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Spatiotemporal evolution and determinants of urban land use efficiency under green development orientation: Insights from 284 cities and eight economic zones in China, 2005–2019

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ABSTRACT

Green development is essential for improving urban land use efficiency (ULUE) as it seeks to optimize resource utilization and minimize waste and pollution. However, a long-term evolution of ULUE and its determinants under the context of green development are less discussed in existing studies. Drawing on remote sensing and statistical data and utilizing the super efficiency slack-based model (SBM) and the geographically and temporally weighted regression (GTWR) model, this study evaluates green development-oriented ULUE and its spatiotemporal associations with determinants across 284 cities and eight economic zones in China from 2005 to 2019. We found that the green development-oriented ULUE in China generally increased in 15 years (from 0.404 to 0.55), with higher levels in coastal and northwestern regions than in central regions. Besides, per capita GDP, investment in technology and science, and degree of openness generally contributed to ULUE (over 75% observations showed positive coefficients), while investment in real estate had a negative impact on ULUE. The impact of industrial structure on ULUE experienced a transition from positive to negative in northern and eastern cities, with the highest coefficient decreasing from 0.194 in 2005 to −0.032 in 2019. Population density contributed to ULUE in southern and northwestern cities during 2005–2010 (coefficients ranging from 0.008 to 0.198), while it negatively influenced ULUE in most cities since 2015 (coefficients ranging from −0.009 to −0.283). The correlation between nighttime light, per capita road, and ULUE showed noticeable south-north differentiation. Our study provides valuable guidelines for Tailor-made strategies of efficient urban management towards sustainable urbanization.

1. Introduction

Rapid urbanization is happening in the world in the last few decades, due to the rapid growth of urban population. More than 60% of the world's population will live in urban areas by 2030, with nearly 90% of the population increase happening in the cities (Ramaiah & Avtar, 2019). As the most populous country and the second-largest economy, China has witnessed the largest and fastest urbanization in the history during the past four decades (Tan et al., 2016). According to the Chinese construction statistics yearbooks, the urban land in mainland China increased eight folds from nearly 7000 km^2 to over 58,000 km^2, between 1978 and 2020. Urban expansion in China will accelerate in the coming years, with the projection of urban land probably reaching over 80,000 km^2 by 2030 (Cui et al., 2019). Excessive expansion of urban land has led to certain issues including regional incoordination, destruction of urban nature, air pollution, and natural ecosystem degradation, which lower the urban land use efficiency and constrain urban sustainability (Chen et al., 2018; Liu et al., 2020; Peng et al., 2021; Song et al., 2022). In recent years, green development is thought to be a key strategy in achieving sustainable and efficient urban development. In 2020, China's government put forth the objective of "dual carbon", which entails achieving the peak of carbon dioxide (CO2) emissions by 2030 and attaining carbon neutrality by 2060, as part of their overarching goal of achieving green development (the Xinhua News Agency, 2020). Green development contributes to the coordination between the economy, society, and ecology by reducing resource consumption, pollution, and emissions of greenhouse gas without reducing living quality and economic growth (Sun et al., 2018). In pursuit of effective strategies for

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efficient management of urban growth and sustainable urbanization, an essential prerequisite involves comprehending the spatiotemporal dynamics of urban land use efficiency (ULUE) under green development orientation and its potential influencing factors.

ULUE refers to the relative efficiency with which a spectrum of socioeconomic resources including land, capital, and labor, is employed to optimize outcomes within a given unit of urban land. Through effective resource inputs, urban planners endeavor to enhance economic growth, improve social welfare, and cultivate environmental benefits, while concurrently minimizing waste and inefficiencies (Liu et al., 2021; Zhu, Li, et al., 2019). ULUE is generally influenced by economic, social, and environmental factors (Hu et al., 2022). The rapid urban expansion in China will probably lower ULUE due to increasing energy consumption and environmental pollution, bringing challenges to efficient urban growth. ULUE under green development orientation should consider expected outputs, such as economic, societal, and ecological benefits, as well as adverse consequences including diverse environmental pollution, under certain resource conditions. Due to the unavailability of certain traditional statistical data, some studies of ULUE fail to consider some undesirable outputs under the concept of green development, such as the emissions of CO_2, and the concentrations of fine particulate matter (PM2.5). In addition, previous studies often omitted the spatiotemporal disparities of varying impacts of socioeconomic factors on ULUE, consequently failing to adequately depict the dynamics of these effects over space and time, and creating challenges for policymakers in formulating tailored strategies.

Hence, we proposed three research questions in this study (1) how did the ULUE under green development orientation in Chinese cities evolve over space and time during 2005–2019? (2) What are the impacts of different socioeconomic factors on ULUE? (3) How did these impacts vary spatially and temporally? To answer these questions, this study aims to (1) utilize the super efficiency slack-based model (SBM) to assess the green development-oriented ULUE; (2) identify the spatiotemporal evolution of ULUE in 284 cities and eight economic zones in China using the Exploratory Spatial Data Analysis; (3) reveal the spatiotemporal heterogeneity of the associations between ULUE and its determinants using the geographically and temporally weighted regression (GTWR) model. This study makes efforts to understand the spatiotemporal dynamics of ULUE and its determinants under green development orientation in Chinese cities. Such effort not only provide a comprehensive review of ULUE evolution over space and time, but also may help local governments to make informed decision about the urban development policies to achieve sustainable urbanization.

2. Literature review

2.1. Analysis of ULUE in China

ULUE has been widely studied in China with different objectives and backgrounds. Previous studies often analyzed spatiotemporal variations of ULUE and its influencing factors in China's individual provinces (Ge & Liu, 2021; Yao & Zhang, 2021; Zhang et al., 2020). Besides, some studies focused on the ULUE in urban agglomerations in China. including the Yellow River Basin (Xue et al., 2022), the Yangtze River Delta (Wu et al., 2017), and the Yangtze River Economic Belt (Ge et al., 2022). By analyzing ULUE in specific areas, researchers provided suggestions for regional planning and improvement of ULUE. Moreover, there are some nationwide studies investigating the spatiotemporal patterns of ULUE and comparing the differences among eastern, central, and western regions. For example, Zhang et al. (2022) utilized the ratio of urban build-up land and constant price of GDP as a proxy to evaluate ULUE in Chinese cities and found ULUE increased significantly in the eastern regions from 2000 to 2015, while many cities in the central regions exhibited low ULUE. To date, there is no nationwide study that has comprehensively compared the regional disparities in ULUE over space and time with a fine-grained regional classification.

In the other research front, scholars conducted substantial research on ULUE under different backgrounds based on the various requirements of urban development. For example, Liu et al. (2022) adopted super efficiency SBM and difference-in-difference method to evaluate the impact of the low-carbon city pilot policy on ULUE. They showed a downward trend of ULUE in these 186 cities and demonstrated that the low carbon city pilot policy negatively influenced ULUE. To explore development strategies for resource-based cities, Song et al. (2022) utilized SBM and the Tobit model to assess the ULUE and its determinants in 115 resource-based cities from 2000 to 2018. They found that the ULUE in these cities generally increased despite some fluctuations and suggested that natural resource endowments and socioeconomic structure could influence different types of resource-based cities to various degrees. Under the context of urban agglomeration (UA) development, Yu et al. (2019) employed SBM model to examine the spatiotemporal pattern of ULUE in 12 UAs and suggested that Yangtze River Delta and Pearl River Delta kept efficient urban land use, while central China had lowest ULUE over time. Despite such research efforts, a comprehensive examination of ULUE in Chinese cities under the concept of green development remains unexplored in existing studies.

2.2. Measurements of ULUE

Previous research has witnessed numerous debates surrounding the measurement of ULUE. According to the sustainable development goal (SDG) 11.3.1 proposed by the United Nations (United Nations, 2018), some scholars measured ULUE by calculating the ratio of urban land consumption to the population growth rate (Estoque et al., 2021; Koroso et al., 2020, 2021). Besides, ULUE is more commonly measured using input-output functions, which are more reliable and closely related to its definition. For example, Jiao et al. (2020) established scale-adjusted functions of land input-output performance to evaluate the ULUE. They derived the land input performance by considering built-up areas and population, while the land output performance was evaluated based on the value of gross regional products and population. This approach, however, neglected to consider inputs of other social resources and outputs of societal and environmental benefits.

To address the limitation, many researchers use the Data Envelopment Analysis (DEA) to evaluate ULUE by measuring how efficient the outputs of a set of cities are with a combination of multiple inputs (Chen et al., 2019). Among the DEA methods, the SBM is always conducted to assess urban land use efficiency by considering both desirable outputs and undesirable outputs. The SBM can measure ULUE regarding situations of excess inputs and undesirable outputs or insufficient desirable outputs (Tan et al., 2021). Moreover, some studies developed the super-efficiency SBM to further compare ULUE across different cities (Ge et al., 2022; Pang & Wang, 2020; Tang et al., 2021). In the DEA approach, land, labor, and capital are three key inputs of the model, while economic benefits, society benefits, as well as environmental benefits are the three main desirable outputs (Cui et al., 2021; Lu et al., 2020). Industrial pollution is always considered as undesirable output (Ge et al., 2021; Wu et al., 2022). However, the indicators used in previous studies were usually derived from statistical data, which limited the comprehensive evaluation of ULUE. For instance, carbon emissions and PM2.5 concentrations, 2 elements considered to constrain green development, are usually omitted in existing studies due to limitation of statistical data. Few studies used remote sensing data to make up the limitation of statistical data and simultaneously consider pollution and greenhouse gas as undesirable outputs to measure ULUE.

2.3. Detecting determinants of ULUE

In previous studies, diverse socioeconomic factors are considered to have great impacts on ULUE. For example, urban capital is proven to have negative impacts on ULUE, while total external economic linkage, per capita GDP, and industrial structure upgrading positively influence

ULUE (Gao et al., 2020). Zhu, Zhang, et al. (2019) proved that infrastructure, economics, as well as markets, have positive impacts on ULUE, while land systems negatively influence ULUE. Also, urbanization level, ecological input, and government regulation influence ULUE to various degrees (Han et al., 2020; Wang et al., 2023). Moreover, the impacts of the degree of openness, construction of roads, as well as population density on ULUE remain inconclusive, with previous studies reporting mixed effects and varied outcomes (Cao et al., 2019; He et al., 2020; Lu et al., 2020; Song et al., 2022; Yu et al., 2019). Liu et al. (2021) demonstrated that industrial structure upgrading has a spatial spillover effect, with surrounding values of industrial structure upgrading contributing to improvement of local ULUE. They also found that industrial structure upgrading could previously inhibit and then promote ULUE.

In terms of the methodology, massive studies detected the influencing factors of ULUE from the perspective of economics using the econometric model such as the two-stage least squares method (Zhao et al., 2021) and the Tobit model (Song et al., 2022). Considering the spatial correlation of the residual term, the spatial econometric models including the spatial lag model (SLM) and spatial error model (SEM) are used to explore the impacts of determinants on ULUE with less error (Han et al., 2020; He et al., 2020). Moreover, the spatial Durbin model (SDM) is commonly used to examine the spatial spillover effect of the determinants (Zhang et al., 2022). However, these are global regression models with the assumption of isotropic association between variables, failing to reveal the local situation. Given the spatial non-stationary effects of the determinants on ULUE, a few studies conducted the Geographically Weighted Model (GWR) to explore the spatial heterogeneity of the determinants (Cao et al., 2019; Wu et al., 2017). Apart from spatial heterogeneity, temporal heterogeneity is also a crucial aspect for understanding the temporal dynamics between ULUE and each socioeconomic factor. Considering the spatial and temporal non-stationary effects of such associations contributes to revealing dominant socioeconomic factors influencing ULUE for different regions during different time periods. However, few studies considered both spatial and temporal heterogeneity of the determinants of ULUE in Chinese cities.

2.4. Research gaps

To summarize, existing studies have extensively evaluated spatiotemporal evolution of ULUE in China at different scale (e.g., nation, urban agglomeration, province) under different context such as low-carbon city policy, regional integration, coordination of urban agglomeration. To examine the determinants of ULUE, various econometric regression models including Tobit regression model, spatial econometric models have been conducted. However, there are still some limitations in existing studies. (1) Little is known about the spatiotemporal patterns and the fine-grained regional disparities of the ULUE in Chinese cities under the concept of green development. (2) Few studies incorporated remote sensing data and statistical data to assess green development oriented ULUE. (3) The spatiotemporal heterogeneity of the associations between ULUE and its determinants remains lacking. To address these gaps, we employed remote sensing data to assess CO2 and PM2.5 concentrations at the municipal level, considering them as undesirable outputs of green development oriented ULUE. We also used GTWR model to illustrate how the impacts of socioeconomic development on ULUE varied in 284 Chinese cities and eight economic zones over space and time.

3. Materials and methodology

3.1. Study area

The study area of this thesis is 284 cities in China. Due to the unavailability of relevant data, Hong Kong, Macao, Taiwan, Tibet, and some cities (e.g., Haidong in Qinghai Province, Bijie in Guizhou Province, Tianmen in Hubei Province, etc.) are excluded. The built-up areas of selected cities account for 96% of the built-up areas in mainland China, while the urban population in these cities accounts for 97.2% of the urban population in mainland China (Fig. 1). Due to the differences in socioeconomic status and resource endowment in China, the sample cities could be divided into eight economic zones proposed by the Development Research Center of the State Council. Specifically, the Northeast economic zone (NEEZ) includes cities in Jilin, Heilongjiang, and Liaoning; the Northern coastal economic zone (NCEZ) includes cities in Beijing, Tianjin, Hebei, and Shandong; the Eastern coastal economic zone (ECEZ) includes cities in Shanghai, Jiangsu, and Zhejiang; the Southern coastal economic zone (SCEZ) includes cities in Fujian, Hainan, and Guangdong; the Yellow river midstream economic zone (YEMEZ) includes cities in Shaanxi, Shanxi, Henan, Inner Mongolia; the Yangtze River midstream economic zone (YAMEZ) includes cities in Hubei, Hunan, Jiangxi, and Anhui; the Southwestern economic zone (SWEZ) includes cities in Guizhou, Sichuan, Chongqing, and Guangxi; the Northwestern economic zone (NWEZ) includes cities in Gansu, Qinghai, Ningxia (Table 1).

3.2. Data collection and pre-processing

Table 2 summarizes the relevant data information. The Center for Global Environmental Research provides the Open-Data Inventory for Anthropogenic Carbon dioxide (ODIAC), presenting the global CO_2 emissions (Oda & Maksyutov, 2022). This dataset contains spatial data of CO_2 emissions from fossil fuels with a high resolution of 1×1km from 2000 to 2019, which can help derive values of CO_2 emissions in Chinese cities in the recent 20 years. In terms of PM2.5 concentration data, the Atmospheric Composition Analysis Group from Washington University in St. Louis estimated PM2.5 concentration by combining various satellite data. They provide global annual mean PM2.5 raster data with a resolution of $0.01^\circ \times 0.01^\circ$ from 1998 to 2020, from which the PM2.5 concentration of Chinese cities can be derived (van Donkelaar et al., 2021). Additionally, the nighttime light data is obtained from the NPP-VIIRS satellite data of the Harvard dataset (Z. Chen, Yu, et al., 2020b). To ensure the consistency of spatial resolution of remote sensing data, we firstly clipped the global data using the boundary of China, and then aggregated the values of each raster grid within each city based on the municipal administrative boundaries. Lastly, we repeated the same processes for each raster image of different years in each dataset to obtain the annual values of each indicator at the municipal level. Other statistical data are from Chinese city statistic yearbooks (2005–2019), Chinese construction yearbooks (2005–2019), various provincial statistic yearbooks (2005–2019), and the statistical bulletins of national economic and social development of cities. A few missing values in several years were supplemented by using linear interpolation according to the trend (Wei et al., 2004; Zhao & Wei, 2019). Besides, all the variables with monetary value were adjusted to the 2005 constant prices using price deflators to ensure comparability.

3.3. Methods

3.3.1. The super efficiency SBM

As mentioned in section 2.2, the DEA method is a mainstream approach to measuring ULUE as it can evaluate the relative efficiency of a set of decision-making units (DMUs) - in this study, cities - without setting prior functions and parameters weights (Wei et al., 2004; Zhao & Wei, 2019). The principle of the DEA is to develop an efficient frontier based on multiple combinations of inputs and outputs and measure the gaps between each DMU and the frontier (Shen & Zhang, 2012). However, the traditional radial DEA model neglect slack variables, and the undesirable outputs are not considered in this approach. To solve this problem, Tone (2001) proposed the SBM by taking into account slack variables in the objective function, which avoids ignoring the effects of

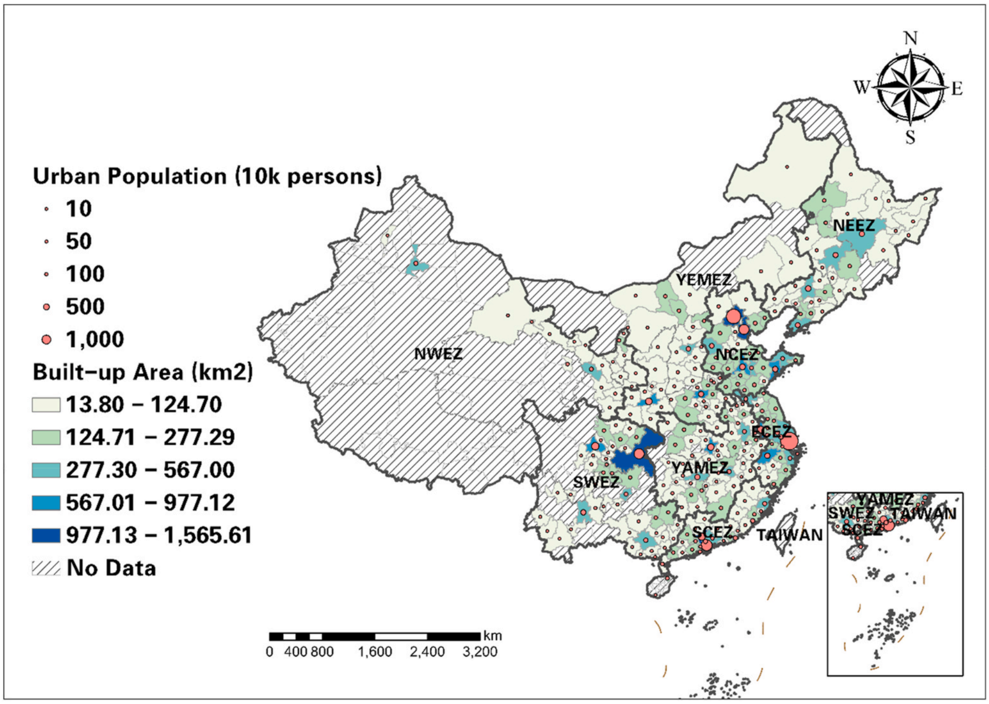

Fig. 1. Overview of the Study area in China.

Table 1
Summary of 8 Economic zones in China.

Abbreviation	Economic Zone	Cities
ECCEZ	The Eastern Coastal Comprehensive Economic Zone	Cities in Shanghai, Jiangsu, and Zhejiang
NCCEZ	The Northern Coastal Comprehensive Economic Zone	Cities in Beijing, Tianjin, Hebei, and Shandong
NECEZ	The Northeast Comprehensive Economic Zone	Cities in Jilin, Heilongjiang, and Liaoning
NWCEZ	The Northwestern Comprehensive Economic Zone	Cities in Gansu, Qinghai, and Ningxia, Tibet, Xinjiang
SCCEZ	The Southern Coastal Comprehensive Economic Zone	Cities in Fujian, Hainan, and Guangdong
SWCEZ	The Southwestern Comprehensive Economic Zone	Cities in Yunnan, Guizhou, Sichuan, Chongqing, and Guangxi
YAMCEZ	The Yangtze River Midstream Comprehensive Economic Zone	Cities in Hubei, Hunan, Jiangxi, and Anhui
YEMCEZ	The Yellow River Midstream Comprehensive Economic Zone	Cities in Shaanxi, Shanxi, Henan, and Inner Mongolia

Table 2
Summary of data.

Data type	Data description	Source (acquisition time)	Spatial Resolution
Remote sensing data	Raster data of annual mean CO_2 emission	https://db.cger.nies.go.jp/dataset/ODIAC/(July 15, 2022)	1 km × 1 km
	Raster data of annual mean PM2.5 concentration	https://sites.wustl.edu/acag/datasets/surface-pm2-5/#versioninfo (July 15, 2022)	0.01° × 0.01°
	Raster data of global NPP-VIIRS-like nighttime light data	https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/YGIVCD (July 15, 2022)	15 arcsec (~500 m)
Statistical data	Socioeconomic data	Chinese city statistic yearbooks (July 01, 2022) Provincial statistic yearbooks (July 01, 2022) The statistical bulletins of national economic and social development (July 01, 2022)	Municipal level
	Urban land-use data	Chinese construction yearbooks (July 01, 2022)	

undesirable outputs. Generally, the SBM model is not able to differentiate among the efficient DMUs as the values for all the efficient DMUs would be 1. However, this shortage can be overcome by the super-efficiency SBM (Tian et al., 2020). Hence, this study adopted the super-efficiency SBM model to estimate ULUE, which allows to compare ULUE values of the efficient cities. The function is shown below:

$$min\,\varnothing = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\bar{x}}{x_{ik}}}{\frac{1}{r_1+r_2}\left(\sum_{s=1}^{r_1}\frac{\bar{y^d}}{y^d_{sk}}+\sum_{q=1}^{r_2}\frac{y^u}{y^u_{qk}}\right)}$$

$$s.t.\left\{\begin{array}{l} x \geq \sum_{j=1,\neq k}^{n} x_{ij}\lambda_j \quad i=1,2,\ldots,m \\ y^d \leq \sum_{j=1,\neq k}^{n} y_{sj}^d\lambda_j \quad s=1,2,\ldots,r_1 \\ y^d \geq \sum_{j=1,\neq k}^{n} y_{qj}^u\lambda_j \quad q=1,2,\ldots,r_2 \\ \lambda \geq 0 \quad \mathrm{j}=1,2,\ldots,\mathrm{n} \\ x \geq x_k \quad \mathrm{k}=1,2,\ldots,\mathrm{m} \\ y^d \leq y_d^k \quad \mathrm{q}=1,2,\ldots,r_1 \\ y^u \geq y_k^u \quad \mathrm{u}=1,2,\ldots,r_2 \end{array}\right\}$$

where, m, r_1, r_2, denote input, desirable outputs, and undesirable outputs respectively; x, y^d, y^u denote elements in the corresponding input matrix, desirable output matrix, and undesirable output matrix; $\varnothing$ is the value of land use efficiency, when $\varnothing \geq 1$, DMU (city in this study) is efficient, while it is inefficient when $\varnothing < 1$.

As for the variables, we selected built-up area, employees of secondary and tertiary sectors, and values of fixed assets investment as land, labor, and capital inputs, respectively (Hu et al., 2022). For the desirable outputs, we selected value-added from secondary and tertiary industries as economic output since it reflects urban economic growth (Dong et al., 2020; Tang et al., 2021). Besides, we selected local government revenue as societal output since it includes urban public utility revenue for social welfare-related development, such as education, public health, science, and culture (Song et al., 2022). In addition, we selected per capita green park area as environmental output because it is a positive indicator of sustainable urbanization (Xie et al., 2021). As for undesirable outputs, sulfur dioxide emissions, industrial wastewater discharge, and industrial soot discharge are included as industrial pollution (Tang et al., 2021). Additionally, according to the requirement of green development, we selected CO_2 emissions, and PM2.5 concentrations as another two undesirable outputs (Lin & Jiang, 2022). The descriptive statistics of input-output variables are shown in Table 3.

3.3.2. Spatiotemporal analysis of ULUE evolution

To investigate the spatiotemporal evolution of ULUE, we first conducted the KDE analysis, which can describe the probability distribution of random variables using continuous curves, to reveal the distribution locations, shape, and ductility of ULUE (Wang et al., 2021). To evaluate whether ULUE in Chinese cities is spatially clustered, dispersed, or randomly distributed, Global Moran's I index will be conducted to examine the spatial autocorrelation of ULUE in each year from 2005 to 2019. Besides, Local indicators of spatial association (LISA) will be further used to demonstrate whether there are high-high clusters, high-low clusters, low-low clusters, or low-high clusters of ULUE in Chinese cities in particular years (Anselin, 1995). The Global Moran's I index can be expressed as:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i-\overline{x})(x_j-\overline{x})}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\right)\sum_{i=1}^{n}(x_i-\overline{x})^2}$$

LISA can be calculated as:

$$I_i = \frac{\sum_{j=1}^{n} W_{ij}(x_i-\overline{x})(x_j-\overline{x})}{\frac{1}{n}\sum_{i=1}^{n}(x_i-\overline{x})^2}$$

Where x_i and x_j are the values of ULUE of cities i and j. $\overline{x}$ is the average value of ULUE of all cities. W_{ij} is the spatial weight matrix corresponding to the cities pair i and j; and n is total number of cities. The positive Global Moran's I value means cluster pattern, while negative value means disperse pattern. Besides, the positive value of local indicators means the correlation becomes increasingly significant with the aggregation of locations, and vice versa.

3.3.3. Geographically and temporally weighted regression model

The GTWR model is an extension of the GWR model by introducing temporal effects based on the GWR model (Huang et al., 2010). Traditional econometric regression models such as the ordinary least square model (OLS) can only present the global impacts of explanatory variables on the independent variable, which is an average effect. However, most geographic phenomena such as ULUE are sensitive to space and time, which contain both spatial and temporal correlations. The GTWR model can take into account spatial and temporal non-stationary effects, producing more accurate results for the assessment. Hence, this study employs the GTWR model to investigate the impacts of socio-economic activities on the ULUE of Chinese cities over space and time. The GTWR function is defined as:

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

Where (u_i, v_i, t_i) denotes the spatiotemporal coordinates of the i^{th} city; $\beta_0(u_i, v_i, t_i)$ denotes the intercept; $\beta_k(u_i, v_i, t_i)$ denotes the estimated coefficient of the determinant of ULUE X_{ik} and ε_i is the residual error term. The estimated coefficient of the k^{th} determinant of i^{th} city can be defined as:

$$\widehat{\beta}(u_i, v_i, t_i) = \left[X^T W_i X\right]^{-1} X^T W_i Y$$

Where X and Y denotes a $n \times (p+1)$ matrix of the determinants and the vector of dependent variables, respectively; W_i is an $n \times n$ diagonal matrix of spatiotemporal weight, which can be calculated using a Gaussian kernel function:

$$w_{ij} = \exp\left(\frac{\lambda\left(d_{ij}^S\right)^2 + \mu\left(d_{ij}^T\right)^2}{h_{ST}^2}\right)$$

Where λ and μ respectively denote scale factors in the spatial metric

Table 3
Descriptive statistic of input-output variables of the ULUE.

variable	Description	Mean	Std. dev.	Max	Min	Unit
Land input	Built-up area	156.38	187.73	1515.41	6	km^2
Capital input	Values of fixed assets investment	10,715,157	12,935,036	147,000,000	273,351	100,00 yuan
Labor input	Employees of the secondary and tertiary sectors	511,626	768,246.4	9,518,500	42,000	persons
Economic output	Value-added from secondary and tertiary industries	15,166,397	23,678,128	283,000,000	320,157	10,000 yuan
Societal output	Local government revenue	1,450,226	3,455,746	58,292,510	14,024	10,000 yuan
Environmental output	Per capita Park green area	12.03	5.03	75.05	0.89	m^2/person
Undesirable output	Sulfur dioxide emission	49,981.85	56,044.23	683,162	2	ton
	Industrial wastewater discharge	7611.89	20,403.74	704,746	7	10,000 tons
	Industrial soot discharge	30,438.92	116,698.8	5,168,812	34	10,000 tons
	CO_2 emissions	785.50	848.23	7953.48	21.03	10,000 tons
	PM2.5 concentrations	45.75	15.85	108.87	13.34	$\mu g/m^3$

system and the temporal metric system; d_{ij}^S and d_{ij}^T denote spatial distance and temporal distance between object i and j; h_{ST}^2 denotes spatiotemporal bandwidth satisfying the following relationships with spatial bandwidth h^S and temporal bandwidth h^T:

$$\begin{cases} \left(h^S\right)^2 = h_{ST}^2 / \lambda \\ \left(h^T\right)^2 = h_{ST}^2 / \mu \end{cases}$$

In this study, ULUE is the dependent variable, and the independent variables include diverse socio-economic activities. Specifically, per capita GDP (PGDP) reflects economic development and is supposed to have a positive impact on ULUE (Yu et al., 2019). Industrial structure (IDS) is measured by the proportion of value-added from secondary industry to GDP, which is supposed to be negatively related to ULUE because of heavy energy consumption and environmental pollution (Cao et al., 2019). Due to the availability of data, the value of import and export was used as a proxy to measure the degree of openness (OPEN). The degree of openness is supposed to have various impacts on ULUE according to different modes of foreign investment (Lu et al., 2020). Investment in real estate (REI) reflects dependency on natural endowments and exploitation of land resources, which should influence ULUE to various degrees (Song et al., 2022). Urban population density (PD) and nighttime light (NTL) can reflect degrees of urbanization and urban sprawl, which is anticipated to positively influence ULUE based on the global regression analysis (Zhang et al., 2022). Per capita road areas (ROAD) are also selected to represent the construction of infrastructure in a city, which can promote urbanization but probably disrupt urban landscapes. Therefore, it is supposed to have both positive and negative impacts on ULUE (He et al., 2020). Investment in technology and science (TECH) is supposed to positively influence ULUE due to it is beneficial to the transformation of production mode that can reduce undesirable outputs (Song et al., 2022). The descriptive statistic of dependent and independent variables is shown in Table A1. To avoid the effects of multicollinearity, the variance inflation factors (VIF) test is used to detect the multicollinearity of 8 explanatory variables. The result shows that VIF is less than 5 for all variables, indicating that there is no multicollinearity in the explanatory variables. The performance of the GTWR model was evaluated by adjusted R^2 and the Akaike information criterion (AICc). The higher R^2 and lower AICc represent better performance. The overall workflow of this study is presented in Fig. 2.

4. Results

According to the results of the super efficiency SBM, the annual average ULUE score of China saw a noticeable growth from 0.404 to 0.550 during 2005–2019, despite fluctuation. The number of efficient cities in China significantly increased from 30 in 2005 and achieve a peak of 61 in 2018 before decreasing to 52 in 2019.

4.1. Spatiotemporal evaluation of ULUE at regional scale

The temporal evolution of ULUE in eight economic zones is shown in Fig. 3. ULUE of all economic zones presents the tendency to generally increase with slight fluctuations from 2005 to 2019. Generally, SCEZ

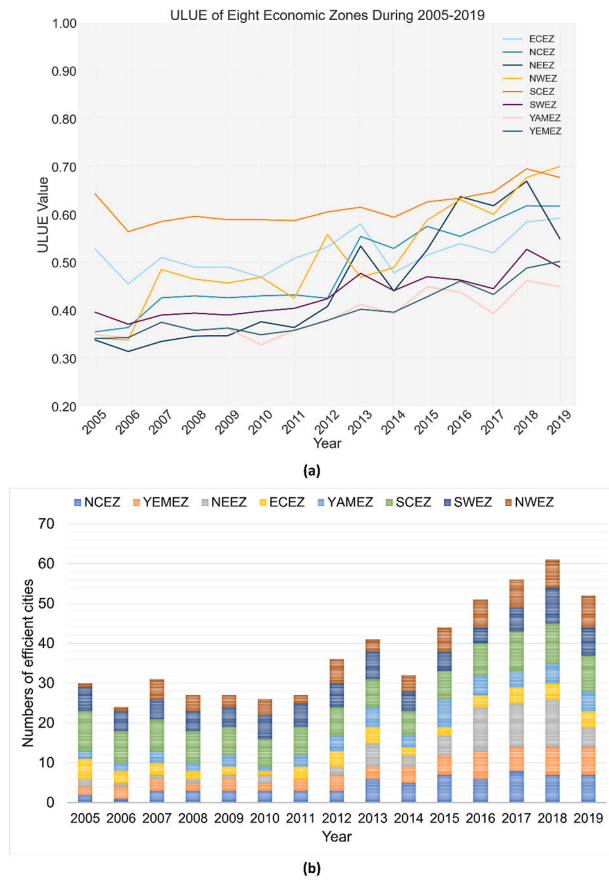

Fig. 3. Spatiotemporal patterns of ULUE in eight economic zones during 2005–2019.

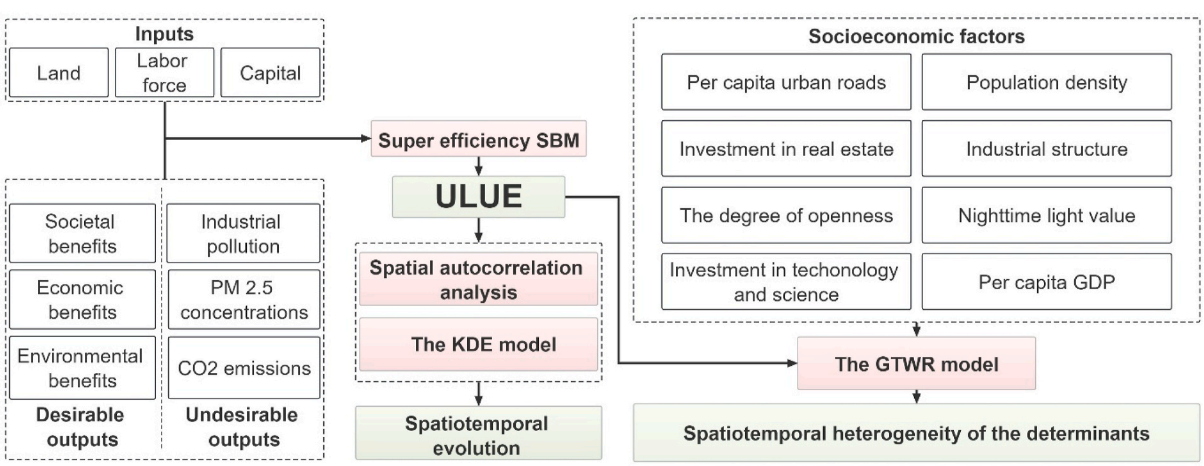

Fig. 2. The overall workflow of this study.

kept relatively high ULUE during 2005–2019, with ULUE values higher than 0.550 each year, which is significantly higher than the average level in the whole of China. By contrast, the YAMEZ and the YEMEZ showed relatively low ULUE, being lower than the average level in the whole of China each year. Moreover, ULUE of NCEZ, NEEZ, and NWEZ saw a significant increase during 2005–2019, with added values of 0.262, 0.211, and 0.358, respectively, indicating that these regions made great progress in green development and sustainable urbanization during 2005–2019. In terms of the number of efficient cities, SCEZ included the largest number of efficient cities in most years, while NWEZ witnessed great progress in increasing efficient cities, with an increasing number from 1 in 2005 to 8 in 2019. However, an unexpected result shows that although the average ULUE of ECEZ is relatively high, the proportion of efficient cities in various years is relatively small. This result illustrates that despite the high value of ULUE, the urban land use of most cities in ECEZ did not achieve an efficient level under green development orientation.

4.2. Spatiotemporal evaluation of ULUE at city scale

Fig. 4 demonstrates the spatiotemporal distribution of ULUE in Chinese cities, showing the intraregional differences within eight economic zones. We divided the cities into 5 groups based on the values of ULUE. Specifically, cities with ULUE value ≥ 1 were categorized as efficient cities according to the principle of the super efficiency SBM, which means the inputs and outputs in these cities attained a relatively balance state. For cities exhibiting inefficiency (e.g., ULUE < 1), we followed one previous study and equally divided the ULUE values into four ranges, thereby establishing four distinct categories: highly inefficient cities (ULUE ≤ 0.25), moderately inefficient cities ($0.25 <$ ULUE ≤ 0.5), slightly inefficient cities ($0.5 <$ ULUE ≤ 0.75), and nearly efficient cities ($0.75 <$ ULUE < 1) (Cao et al., 2019). In 2005, slightly efficient cities and efficient cities were concentrated in the southern coastal economic zone and the eastern coastal economic zone of southeastern China, especially in 2 developed regions, that is, Pearl

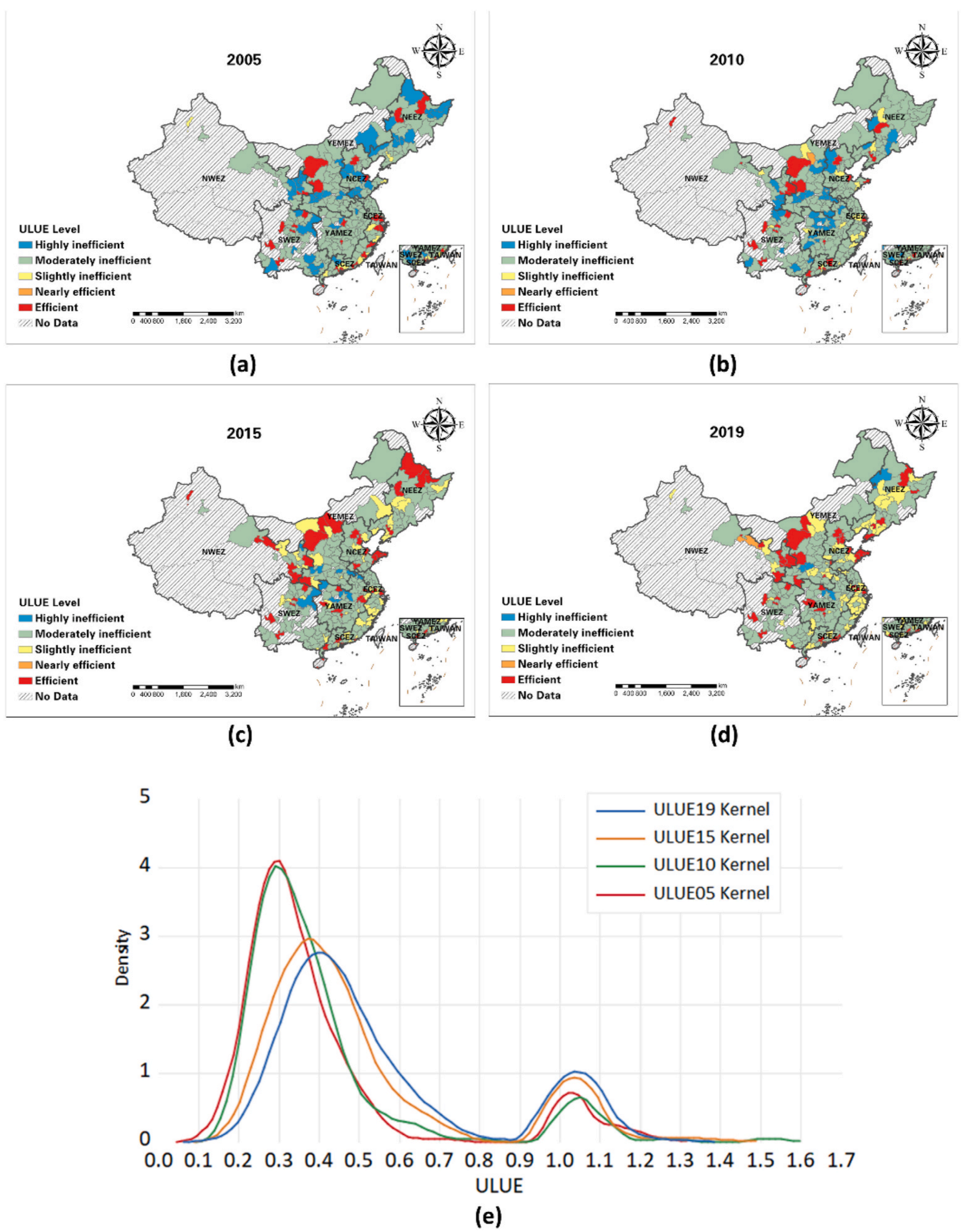

Fig. 4. Spatiotemporal patterns of ULUE in Chinese cities during 2005–2019.

Reiver Data (PRD) and Yangtze River Delta (YRD). Urban land use of 9 cities in the 2 regions including Shenzhen, Foshan, Dongguan, Zhongshan, Shanghai, Wuxi, Suzhou, Ningbo, and Shaoxing achieved an optimal level of ULUE. Besides, many Northern cities and western cities performed at a highly inefficient level of ULUE despite there being certain efficient cities, such as Zigong, Daqing, Lijiang, ordos, etc. In 2010, the number of highly inefficient increased in the Yangtze River midstream economic zone of central China, whereas it noticeably declined in the southwestern economic zone, the northern coastal economic zone, and the northeast economic zone. Moreover, the number of efficient cities within southeastern China slightly declined. From 2010 to 2015, most cities presented an increasing trend of ULUE, suggesting that green development of urban land use made great effects. Many northwestern cities in the Yellow River midstream economic zone and the northwestern economic zone and northeastern cities in the northeast economic zone achieved an efficient level of urban land use, such as Baotou, Eros, Zhangye, Qingyang, Jiayuguan, Hegang. In 2019, the number of efficient cities continuously increased, and many cities transferred from moderately inefficient cities to slightly inefficient cities, with only a few highly inefficient cities remaining in inland China, such as Yuncheng, Weinan, Qiqihar, Xiaogang, and Huanggang. Overall, although highly inefficient cities and moderately inefficient cities gradually decreased during 2005–2019, a large proportion of cities still witnessed a moderately inefficient level and 80% of cities did not achieve an efficient level, revealing great challenges for efficient urban management.

In terms of the KDE result, the curve shows the characteristics of double peaks since 2005, indicating that there is a polarization effect of ULUE in 284 Chinese cities (Fig. 4e). The kernel density of the first peak is much higher than that of the second peak, which implies that the proportion of cities with low ULUE is higher than that of cities with high ULUE. Besides, the curve shape of the main peak become smoother, and the peak value become smaller from 2005 to 2019, suggesting that the degree of polarization effect declined noticeably, and the regional differences enlarged. As for the curve position, the center of the curve moves to the right and the value of the second peak continuously increases during 2005–2019. This pattern indicates that cities gradually moved from the low-ULUE group to the high-ULUE group and the proportion of cities with high ULUE became larger whilst the proportion of low-ULUE cities became smaller during 2005–2019.

Besides, the positive Moran's I value demonstrates that ULUE was spatially clustered during 2005–2019, which means the ULUE performance of a city is supposed to be influenced by its neighboring cities (Table A2). The local autocorrelation results show that in 2005, high-high agglomerations were mainly located in the southern coastal economic zone and the eastern coastal economic zone of southeastern China, indicating high-ULUE cities often cluster together. In addition, low-high outliers mainly occurred in cities surrounding these regions, indicating that low-ULUE cities were surrounded by high-ULUE cities. On contrary, the largest low-low agglomerations were approximately located in central China across the northern coastal economic zone, the Yangtze River midstream economic zone, and the Yellow River midstream economic zone, in which certain cities such as Dongying, Puyang, Xucang, Luohe, and Jincheng showed patterns of high-low outliers. Moreover, there were certain low-low agglomerations located in the north of the northeast economic zone, the southeast of the southwestern economic zone, and the east of the northwestern economic zone (Fig. 5a). From 2005 to 2010, low-low clusters in the northeast economic zone and the northwestern economic zone were eliminated, while the central low-low agglomeration expanded to the west and south. In addition, the high-high cluster of the eastern coastal economic zone was also eliminated, while the high-high clusters in the southern coastal economic zone recessed, with several cities in PRD and eastern Guangdong including Guangzhou, Foshan, Zhongshan, Zhuhai, Zhaoqing, Jieyang, Chaozhou, Shantou, and Shanwei remaining. Besides, 2 emerging low-high clusters occurred in Jiuquan and Yulin, which means

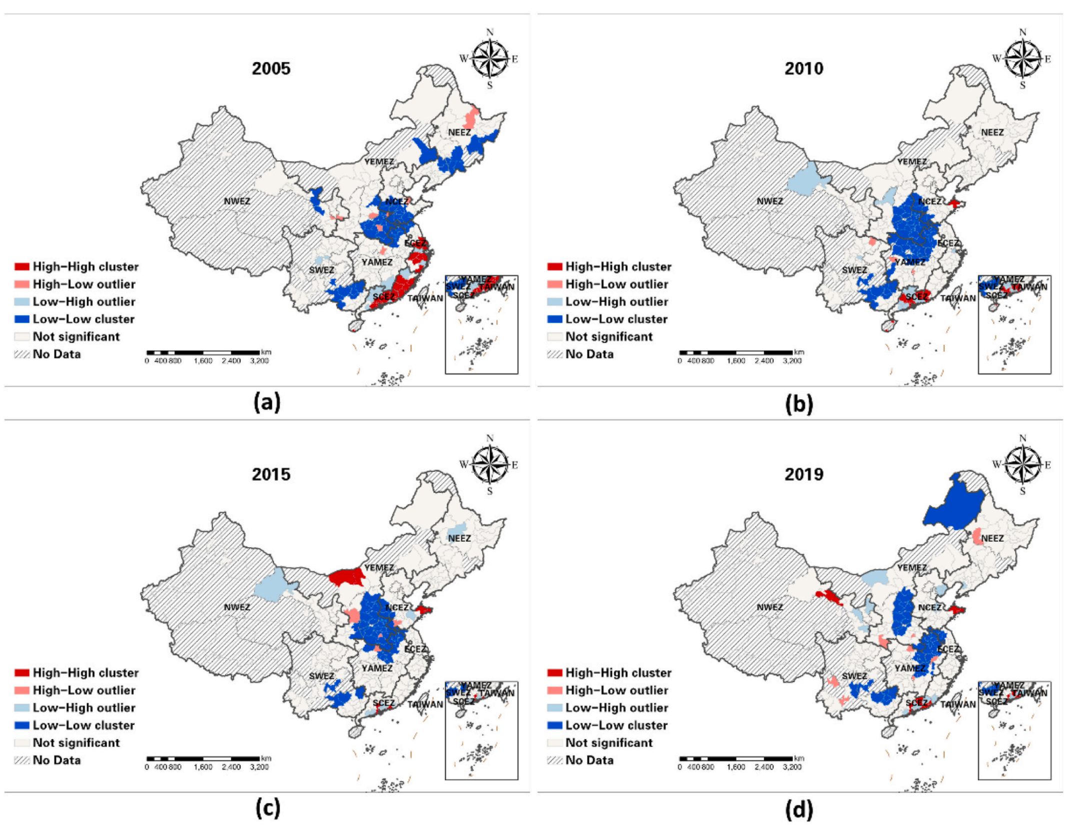

Fig. 5. LISA map of ULUE in Chinese cities during 2005–2019.

these 2 cities were surrounded by cities with relatively high ULUE values (Fig. 5b).

In the next 5 years, the high-high clusters in PRD and the low-low clusters in the southwestern economic zone continuously recessed, while there were 2 emerging high-high clusters located in the Bayan Nur, Baotou, Yantai, and Weihai. Additionally, the low-low clusters in central China expanded from the south to the north. Moreover, certain emerging high-low clusters occurred in cities near or inside the central low-low agglomeration, for example, Yanan Jilin, Suizhou, and Luohe, which is probably because ULUE of these cities noticeably increased during this period. In addition, an emerging low-high agglomeration in Suihua and Weifang, indicating that they were surrounded by cities with relatively high ULUE (Fig. 5c). In 2019, the most noticeable pattern was that the low-low clusters in central China were eliminated, replaced by 2 emerging low-low clusters in the Yellow River midstream economic zone and the Yangtze River midstream economic zone. Surprisingly, the high-high cluster in Bayan Nur transferred into low-high outliers, which is probably because the ULUE value in Bayan Nur increased slower than in surrounding cities. Besides, a high-high cluster occurred in Zhangye, while several low-high agglomerations occurred in Baiyin, Wuzhong, Yinchuan, and Tianshui. Moreover, a few high-low agglomerations are scattered in various regions (Fig. 5d).

4.3. Spatiotemporal impact of the determinants on ULUE

4.3.1. General results of the GTWR

The OLS model, the TWR model, the GWR model, and the GTWR were conducted to estimate the impacts of the determinants on ULUE of Chinese cities, respectively. Compared with other 3 models, the GTWR model presents the highest adjusted R^2 and the smallest AICc, indicating that the GTWR performed the best among the models (Table A3). The adjusted R^2 of the GTWR model is 0.442, which means the selected variables can explain 44.2% of the identified variance in ULUE. The coefficient summary reveals that the impacts of per capita GDP, investment in technology and science, and the degree of openness on ULUE are predominantly positive, albeit with slight heterogeneity, which is evident from the positive lower quartile coefficients of these variables. Conversely, the generally adverse effects of investment in real estate, the industrial structure, and population density on ULUE are shown despite of slight heterogeneity because of the negative upper quartile coefficients. However, the associations between per capita urban road and nighttime light value and ULUE exhibit relatively notable spatiotemporal heterogeneity, as evidenced by the divergent directions of the lower quartile and upper quartile coefficients (Table 4).

4.3.2. Temporal heterogeneity of determinants at regional scale

Figs. 6 and 7 illustrates the temporal variations in mean coefficients of determinants in eight economic zones in China. We found that per capita GDP generally positively influenced ULUE in eight economic zones over time. However, such positive correlation declined by various degrees in each economic zone from 2005 to 2019 in addition to the eastern coastal economic zone and the Yangtze River midstream economic zone. The decreasing trend reveals that the impacts of per capita GDP on ULUE were weakened over time, which is probably because economic growth was no longer the decisive criterion of efficient urban growth in cities within these regions under the concept of green development. The coefficients of industrial structure present a decreasing trend from positive to negative in the eastern coastal economic zone, the northern coastal economic zone, the southwestern economic zone, the Yangtze River midstream economic zone, and the Yellow River midstream economic zone. Such a trend reveals that secondary industry in these zones could improve ULUE in the early years but had negative impacts on ULUE in recent years, which is mainly because of the transformation of industrial structure. Besides, the south coastal economic zone and the southwestern economic zone presented an increasingly negative correlation between industrial structure and ULUE, indicating that secondary industry increasingly constrained ULUE in these economic zones during 2005–2019. However, the coefficient of industrial structure in the northeast economic zone declined and then increased during 2005–2019, which is further interpreted in the discussion section. Coefficients of the openness degree show a noticeable temporal heterogeneity in eight economic zones. Despite the fluctuation over time, the openness degree is positively related to ULUE in most regions except the south coastal economic zone and the southwestern economic zone, which means openness to the outside world contributed to improving ULUE. Nevertheless, the coefficient in the south coastal economic zone kept negative with fluctuation to increase from 2005 to 2015 and then decreased later, which is probably related to the relatively high openness degree in this region. Additionally, associations between the investment in real estate and ULUE kept a long-term negative pattern in each economic zone, with a generally strengthening trend in the eastern coastal economic zone and the northern coastal economic zone, and a weakened trend in the northeast economic zone, the south coastal economic zone, the southwestern economic zone, and the Yellow River midstream economic zone.

In terms of population density, it shows a strengthening negative association with ULUE over time in most economic zones except for the south coastal economic zone, indicating that population density continuously constrained ULUE in many regions. Population density in the south coastal economic zone positively influenced ULUE from 2006 to 2010, after then the influence transferred to negative. Besides, in the eastern coastal economic zone, the south coastal economic zone, the southwestern economic zone, and the Yangtze River midstream economic zone, the impacts of nighttime light on ULUE were decreasingly positive during 2005–2019. Despite the negative correlation between nighttime light and ULUE in the northern coastal economic zone, the northwestern economic zone, and the Yellow River midstream economic zone, such correlation became weakened in recent years. Moreover, the negative association between nighttime light and ULUE gradually weakened during 2005–2014, and then transferred to increasingly positive during 2015–2019. Additionally, the coefficient of per capita urban roads in the south coastal economic zone, the Yangtze River midstream economic zone, and the Yellow River midstream economic zone showed increasingly negative patterns during 2005–2019, indicating that per capita urban roads negatively influenced ULUE in these regions to some degree. Furthermore, although per capita urban roads improved ULUE in the northeast economic zone, the northwestern economic zone, and the southwestern economic zone, this effect, however, weakened over time. Similar patterns were shown in the eastern coastal economic zone and the northern coastal economic zone, in which the association between per capita urban roads and ULUE transferred from positive to negative. Similar to per capita GDP, investment in technology and science is demonstrated to improve ULUE over time. The northwestern economic zone saw noticeably high coefficients from 2006

Table 4
Summary of parameters and coefficients of GTWR.

	Minimum	Lower Quartile	Median	Upper Quartile	Maximum
Intercept	−0.124	0.156	0.216	0.293	0.580
PGDP	−0.493	0.630	0.925	1.176	3.868
TECH	−1.187	0.128	0.217	0.317	4.873
REI	−5.799	−0.055	−0.405	−0.230	0.517
OPEN	−3.126	0.074	0.327	0.562	11.620
IDS	−0.733	−0.186	−0.093	−0.015	0.194
PD	−0.401	−0.147	−0.100	−0.061	0.199
ROAD	−0.266	−0.094	−0.021	0.109	1.462
NTL	−3.703	−0.393	0.162	0.552	5.414
Diagnostic information					
Adj $R^2 = 0.442$					
RSS = 68.65					
AICc = −5259.49					
Bandwidth = 0.115					

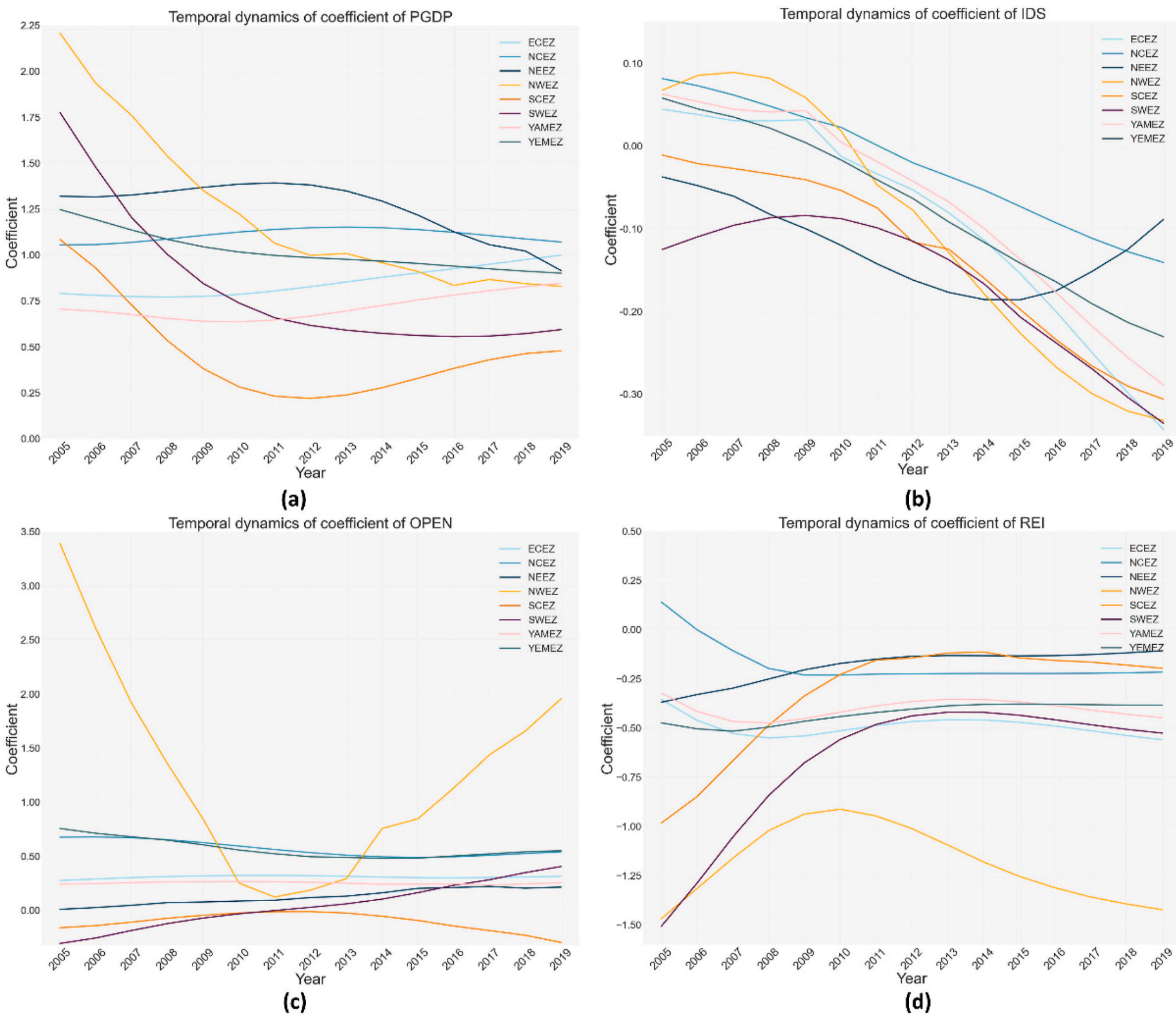

Fig. 6. Temporal heterogeneity of correlation between PGDP, IDS, OPEN, REI and ULUE.

to 2019. Unexpectedly, the positive influence of investment in technology and science performed a trend to weaken in most regions, which is likely because there were increasing other factors that can improve ULUE over time.

4.3.3. Spatiotemporal heterogeneity of determinants at city scale

As shown in Fig. 8 a-d, the coefficient of per capita GDP presents a decreasing trend from west to east in 2005, indicating that PGDP had a stronger positive association with ULUE in western cities than in eastern cities. This is probably because, in the early stage of the West China Development, economic growth effectively promoted urban growth in western cities. Such decreasing trend transited from west-east to north-south since 2010. Furthermore, in 2019, the positive coefficient of per capita GDP increased from south to north, and the northern coastal and the eastern coastal cities presented a higher coefficient than other cities, while certain cities in Heilongjiang province show negative coefficients. In terms of the coefficient of industrial structure, a decreasing trend was shown from coastal cities to inland cities between 2005 and 2015, with negative values shown in southwestern cities and northeastern cities (Fig. 8 e-h). Since 2015, a negative association between industrial structure and ULUE emerged in eastern coastal cities, whilst the negative association of northeastern cities gradually transited to positive due to industrial upgrading. For the coefficient of the openness degree, it showed a pattern that decreased from northern and western cities to northeast and south during 2005–2019 (Fig. 9 a-d). Although most cities presented a positive association between the openness degree and ULUE, a few cities (e.g., Baise, Chongzuo, Zhanjiang, Maoming, Heihe, Suihua, etc.) always presented a negative or insignificant correlation. In addition, the coefficient values of Investment in real estate decreased from east to west in 2005, and after then, most cities showed a negative association (Fig. 9 e-f). Specifically, noticeably negative associations were mainly concentrated in southeastern cities and western cities, while the negative associations were relatively weak in southern and northeastern cities.

Positive coefficients of population density were mainly presented in cities of the Yellow River midstream economic zone and southern cities, while negative coefficients of population density were shown in the rest of the cities in 2005 and 2010 (Figure A1 a-d). Specifically, the negative correlation was stronger in cities within the southwestern economic zone, the Yangtze River midstream economic zone, as well as the eastern coastal economic zone than cities in other regions. In 2015 and 2020, however, most cities presented a negative coefficient, while a few cities including Ordos, Bayan Nur, Jixi, and Jiamusi showed a positive coefficient. Moreover, the negative association between population density and ULUE was more significant in southwestern cities and eastern cities than in southern cities and northwestern cities. The coefficient of nighttime light presents noticeable variation from south to north, with positive values concentrated in southern cities and negative values concentrated in northern cities (Figure A1 e-h). Nevertheless, certain northwestern and northeastern cities such as Jiuquan, Yichun, Jixi,

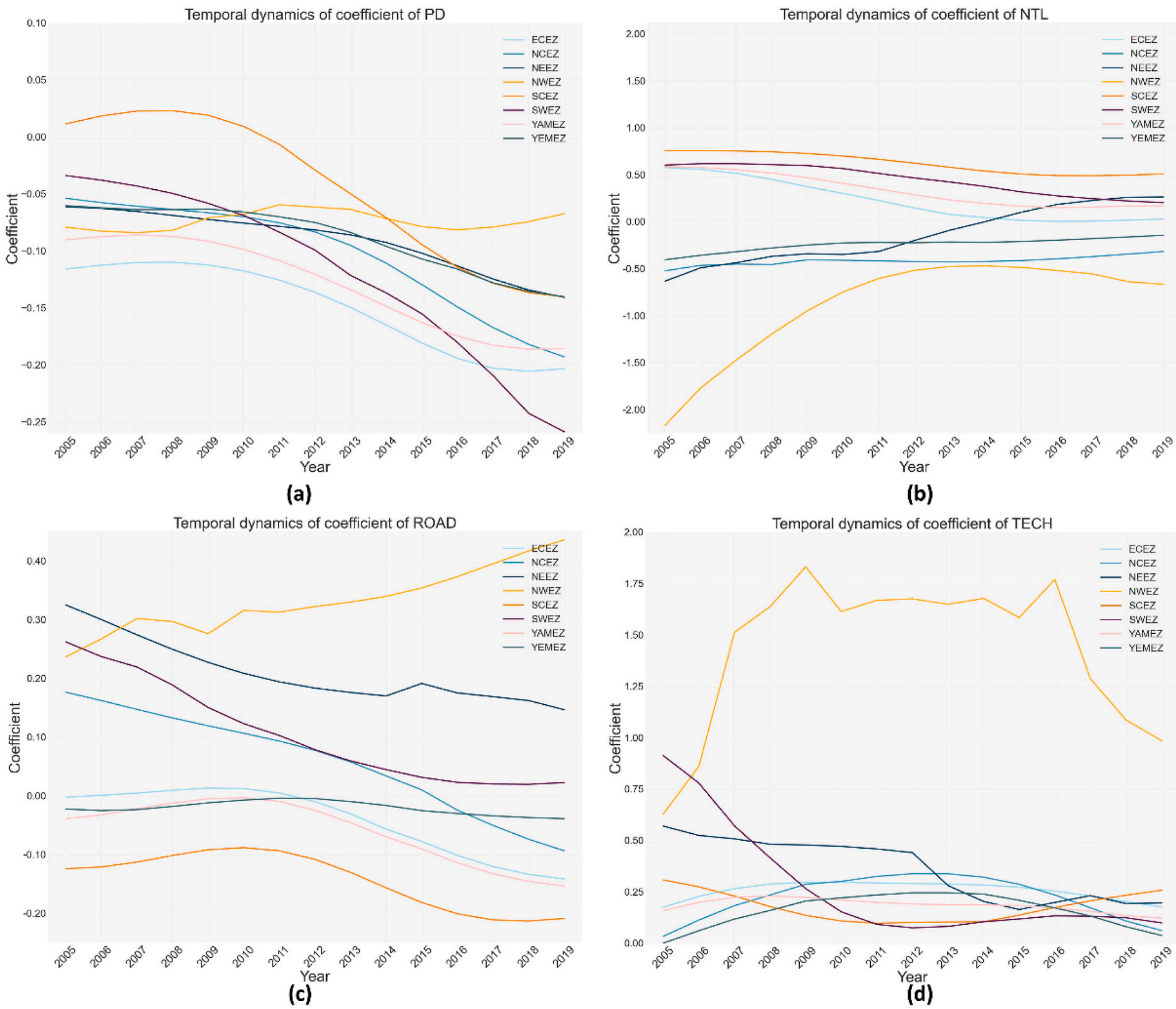

Fig. 7. Temporal heterogeneity of correlation between PD, NTL, ROAD, TECH and ULUE.

Shuangyashan, etc. presented a positive correlation since 2015. Interestingly, several northeastern cities with a negative relation between nighttime light and ULUE during 2005–2010 showed a positive correlation since 2015. For per capita urban roads, the coefficients generally increased from south to north (Figure A2, a-d). The significantly positive values were mainly concentrated in western cities and northeastern cities during 2005–2019, indicating that urban roads can improve ULUE in such areas. By contrast, the opposite impact of per capita urban roads on ULUE was shown in most southern and northern cities. Additionally, investment in technology and science positively influenced ULUE in most cities, except for several cities in Inner Mongolia, Gansu province, Hebei province, Shanxi province, and Shaanxi province in 2005 (Figure A2, e-h). Since then, the positive correlation presented a decreasing trend from coastal cities to inland cities, indicating that investment in technology and science in coastal cities could improve ULUE more effectively than that in inland cities.

5. Discussion

5.1. Spatiotemporal evolution of ULUE

This study reveals the spatiotemporal patterns of ULUE under green development orientation by using the super-efficiency SBM. Compared to the previous studies, this study introduces two important indicators of green development, that is, PM2.5 concentrations and CO_2 emission, to accurately measure ULUE (Han et al., 2020; Tang et al., 2021). From 2005 to 2019, ULUE in China generally increased with fluctuations. Judging from the national level, from 2005 to 2011, ULUE increased slowly, maintaining a value of ULUE around 0.41. With the national effort to promote sustainable urbanization (or called new-type urbanization in China) since 2012, ULUE experienced a noticeable increase from 0.418 to 0.550 during 2012–2019. This indicates that sustainable urbanization may effectively contribute to efficient urban management, and China is making noticeable efforts to develop sustainable urbanization (Wang et al., 2020).

Regarding the regional level, coastal regions showed higher ULUE than inland regions during 2005–2013, which is mainly due to the high-speed economic growth in the coastal regions. In recent years, the policy-oriented regional coordination weakened such spatial disparity, with ULUE in inland regions significantly improved. Noticeably, ULUE in the northwest economic zones, exhibited a significant increase, rising from 0.47 in 2013 to 0.70 in 2019. Meanwhile, the number of efficient cities within the Yellow River midstream economic zone increased from 3 to 7 during 2013–2019. These changes narrowed the gap of ULUE between coastal regions and inland regions, consistent with a previous study (Han et al., 2020). Additionally, ULUE in the northwestern economic zone made significant progress during 2005–2019, which is likely because of the West China Development. Relatively cheap land costs and sufficient natural resources attracted investment in western regions, contributing to beneficial outputs of urban land use (Grewal & Ahmed, 2011; He et al., 2020). Moreover, the revitalization of northeast China brought about more sustainable urbanization in the northeastern

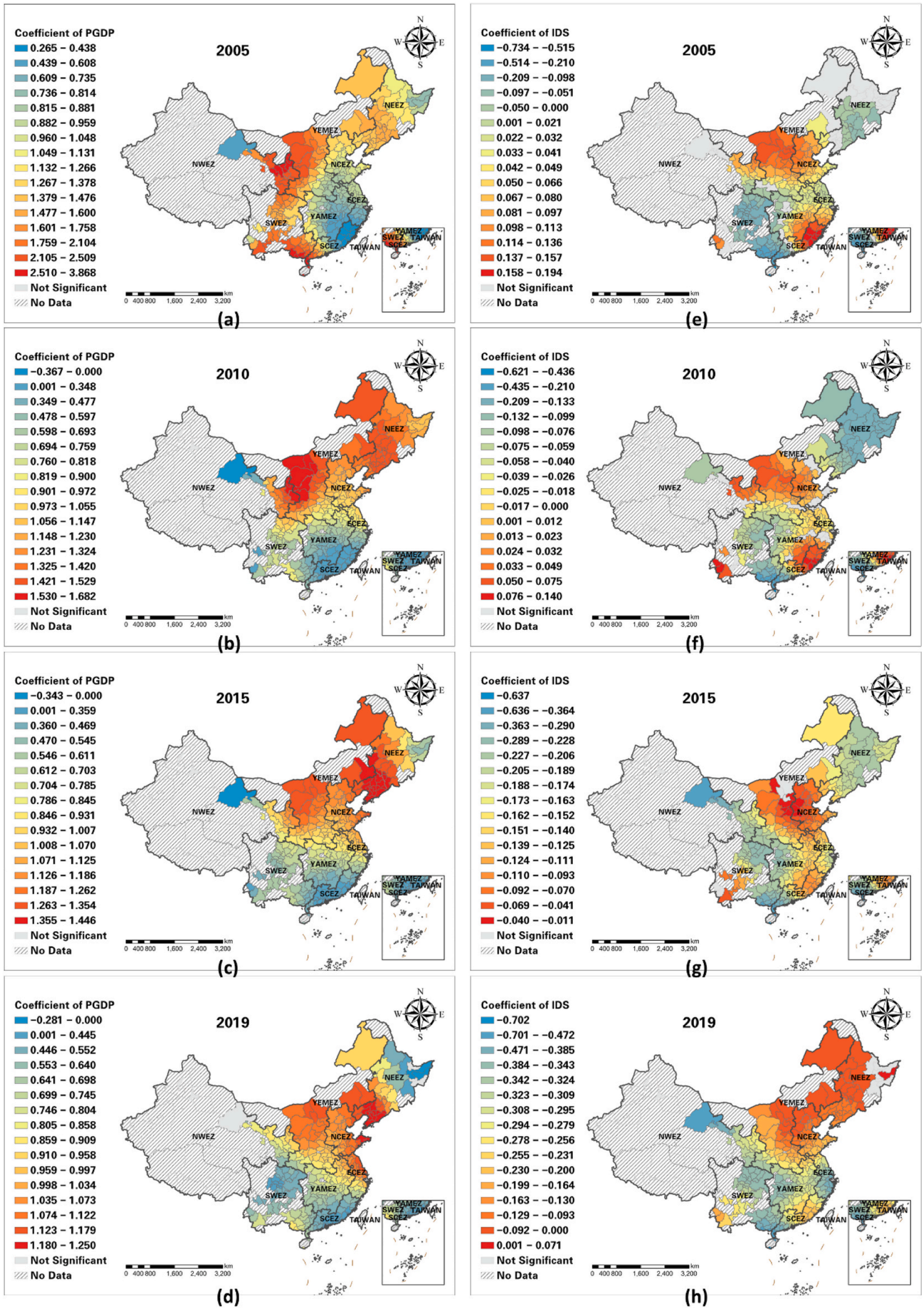

Fig. 8. Spatial heterogeneity of correlation between PGDP, IDS, and ULUE.

economic zone.

In terms of the city level, despite the significant spatiotemporal variations of ULUE, ULUE in a few cities maintains an efficient level during 2005–2019, such as Beijing, Shanghai, Shenzhen, Ordos, Pingxiang, Foshan, Sanya, Zigong, Bazhong, Ziyang, and Lijiang. Generally, despite the progress, China is still experiencing a polarization effect at the city level, with most cities, especially cities in central China still maintaining moderately inefficient levels. Such finding suggests that there is a long way to achieve overall green development in Chinese cities.

5.2. Spatiotemporal heterogeneity of the determinants' effects

Our study revealed significant spatiotemporal heterogeneity in the impacts of potential determinants, incorporating various underlying mechanisms. Specifically, per capita GDP positively influences ULUE

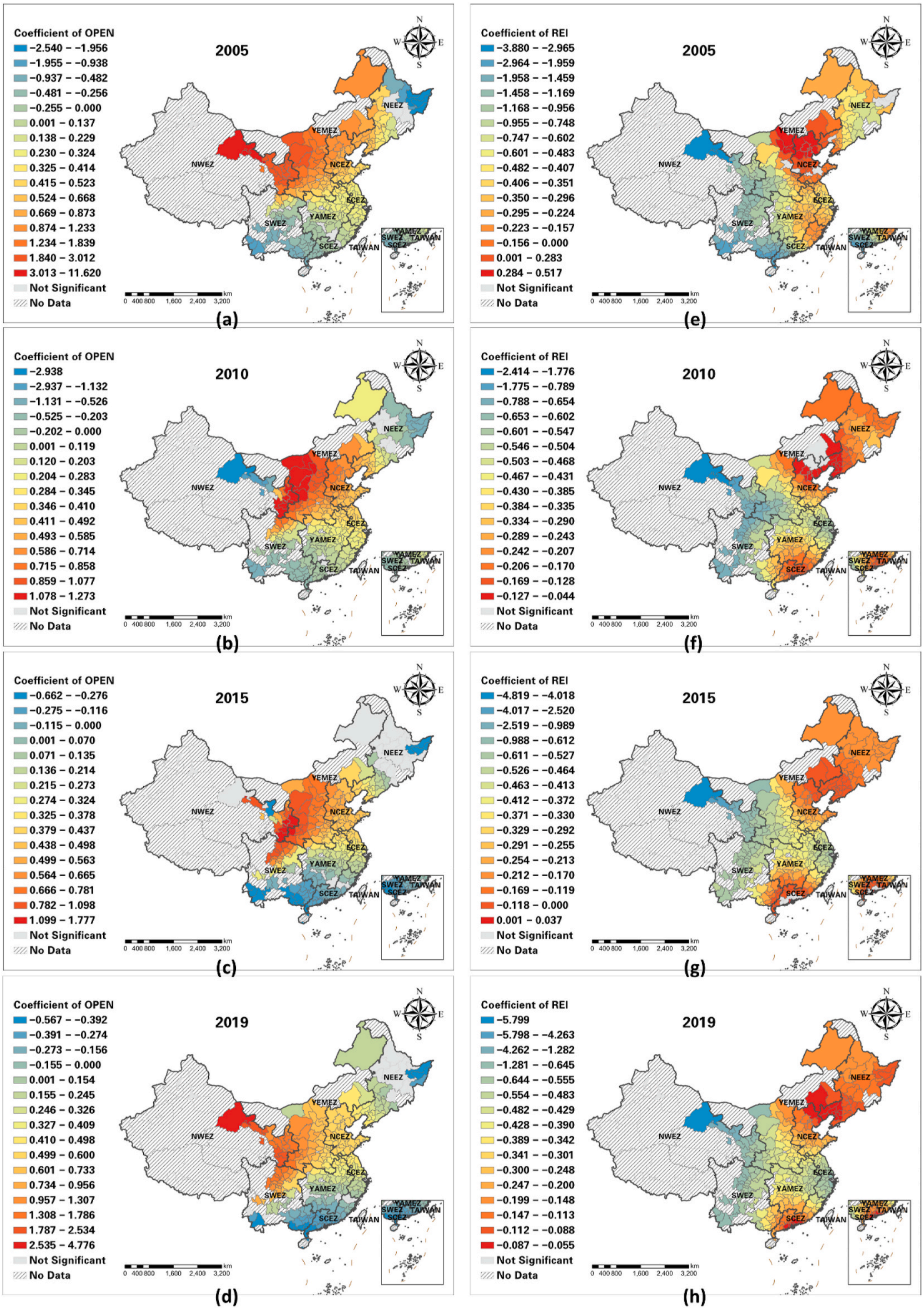

Fig. 9. Spatial heterogeneity of correlation between OPEN, REI, and ULUE.

mainly because the development of the endogenous economy is beneficial to increasing land use benefit. On the contrary, following urban land use increases development transiting to land stock development, efficient utilization of urban land can stimulate economic growth (Yu et al., 2019). Such relationships have been more sensitive in coastal cities in eastern and northern China in recent years, consistent with previous studies (Cao et al., 2019). As for industrial structure, in the early stage, the secondary industry could promote urban expansion and then stimulate economic growth in central and eastern cities (Li et al., 2019). However, because of the extensive development of the heavy industry, secondary industry negatively influenced ULUE in northeastern cities (Chen et al., 2018). Since then, the strategy for revitalization of old industrial bases in northeast China upgraded the industrial structures, improving ULUE in northeastern cities (Guo et al., 2020). However, following the increasing proportion of the tertiary industry, the positive effects of secondary industry gradually decreased and even transferred to negative in most cities, especially in eastern China.

The positive impact of the openness degree on ULUE in most regions is probably because the market openness to the international world promotes the transformation of industrial structure, and then improves the benefits of urban lands (Yu et al., 2019). Moreover, such positive influence strengthens with the increasing openness degree in several regions over time. Unexpectedly, such a positive association was stronger in western China rather than eastern China, which is inconsistent with a previous study (Cao et al., 2019) and needs further examination. A possible interpretation is the openness degree in western China is relatively lower than in eastern China, so the openness degree brings a higher marginal effect in western region than in eastern region. Furthermore, according to the Pollution Heaven Hypothesis, it should be noticed that international trade can probably result in excessive consumption of resources and environmental pollution, which is adverse to ULUE, especially for those areas with high openness degrees (An et al., 2021; Lu et al., 2020). This can partially explain the negative coefficients in a few cities. In terms of the investment in real estate, one possible reason for the negative association in most western and eastern cities over time is that the conversion of urban land use to residential purpose results in diminished socioeconomic returns, thereby leading to a decrease in ULUE within these cities (Song et al., 2022).

The positive association between population density and ULUE can be explained as follows. The growth of labor improves productivity, which strengthens the economic effects of urban lands to some degree. Therefore, the positive coefficient of population density in Southern China in the early stage can be partially explained by labor inflow (Chan, 2012). Similarly, the increasing labor flow to western cities improves the vitality of urban land use because of the West China Development. However, the increase in population denisity will probably result in excessive urban expansion and resource consumption, which negatively influences ULUE. Such association is presented in the majority of cities since 2015, which is corresponding to previous studies (Yu et al., 2019). In addition, a long-term and strong negative relation between population density and ULUE in cities of the southwestern economic zone and the Yangtze River midstream economic zone can be probably explained as the positive correlation between population density and PM2.5 concentrations (Liu et al., 2020). Nighttime light can partially reflect economic activities and urbanization levels. For one thing, frequent economic activities can increase economic outputs. For another, such activities are closely related to PM2.5 concentrations and CO2 emissions, which increase undesirable outputs of urban lands (Zhao et al., 2019; Zhao & Xu, 2021). Therefore, the positive coefficient in Southern cities can probably be explained as a greater increase in economic benefits than environmental pollution, while the negative coefficient in northern cities can be explained as greater pollution than economic growth. Furthermore, the interesting pattern shown in northeast China can partially be explained as the transformation of economic production. Specifically, due to the underdeveloped industry, economic activities in the early stage were inefficient, with high consumption and pollution, resulting in a negative relation between nighttime light and ULUE. Since 2015, the updated economic activities contributed to efficient production, resulting in a positive correlation between nighttime light and ULUE in the northeast economic zone.

Per capita urban roads is supposed to have a mixed impact on ULUE. On one hand, high accessibility benefits organic economic growth, which positively influences ULUE (Song et al., 2022). On the other hand, the transportation network probably causes landscape fragmentation and environmental disruption, which have negative impacts on ULUE (He et al., 2020). Therefore, for cities with slow urban expansion, such as cities in the northwestern economic zone and cities in the northeast economic zone, per capita urban roads contributed to urbanization and economic growth, showing an increasingly positive correlation. On the contrary, for cities with rapid urban expansion, especially certain coastal cities in the southern coastal economic zone and the northern coastal economic zone, per capita urban roads was negatively related to ULUE. Moreover, with the development of urbanization, the positive externalities of per capita urban roads on ULUE in northern China, especially cities in the northern coastal economic zone, gradually transferred to negative, while the negative externalities of per capita urban roads in southern and eastern cities strengthened. Furthermore, technological development can significantly improve ULUE by upgrading the industrial structure, eliminating industry with backward production, and reducing industrial and domestic pollution (Han et al., 2020). The findings demonstrate that such positive influence weakens from coastal cities to inland cities and strengthens over time. Furthermore, the negative relation between Investment in technology and science and ULUE in western cities and northeastern cities is likely due to the low level of technological development.

5.3. *Policy implication*

Sustainable urbanization under the green development initiatives requires rational and efficient utilization of urban land. To improve ULUE, some policy recommendations are proposed. Firstly, it is necessary to increase investment in technology and science to promote technological innovation and develop high-tech techniques. Relying on technological innovation, the government may accelerate industrial structure upgrading, and develop high-tech industry to reduce energy consumption and industrial pollution. Particularly, for industrial bases in northeast China, it needs to develop environmental-friendly equipment manufacturing, which can re-stimulate the industrial vitality in this area. Moreover, the government should further promote technological innovation in west China and coordinate the allocation of investment between Coastal regions and inland regions. This is especially important considering that the northwest regions exhibited the most pronounced positive effects of technological innovation on ULUE. Secondly, the government is supposed to strengthen international trade and attract more foreign investment to adjust the industrial structure. Meanwhile, the government should pay attention to the types of foreign investment as some labor-intensive industries may negatively influence ULUE over time, especially in southern China. To avoid the occurrence of the Pollution Heaven Hypothesis, foreign investment should be encouraged in high-tech intensive industries rather than labor-intensive industries.

Thirdly, considering population density has negative impacts on ULUE in most cities, it is necessary to adjust the spatial structure of the population. The government should improve the policy to attract talent migration from east to west, which can ease the pressure on the population in eastern cities and increase the vitality of economic growth in western cities. This is also an essential way of ensuring reasonable allocation of labor resources, which contributes to regional integration and regional coordination. Finally, the government should balance urban development and environmental protection to achieve sustainable urbanization. Specifically, it needs to avoid excessive expansion of urban areas, and protect the green resources including croplands and forests in the process of urban expansion. Besides, it is essential to evaluate urban land use from the green development perspective, with particular attention paid to accurately quantifying emissions of solid waste, greenhouse gases, and air pollutants.

5.4. *Limitations and future work*

Despite the insights of the study, it still has several limitations. Firstly, the combined usage of remote sensing data and statistical data could introduce uncertainties, as these distinct data-collection approaches might result in potential spatial and temporal mismatches. Second, considering data availability, we only considered the direct CO_2 emissions from fossil fuels based on the ODIAC dataset, which may underestimate the undesirable output of CO_2 emissions. CO_2 emissions can be also produced by other energy such as electricity, and by diverse types of land use directly or indirectly (Cao et al., 2019). In addition, Chen, Yu, et al. (2020a) provided a method for estimating more accurate and higher-resolution CO_2 emissions based on DMSP/OLS and

NPP/VIIRS satellite imagery, which has the potential to estimate more accurate undesirable outputs and contributes to a more accurate evaluation of ULUE under the concept of green development in further studies.

Third, due to the complex mechanism of spatiotemporal variation of ULUE, although we described and explained the general picture of ULUE and its determinants in this study, the selected indicators could not fully explain the spatiotemporal dynamics of ULUE. Some basic indicators, such as urban form, marketization, and environmental regulation were not included in this study (Wang & Shen, 2016; Wu et al., 2020; Yang et al., 2020). Future works may consider the individual and interactive impacts of other socioeconomic and environmental factors on ULUE by employing appropriate methods. For example, the geographic detector model is suitable for detecting whether any two factors will have a greater or weaker impact on ULUE than a single factor (Wang et al., 2010). Apart from data and methodological aspects, to understand the disparities of ULUE among eight economic zones under the background of regional integration, more studies can be conducted to further investigate the ULUE in eight economic zones from the perspective of cluster analysis and efficiency decomposition (Yu et al., 2019). Overall, the evolution of ULUE and its driving mechanism could be more deeply analyzed from diverse perspectives by using multiple data and multi-disciplinary methods.

6. Conclusion

This study examined the ULUE under green development orientation in 284 Chinese cities and eight economic zones and the spatiotemporal non-stationary effects of its potential determinants. This study identified the spatial and temporal evolution of green development oriented ULUE and highlighted the spatiotemporal heterogeneity of its association with socioeconomic activities. To address the deficiencies of existing studies, this study combined remote sensing data and statistical data to incorporate CO2 emissions, PM 2.5 concentrations, as well as other socioeconomic and eco-environmental effects in the estimation of ULUE. We further revealed the spatiotemporal dynamics of socioeconomic effects on ULUE by using the GTWR model, providing more robust evidence for policymakers to implement tailored strategies. The findings show that ULUE in Chinese cities generally increased from 2005 to 2019, with the highest level in coastal regions and certain northwestern regions. We suggest that ULUE can be improved by increasing technological innovation, upgrading industrial structure, improving openness degrees and international trade, adjusting urban structure, and establishing an efficient evaluation system for urban land use. Meanwhile, the decision-makers should adjust policies considering local conditions including historical development, urbanization degree, the future development direction, in other to achieve coordinated development of efficient urban growth under the green development orientation.

CRediT authorship contribution statement

Yuxuan Zhou: Conceptualization, Data curation, Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Yi Lu:** Supervision, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Table A1
Independent variables of ULUE

Variable	Description	Observation	Mean	Std. dev	Max	Min	Unit
Dependent variable							
ULUE	Urban land use efficiency	4260	0.46	0.26	1.59	0.08	–
Independent variables							
PGDP	Per capita GDP	4260	35,484.86	28,551.81	397,976.1	2396	10,000 yuan
TECH	Investment in technology and science	4260	61,083.27	228,732.9	4,273,784	0.13	10,000 yuan
REI	Investment in real estate	4260	1,988,429	3,746,965	50,113,283	4606.27	10,000 yuan
OPEN	The degree of openness	4260	6,759,039	25,026,699	283,000,000	15.11	10,000 yuan
IDS	Industrial structure	4260	47.65	11.07	90.97	10.68	Percent
PD	Population density	4260	3750.15	2791.83	20,093	27	Person/km^2
ROAD	Per capita urban roads	4260	15.37	6.98	60.07	0.39	km^2/person
NTL	Nighttime light value	4260	0.84	1.82	20.85	0.003	–

Table A2
Global spatial autocorrelation result

Year	Moran's I index	Z score	*P*-value
2005	0.1479	6.0998	0.0000
2006	0.0999	4.1777	0.0000
2007	0.0737	3.1107	0.0017
2008	0.0885	3.7141	0.0002
2009	0.1310	5.4267	0.0000
2010	0.1159	4.8206	0.0000
2011	0.0937	3.9244	0.0000
2012	0.1211	5.0144	0.0000
2013	0.0609	2.5911	0.0096
2014	0.0702	3.6493	0.0002
2015	0.1027	4.2594	0.0000
2016	0.1357	5.5812	0.0000
2017	0.1423	5.8300	0.0000
2018	0.1085	4.4854	0.0000
2019	0.1049	4.3433	0.0000

Table A3
Regression results of each model

	R2	Adj. R^2	Bandwidth	AICc
OLS	0.247	–	–	−4199.12
TWR	0.282	0.280	0.152	−4339.08
GWR	0.408	0.407	0.115	−5105.69
GTWR	0.443	0.442	0.115	−5259.49

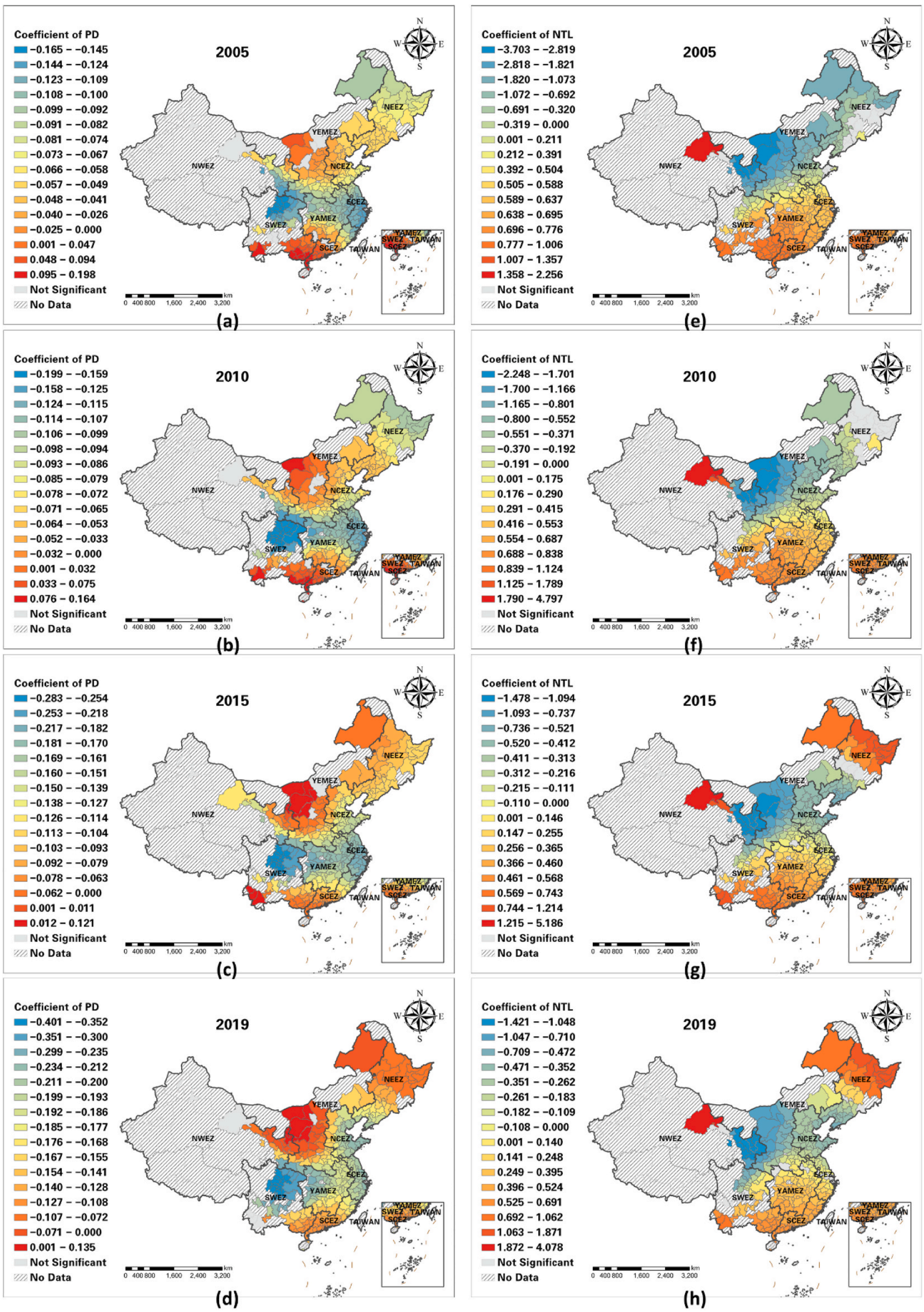

Fig. A1. Spatial heterogeneity of correlation between PD, NTL and ULUE.

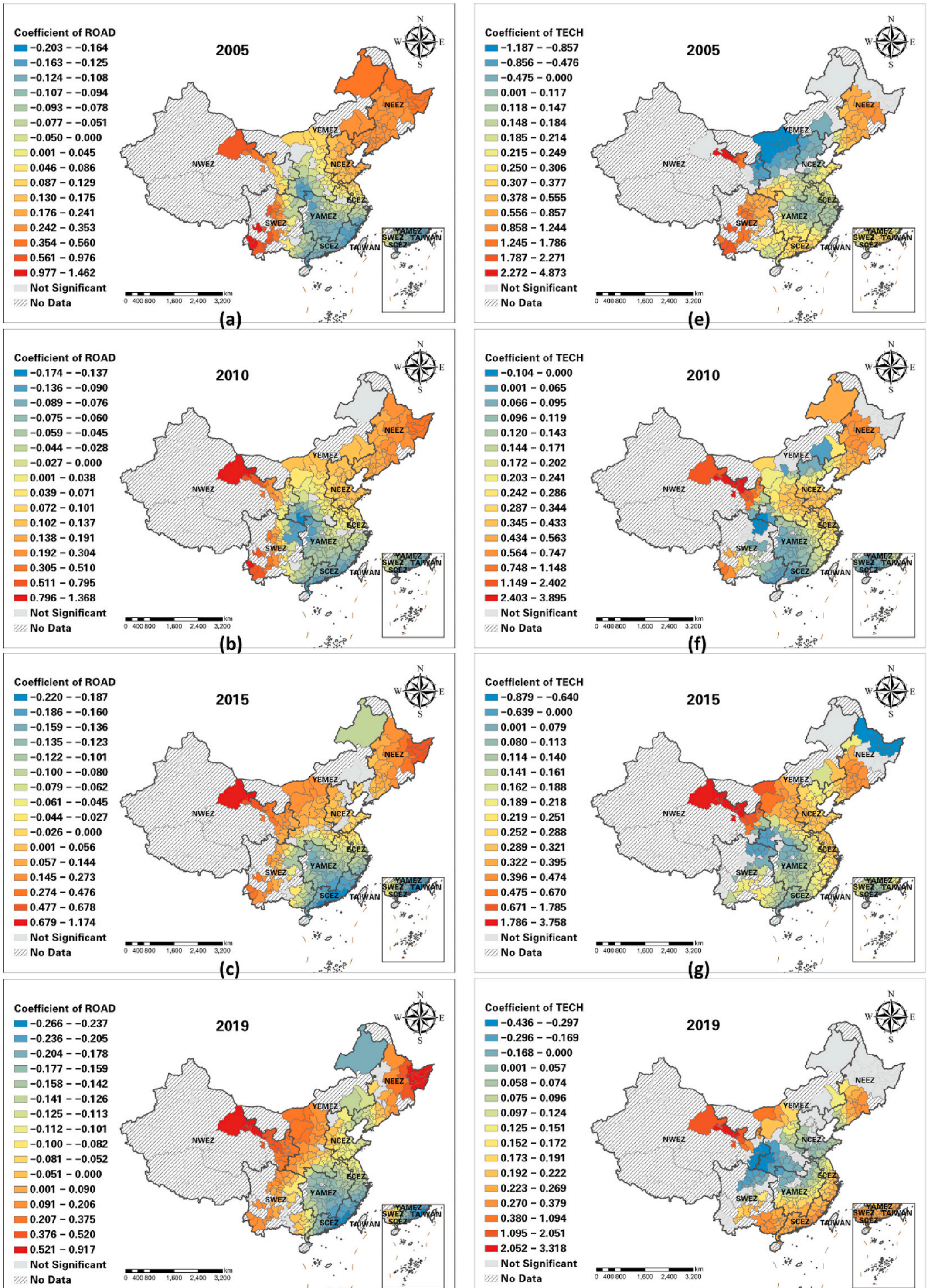

Fig. A2. Spatial heterogeneity of correlation between ROAD, TECH and ULUE.

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