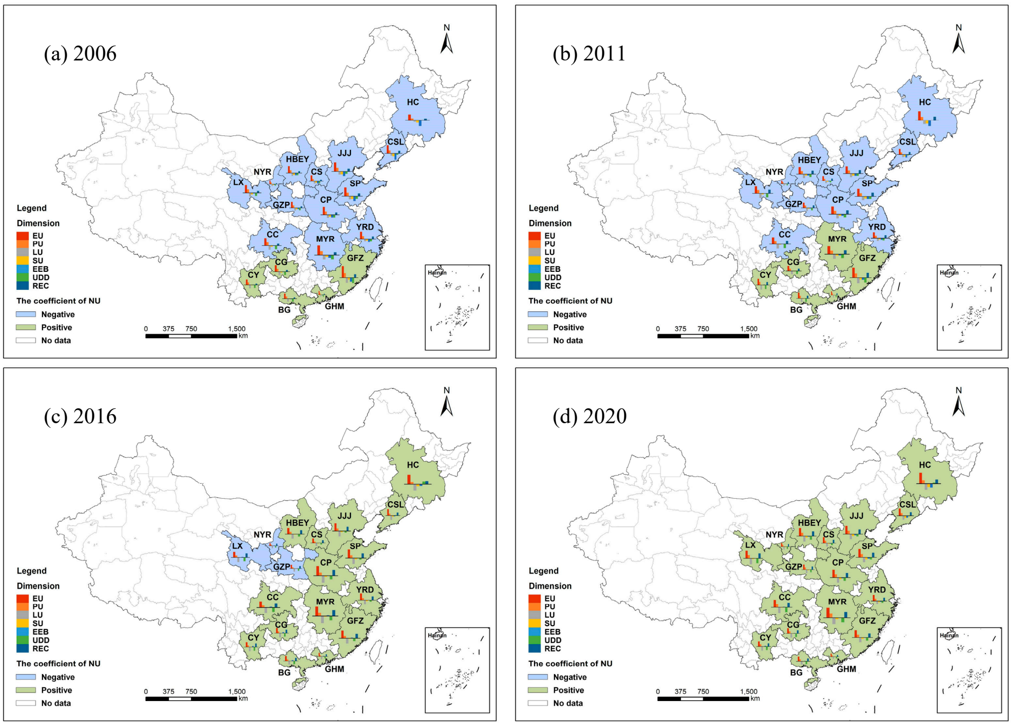

Figure 9. Coefficient distribution of NU's impact on GEULU at urban agglomeration scale.

Regarding UDD (Figure 11c,d), in 2006 it only promoted the GEULU in nine northeastern cities, including Qitaihe (in Heilongjiang Province), Shuangyashan (in Heilongjiang Province), and Suihua (in Heilongjiang Province), while negatively impacting most other cities, with the negative impact intensifying towards the southwest. By 2020, although UDD had started to positively influence the GEULU in a few more cities and its positive impact had strengthened, its negative impact on southwestern cities had also intensified. Observing the REC coefficient (Figure 11e,f), from 2006 to 2020, the positive correlation between REC and the GEULU transitioned from high in the northeast to low in the southwest, evolving towards high in the northwest and low in the northeast and southeast. Such a shift may have been driven by differences in research and education investment and land use policies across various cities in China, leading to changes in regional development patterns.

Overall, the impact of NU on the GEULU at the city scale (Figure 11g,h) showed a notable shift from 2006 to 2020. In 2006, NU had a slightly adverse effect on the GEULU for most cities, promoting the GEULU in only 25.35% of cities, primarily located in the southern regions. By 2020, this trend had reversed, with NU positively impacting the GEULU across 85.56% of cities. This suggests that many cities have likely implemented a series of reforms and made adjustments in planning and management to enhance their environmental sustainability and land use efficiency. However, in northeastern cities like Baishan of Jilin Province and Fushun of Liaoning Province and northwestern cities like Yinchuan (in Ningxia Province), Baoji (in Shaanxi Province), and Zhangye (in Gansu Province), NU continues to affect the GEULU negatively. These cities may require targeted policies and measures focused on environmental management, resource conservation, and industrial restructuring to address these challenges.

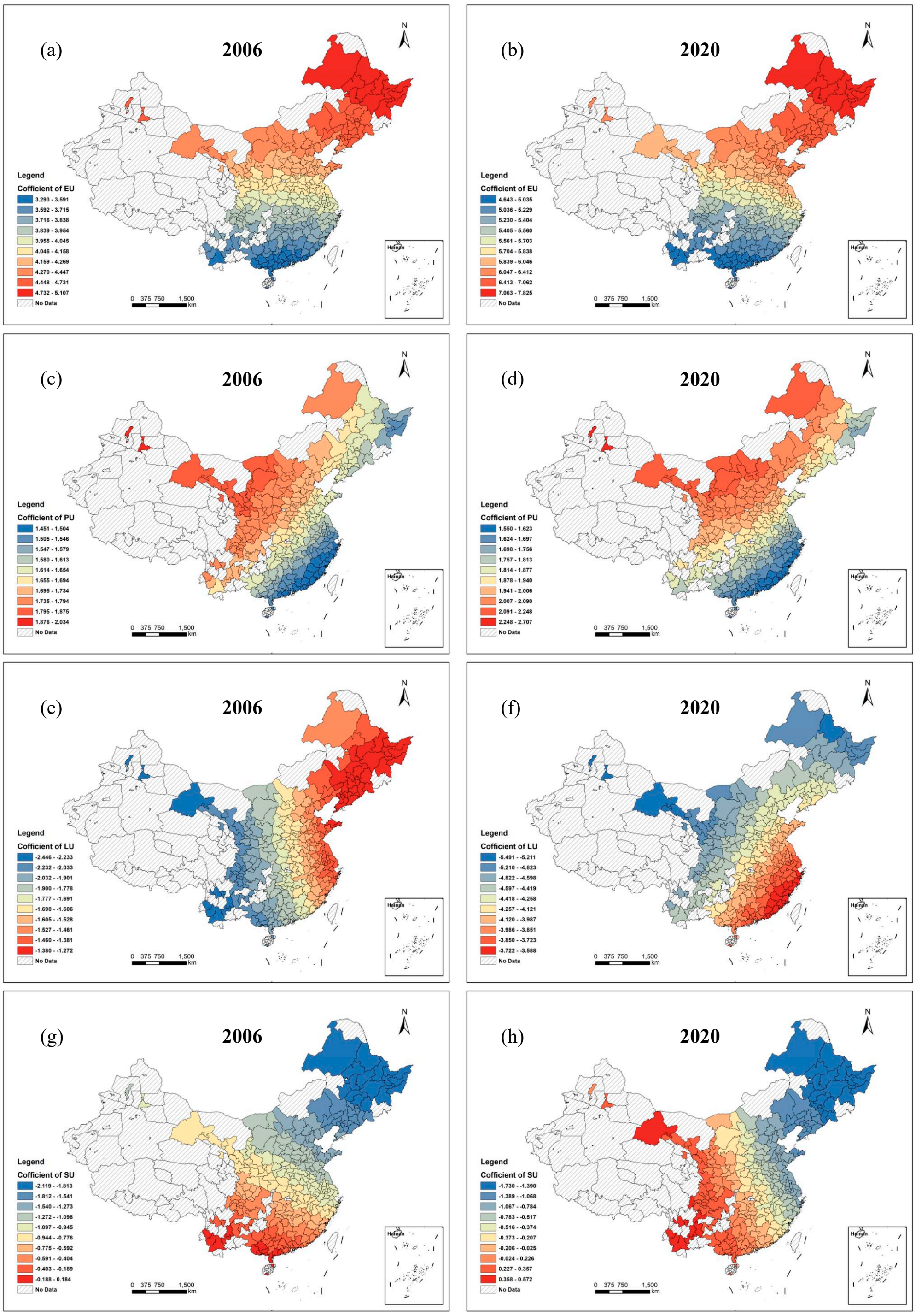

Figure 10. Spatiotemporal distribution of the coefficients for EU, PU, LU, and SU at the city scale.

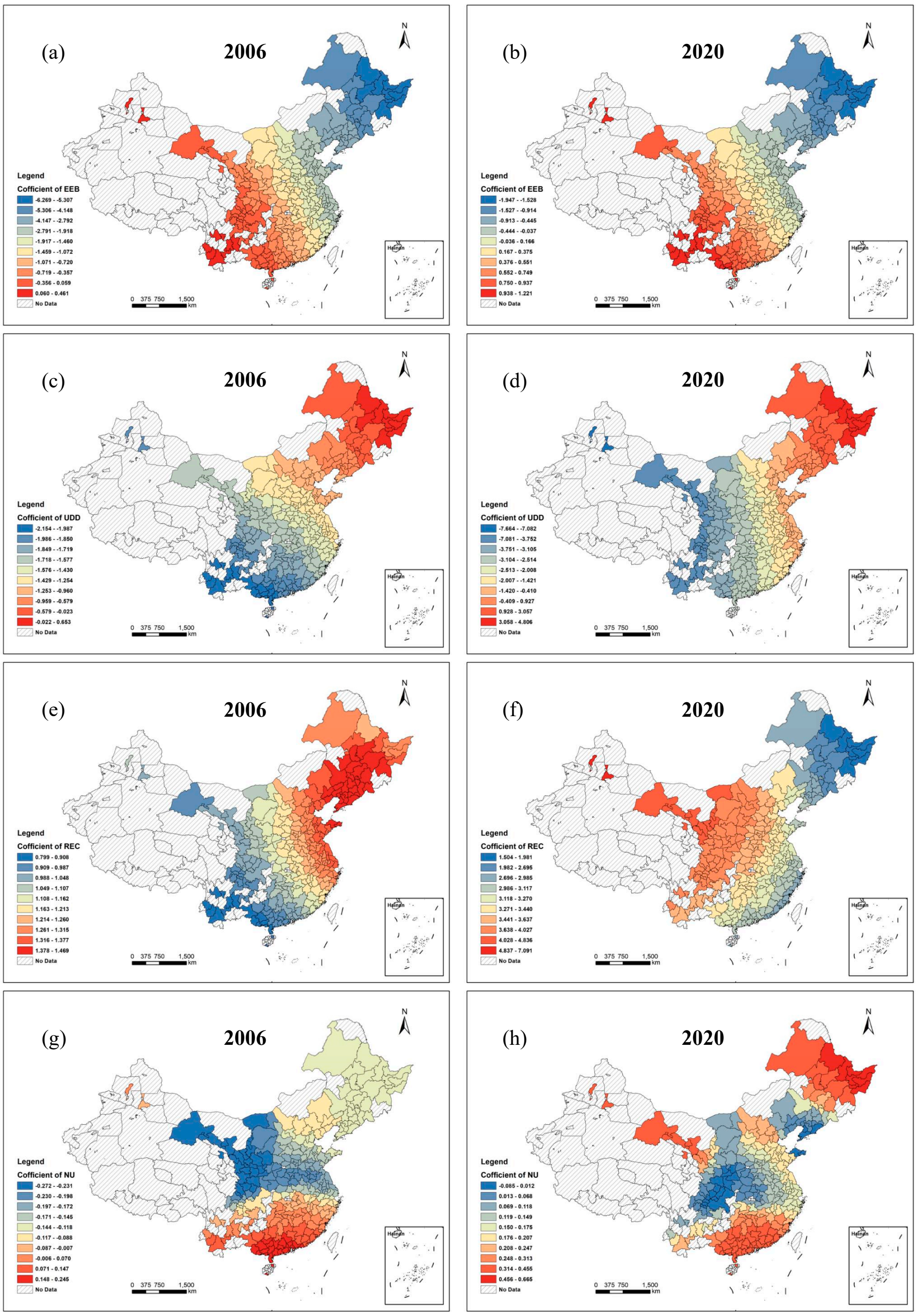

Figure 11. Spatiotemporal distribution of coefficients for EEBs, UDD, REC, and NU at city scale.

5. Discussion and Policy Implications

5.1. Interpretation of Findings

China's GEULU exhibited a "U-shaped" tendency, initially declining before rising between 2006 and 2020. Cities in western China showed higher absolute levels and slower development rates, while cities in eastern areas had lower absolute levels yet developed more rapidly. This pattern somewhat differs from previous research findings. For example, Zhou and Lu (2023) found that the GEULU generally increased over the past 15 years, with higher levels in coastal and northwestern regions compared to central areas [53]. Li et al. (2023), in their study of the Yellow River Basin, identified a sharp increase in the GEULU after 2015 [57]. They found that the middle reaches significantly outperformed the lower reaches and slightly exceeded the upper reaches; however, the upper reaches exhibited the highest growth rate compared to other sections of the basin. Our study found that the GEULU exhibits a significant spatial autocorrelation, aligning with the conclusions of Bai et al. (2018) and Huang et al. (2023) [49,68]. Unlike these studies, which primarily emphasized absolute levels and regional disparities at specific time points, our research highlights the nonlinear temporal evolution of the GEULU and the shifting spatial clustering patterns over time. Our analysis of spatial clustering characteristics revealed a novel finding: there is a trend of "high-high (HH) clusters" shifting from the western to eastern regions, while "low-low (LL) clusters" are moving from the eastern to western regions.

This study explored spatiotemporal heterogeneity in the influence of China's NU and its seven sub-dimensions on the GEULU. It was found that NU has a positive impact on the GEULU in the eastern and central areas, whereas it exerts a negative influence in the western area. Specifically, economic urbanization (EU), population urbanization (PU), and research and education clustering (REC) positively impact the GEULU. In contrast, land urbanization (LU) significantly hinders the improvement of the GEULU. Social urbanization (SU) and urban digital development (UDD) generally exhibit a negative impact, with over 75% of observations showing negative coefficients. Ecological and environmental benefits (EEBs) promote the GEULU in southwestern cities but impede it in northeastern cities. Over time, the influence of NU and its seven dimensions on the GEULU shows a positive trend, with a weakening of negative effects and a strengthening of positive impacts. This research provides a novel perspective by identifying NU as a driving factor for the GEULU. Previous studies addressed how factors like the per capita GDP, financial development, industrial upgrading, technological progress, foreign investment, and market openness influence the GEULU [49,89], but there has scant research into urbanization, particularly the NU practice in China.

The definition and measurement of NU in this study also contribute to the literature. Unlike existing research that treats NU as a policy to assess its effectiveness [11], we argue that NU had been influential long before the concept was formally introduced in 2014. This paper covers the period from 2006 to 2020. When constructing the NU index, besides the traditional dimensions of the economy, population, land, and society, we introduced three new dimensions: EEBs, UDD, and REC. These dimensions reflect the "new" aspects of NU, which aligns urbanization with current environmental constraints, digital lifestyle trends, and integration with high-level scientific and educational resources. This approach distinguishes our study from traditional urbanization-related research [60,90].

5.2. Policy Implications

The development of NU should be promoted through enhanced policy management by all levels of government, thereby facilitating green land use. First, the central government should enhance strategic planning and offer region-specific guidance tailored to the distinct development characteristics of the GEULU. For the eastern and central areas, new urbanization reforms should be further advanced, urban spatial layouts optimized, and the overall urbanization efficiency and green standards improved. In the western region, ecological protection should be the main priority, avoiding excessive development and resource waste, thereby enhancing the environmental benefits and sustainability of land use. Second, major urban agglomerations should foster regional cooperation, promoting region-specific green urbanization paths based on their unique characteristics. For instance, urban clusters that are positively influenced by EEBs should make concerted efforts to advance green transformation. In contrast, those that benefit from UDD should accelerate the construction of digital infrastructure and smart cities, thereby improving the land resource utilization efficiency. Third, at the city level, municipal governments should formulate urbanization development strategies tailored to the economic and demographic characteristics of their cities. The proactive supervision and performance evaluation of land use should be conducted, with dynamic monitoring and assessment mechanisms in place to promptly identify and rectify unreasonable land use practices, ensuring the achievement of green transformation objectives in land use.

Enterprises should be encouraged to participate actively in the land resource market, thereby promoting the prudent and effective allocation of land resources. In one respect, enterprises should respond proactively to government-established land transfer mechanisms. They can assist in developing detailed transaction rules and operational guidelines, ensuring transparency, fairness, and efficiency in the land transfer process, and guiding land resources toward green industries and eco-friendly projects. In another respect, enterprises should increasingly prefer leasing land resources as a means of facilitating production expansion and industrial upgrading. For land leases that align with green industries and eco-friendly projects, enterprises should actively seek financial support from government departments, industry organizations, or financial institutions in the form of subsidies and tax incentives. While pursuing market benefits, enterprises must also fulfill their social responsibilities, prioritizing environmental protection and sustainable development in land use, thereby enhancing the overall benefits. Finally, a public–private partnership (PPP) model can be an effective tool in this process. By facilitating collaboration between the government and businesses, PPPs can support sustainable land use practices, integrate ESG factors into development projects, and help align public policies with private sector investments, fostering a more efficient and environmentally responsible land market.

It is necessary to promote public participation and further enhance residents' environmental awareness. Firstly, the government should strengthen environmental education and advocacy by organizing environmental exhibitions and environmental days, setting up environmental bulletin boards, and establishing online platforms to disseminate environmental knowledge, encouraging urban residents to develop a conservation and environmental protection mindset. Secondly, residents should be encouraged to participate in environmental governance and green development, with mechanisms for public participation further improved. Relevant departments can create feedback platforms for the public, encouraging their involvement in the decision-making procedures of land use projects and increasing public participation and democratic engagement in urban development affairs, such as by organizing public forums, symposiums, and hearings. Lastly, urban development should recruit more volunteers with a green mindset and expertise in land management. Establishing volunteer training programs and incentive mechanisms can attract volunteers to participate; they can play vital roles in regional inspections, environmental monitoring, and advocacy, contributing to efficient land utilization and urban green development.

There is a need to enhance digital development that aligns with new urbanization and improves the GEULU. Digital transformation is essential for enhancing resource efficiency and fostering improvements in environmental quality. To mitigate its negative environmental effects, policies should promote energy-efficient digital infrastructure and responsible e-waste management. Therefore, firstly, the application of digital technology in urban planning and management should be promoted, supporting cities in utilizing big data and artificial intelligence (AI) in areas such as transportation, energy, and the environment to improve resource utilization efficiency. Secondly, a digital development system adapted to new urbanization should be constructed. For example, leveraging Geographic Information Systems (GIS) and remote sensing (RS) technologies enables the more effective monitoring and planning of land resources, and constructing intelligent traffic management systems can enhance urban transportation efficiency and eliminate land resource wastage, among other uses. Finally, the digital development system should emphasize data sharing and openness, promoting cross-departmental and cross-regional data integration and application while encouraging enterprises and research institutions to participate in digital land resource management. Through interconnected data, it is possible to achieve refined and intelligent urban land resource management to enhance the efficiency and sustainable development capability of land resources.

5.3. Validation and Future Directions

This study was mainly divided into two parts: measuring the GEULU and exploring the impact of NU on the GEULU. Both parts of the research process used mature and reasonable models to conduct extensive analysis to ensure the reliability and universality of the conclusions. Our conclusions introduce new insights into the dynamics of NU and the GEULU, which have theoretical and practical significance. We recognize four key limitations that future research could explore and address. Firstly, the dataset, although comprehensive, was limited to a specific temporal and spatial scope. Future studies should expand the temporal range and include additional regions or countries to test the universality of the findings. Secondly, we mainly examined the direct effect of NU on the GEULU, leaving scope for future research to investigate potential mediating and moderating factors that may shape this relationship. For instance, future research could examine how the governance quality, policy interventions, or socio-economic conditions mediate the effect of NU on the GEULU. Thirdly, while this study introduces new dimensions to measure NU, the further refinement and validation of these indicators are still needed. Future research could explore alternative methodologies or incorporate qualitative data to complement the quantitative findings. Lastly, the rapid advancements in digital technologies and environmental policies suggest that the relationship between NU and the GEULU is likely to evolve, necessitating the continuous monitoring and updating of the analytical frameworks used. Future research can further explore the dual effects of digital transformation on green land use. Digitalization has the potential to enhance the GEULU, but it may also increase energy consumption and carbon emissions, requiring a balanced approach to its integration into sustainable urbanization strategies. Leveraging insights from the UN Digital Economy Report 2024, future studies could investigate policy mechanisms that mitigate digitalization's ecological footprint while maximizing its benefits. By addressing these gaps, future research can contribute to a more nuanced understanding of the interplay between urbanization processes and sustainable land use, thereby offering actionable insights for policymakers and urban planners.

6. Conclusions

This study examined the spatiotemporal heterogeneity of the impact of China's NU on the GEULU across the regional, urban agglomeration, and city scales. Using the expanded connotation of an "economic-fiscal-social-environmental" perspective, a super SBM-DDF-GML model was used to measure the GEULU from 2006 to 2020, accompanied by exploratory spatial data analysis. A framework for elaborating how key factors measuring NU characteristics influence the GEULU was constructed. The GTWR model was applied to examine the multidimensional effects of NU on the GEULU, capturing the spatiotemporal heterogeneity of these interactions.

From 2006 to 2020, China's GEULU exhibited a "U-shaped" pattern, starting with a decline before increasing. The absolute level of the GEULU in the cities of west China is higher but progresses more slowly, while cities in east China have lower absolute levels and faster growth. The GEULU demonstrates a significant positive spatial autocorrelation, with high–high clusters shifting from west to east, whereas "low-low clusters" shift in the opposite direction, from the east to the west. The influence of NU on the GEULU is positive in the eastern and central regions but negative in the western areas. Specifically, economic urbanization, population urbanization, and research–education agglomeration positively impact the GEULU. In contrast, land urbanization significantly hinders the improvement of the GEULU. Social urbanization and urban digital development generally exert negative impacts, with over 75% of observations showing negative coefficients. Ecological and environmental benefits promote the GEULU in southwestern cities but hamper it in northeastern cities. Over time, the adverse effects of NU and its seven dimensions on the GEULU have diminished, while the positive effects have strengthened. This study provides valuable insights into formulating effective urban management strategies to achieve more sustainable urbanization in the coming decades.

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Abbreviations

The following abbreviations are used in this manuscript:

GEULU	Green efficiency of urban land use
NU	New-Style Urbanization
SDGs	Sustainable Development Goals
SBM-DDF-	Slacks-based measure–directional distance function–global
GML	Malmquist–Luenberger
SFA	Stochastic frontier analysis
DEA	Data envelopment analysis
ULUE	Urban land use efficiency
GTWR	Geographically and temporally weighted regression
KDE	Kernel density estimation
ESDA	Exploratory spatial data analysis
EU	Economic urbanization
PU	Population urbanization
LU	Land urbanization
SU	Social urbanization
EEB	Ecological and environmental benefits
UDD	Urban development digitalization

REC	Research and education clustering
JJJ	Beijing–Tianjin–Hebei
YRD	Yangtze River Delta
GHM	Guangdong–Hong Kong–Macao Greater Bay Area
CC	Chengdu–Chongqing
MYR	Middle Yangtze River
SP	Shandong Peninsula
CP	Central Plains
GZP	Guanzhong Plains
GFZ	Guangdong–Fujian–Zhejiang Coastal Area
BG	Beibu Gulf
HC	Harbin–Changchun
CSL	Central and Southern Liaoning
CS	Central Shanxi
CG	Central Guizhou
CY	Central Yunnan
HBEY	Hohhot–Baotou–Ordos–Yulin
LX	Lanzhou–Xining
NYR	Ningxia Yellow River

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