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Does Urban Sprawl Inhibit Urban Eco-Efficiency? Empirical Studies of Super-Efficiency and Threshold Regression Models

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Abstract: With rapid urbanization in China, the phenomenon of urban sprawl has become prominent and has severely challenged sustainable urbanization and ecological civilization. Aiming to understand the impact of urban sprawl on the urban environment, this study calculates the eco-efficiency of 264 prefecture-level cities in China from 2003 to 2016 by using a super-efficiency data envelopment analysis model. Then, we establish a panel Tobit model and threshold regression model to empirically test the impact of urban sprawl on eco-efficiency and the threshold effect of the urban scale. The results show that urban sprawl hinders the improvement of urban eco-efficiency, especially in Eastern China, but relatively weak or even insignificant effects are observed in Central and Western China. Additionally, a threshold effect of urban sprawl on eco-efficiency can be found. When the city scale is small, urban sprawl seriously hinders the improvement of eco-efficiency. As the city scale gradually expands, the negative effect of urban sprawl on eco-efficiency first decreases, then the restraining effect is gradually strengthened. Our research findings can aid urban development in cities with different scales to reduce the negative effect of urban sprawl on the urban environment.

Keywords: urban sprawl; eco-efficiency; super-efficiency model; threshold regression model

1. Introduction

Urbanization in China has advanced remarkably, with the urbanization rate increasing from 17.9% in 1978 to 58.5% in 2017 [1]. The average annual growth rate of the permanent urban population has reached 4.05% [1]. China has rapidly completed a historic transformation from a country dominated by agricultural population to urban population. The National New-Type Urbanization Plan (2014–2020) suggests that the concept of ecological civilization should be fully integrated into urban development and that green production and green lifestyles should be emphasized to promote resource recycling and the green development of cities [2]. Differing from the extensive development patterns in the past, new-type urbanization construction in China has focused on intensive, intelligent, green, and low-carbon urbanization [2]. The 13th Five Year Plan of China also highlights the principles of green development, open, innovation, and inclusive development to balance lifestyles, economics, and natural sustainability [3]. However, the pressure on the ecosystem caused by long-term extensive economic development in China has been tremendous. Problems related to air pollution, traffic congestion, and wasted land resources have severely hindered sustainable urban development [4]. For example, 66.3% of the cities have substandard air quality and 32.7% of cities have road traffic noise [5].

Currently, ecological civilization and new-type urbanization are being constrained by the economic slowdown and environmental degradation. As an important spatial carrier of the population and industrial agglomerations, cities often drive regional economic growth and breakthroughs in industrial transformations and upgrades. Therefore, new-type urbanization must balance the contradiction between economic development and the utilization of resources and the environment to promote green and sustainable urban growth.

Urban sprawl is a typical phenomenon associated with the process of urbanization, and occurs when the speed of land urbanization is faster than the speed of population growth due to blind urban expansion. Whyte et al. first proposed the concept of urban sprawl as a "special situation of suburbanization" [6]. Gottman et al., Downs et al., and Burchell et al. expanded the concept and argued that urban sprawl is the expansion of urban fringe areas with extremely low population densities and the inefficient land use of large unexplored areas [7–9]. In such cases, a city experiences a rapid increase in development with a radial and low-density development pattern. Feng et al (2019). and Li et al. (2019) suggested that urban sprawl in China is different from that in the west in terms of driving factors [10,11]. Notably, urban sprawl in China is generally dominated by the fiscal land policies of local governments that over-rely on revenue from land transfers [10]. Land mortgages can provide financial support for urban expansion, triggering the extensive use of urban land. Moreover, to attract investment, local governments are eager to encourage economic-technological development zones in suburban areas. Urban green land is often encroached upon and converted into urban construction land that cannot effectively carry the same population due to the lack of supporting infrastructure, resulting in wasted land resources and the disorderly expansion of urban boundaries [12,13].

Although urban sprawl helps relieve the crowded pressure on city centers, excessive and inefficient urban sprawl can result in ineffective urban spatial structures and urban scales [14]. During periods of overexpansion, a large amount of urban green space is converted to industrial and commercial land, which can adversely affect the urban ecosystem and microclimate regulation. Moreover, the land cannot match the carrying capacities of urban resources and the environment [15,16]. With the expansion of the urban scale, daily commuting must depend on vehicles and other means of transportation, leading to more exhaust emissions, which in turn reduces the air quality. As a stage in the process of industrialization and urbanization, the impact of urban sprawl on urban ecology and the economy is worthwhile to explore to achieve sustainable and healthy urbanization. Ecological efficiency (or eco-efficiency) has been used to measure the comprehensive state of economic development and ecological performance in a certain area [17]. Several scholars have calculated the eco-efficiency at the national or urban scale [18,19]. Moreover, the existing research applies spatial econometrics to eco-efficiency analysis to verify the spatial correlation of eco-efficiency. For example, Zheng et al. (2019) measured the eco-efficiency of 31 provinces in China using the Slacks-Based Measure model. Their results indicated that eco-efficiency has obvious spatial autocorrelative features; all regions (except for the western region) displayed conditional convergence [20]. In addition, there are many studies focusing on the impact factors of eco-efficiency. Hao et al. (2019) used data envelopment analysis (DEA) to measure Kyrgyzstan's eco-efficiency and concluded that economic development can significantly promote eco-efficiency [21]. Moreover, the urban form can also influence urban eco-efficiency and the compact cities may positively influence eco-efficiency [22]. However, few studies have explored the impact of urban sprawl on eco-efficiency. How can urban sprawl influence the eco-efficiency of the urban environment and economy in China? What are the influencing mechanisms? What is the role of the urban scale in affecting eco-efficiency during the process of urban sprawl?

To answer these questions, this study uses eco-efficiency as a comprehensive index of sustainable urbanization that integrates urban economic development and the effects of environmental and resource utilization. To explore the relation between urban sprawl and eco-efficiency, we conduct research through the following steps. Section 2 provides a literature review regarding the influential mechanisms of urban sprawl on eco-efficiency. The relevant methodologies are introduced in Section 3. We use the super-efficiency DEA model to calculate the eco-efficiency of 264 prefecture-level cities in

China from 2003 to 2016. Subsequently, combining the theoretical influential mechanisms of urban sprawl on the eco-efficiency, we construct a panel Tobit model to empirically assess the impact of urban sprawl on eco-efficiency. Furthermore, through a threshold regression model the different effects of urban sprawl are examined considering the urban geographical distribution and urban scale. Section 4 presents the research results, and the discussion is given in Section 5. Finally, we provide policy recommendations to scientifically guide urban sprawl and promote sustainable urbanization in China.

2. Literature Review of the Mechanisms of the Impact of Urban Sprawl on Eco-Efficiency

Eco-efficiency involves obtaining the maximum economic output with the smallest economic input while minimizing pollution and resource consumption. Our literature review mainly focuses on the effects of the urban spatial structure and urban scale, which are consequences of urban sprawl, on the urban eco-efficiency. Thus, the literature study supports the empirical analysis in this paper.

Because the population and industrial areas are often highly concentrated in cities, the rising land rent near a city center will increase the cost of living and working, resulting in expansion from the city center to suburban areas. The structure of the urban space has to be adjusted in such cases [23–25]. However, the inefficient and extensive development of land and infrastructure increases the pressure on the soil, water and energy. Moreover, such expansion can damage the local ecology through the removal of native vegetation and wetlands [16,26,27]. The shrinking of urban green spaces can also influence the function of the urban ecosystem in regulating the microclimate of a city. Additionally, the increasing use of vehicles for commuting can cause further traffic congestion in a city, and vehicle emissions generate air pollution that deteriorates the air quality [28–31]. The manufacturing industry is a main driver of urban sprawl and the expansion of residential and commercial areas. Manufacturing activities often generate environmental pollution, which has been targeted for mitigation in city centers. Therefore, the urban sprawl caused by industrial structure change plays a significant role in urban eco-efficiency. In China, factories are required to move to industrial parks for unified management; therefore, these enterprises have incentives to move to the suburbs, resulting in more green land and high-quality farmland being encroached upon and causing a loss of green space and arable land [32,33]. In addition, if industrial parks lack appropriate environmental management, the industrial development pattern can increase the discharge of industrial waste (e.g., waste water, solid waste, and waste gas) [34], which can aggravate the environment in the suburbs and further increases the environmental costs of development in a city.

Furthermore, the urban scale can influence the urban environment due to urban spatial agglomeration. Urban spatial agglomeration is conducive to promoting the optimal allocation of urban resources, producing scale and technology spillover effects for the labor force and yielding intermediate inputs. Moreover, an appropriate urban scale can improve productivity and reduce automobile exhaust, which is beneficial to enhancing environmental quality. Thus, energy and environmental efficiency can be promoted, which can reduce urban pollutant emissions (e.g., SO2, NOx) [35,36]. In small-scale cities, the effect of spatial agglomeration is more significant, and in large-scale cities, the agglomeration effect may be weakened; therefore, the overexpansion of a city may even have a negative impact on productivity [37,38]. Urban sprawl can hinder the role of spatial agglomeration and has different degrees of influence on small- and large-scale cities.

The above literature provides theoretical evidence for the following empirical research. Eco-efficiency can be used to measure the economic and environmental development of a city. We assume that urban sprawl negatively affects the urban eco-efficiency and that the threshold effect of the urban scale can further affect the urban sprawl process.

3. Methods and Data Collection

In this study, we calculate the eco-efficiency of 264 prefecture-level cities in China from 2003 to 2016 by using a super-efficiency data envelopment analysis model. Then, we establish a panel Tobit model and threshold regression model to empirically test the impact of urban sprawl on eco-efficiency and the threshold effect of urban scale.

3.1. Measurement of the Eco-Efficiency by Data Envelopment Analysis

3.1.1. Methods

Three types of methods are typically used to measure eco-efficiency [20,21,39]. The first type uses the ratio between economic performance and environmental impacts to establish an index evaluation system that integrates multiple indicators into a single indicator that reflects the ecological efficiency [40]. The second type calculates the conversion efficiency of materials and resources based on energy analysis, material flow analysis or ecological footprint analysis [41]. However, these two types of methods are limited to providing objective weights for the indicators to perform comprehensive evaluations, especially in the comparison among decision-making units. DEA can overcome the above deficiencies and has become a mainstream method of measuring ecological efficiency [42]. The traditional DEA method takes environmental pollution as a regular output in the evaluation system, but this approach is not consistent with the actual situation. It is difficult to compare and analyze the optimal decision-making units in the frontier with this approach due to the same efficiency results. Therefore, this study uses a super-efficiency DEA model with undesired outputs to calculate the eco-efficiency of the 264 prefecture-level cities in China from 2003 to 2016 [43,44]. The efficiency of decision-making units is ranked, and the detailed calculation is as follows.

We assume that there are n decision-making units (DMUs, i.e., the sample cities in this research) [45]. Each DMU has m input factors (e.g., the number of employees in a city, the urban construction land area, the total investment in fixed assets, local budgetary expenditure and the total annual water and gas consumption), p desirable outputs (e.g., the GDP of a city), and t undesirable outputs (e.g., the discharge of industrial wastewater, industrial sulfur dioxide and industrial dust) [46,47]. $X_k = (x_{1k}, x_{2k}, \ldots, x_{mk})$ denotes the m input sectors of DMU; $Y_k = (y_{1k}, y_{2k}, \ldots, y_{pk})$ represents the p desirable outputs of the DMU; and $E_k = (e_{1k}, e_{2k}, \ldots, e_{tk})$ represents the t undesirable outputs. (X_k, Y_k, E_k) represent the input-output vector for city unit t. σ denotes the eco-efficiency value of a city. The super-efficiency DEA model is as follows.

$$\sigma = \min\left(\frac{1-\frac{1}{m}\sum_{j=1}^{m}\omega_m \alpha g_{mk}^{x}/x_{mk}}{1+o_p\frac{1}{p}\sum_{p=1}^{p} w_p \beta g_{pk}^{Y}/Y_{pk}+o_t\frac{1}{t}\sum_{t=1}^{t} w_t r g_{tk}^{e}/e_{tk}}\right)\text{s.t.}\begin{cases}\sum_{j=1,j\neq k}^{n}\lambda_j x_j + a g_{mk}^{x} + s^{+} \leq \sigma x_k \\ \sum_{j=1,j\neq k}^{n}\lambda_j Y_j - \beta g_{pk}^{Y} - s^{g} \leq Y_k \\ \sum_{j=1,j\neq k}^{n}\lambda_j E_j + r g_{tk}^{c} + s^{b} = \sigma E_k \\ \lambda_j \geq 0, j = 1, 2\ldots, n; s^{-} \geq 0, s^{g} \geq 0, s^{b} \geq 0\end{cases} \tag{1}$$

In Equation (1), ω_m, w_p, and w_t are the index weights of the input factors, desirable outputs, and undesirable outputs, respectively. g_{mk}^{x}, g_{Pk}^{Y}, and g_{tk}^{C} are the directional vectors of the m inputs, p desirable outputs, and t undesirable outputs, respectively. α, β, and γ are the weights of the directional vector. s^-, s^g, and s^b are the slack vectors of the input factors, desirable outputs, and undesirable outputs, respectively. o_p and o_t are the overall weights of all the desirable and undesirable outputs. Additionally, $\Sigma_{p=1}^{p}\omega_p = p$, $\Sigma_{t=1}^{t}\omega_t = t$, $\Sigma_{m=1}^{m}\omega_m = m$, and $o_p + o_t = 1$. λ_j is a constraint condition.

3.1.2. Indicators for the Super-Efficiency DEA Model

To conduct DEA, we need to select the input and output indicators. In general, production activities generally require the input of labor, capital and energy. Considering the availability of data, we select the following input indicators: the number of employees in a city, the urban construction land area, the total investment in fixed assets, and the total annual water and gas consumption. In terms of the output indicators, GDP (Gross Domestic Product) is selected as the desirable output indicator because GDP is a vital target to measure the urban economy. The higher the level of GDP, the higher the level of economic development. For the undesirable outputs, we focus on the pollution caused by production activities. Thus, the undesirable outputs are mainly related to the discharge of industrial wastewater, industrial sulfur dioxide and industrial dust. Considering the data availability, we select 264 cities with relatively complete datasets to determine their ecological efficiency from 2003-2016. The data of input indicators is from the China Urban Database; the GDP of a city is from China Regional Economic Database; the data of undesirable outputs is from the China Environmental Database and China Urban and Rural Construction Database. We obtain these data through the EPS (Easy Professional Superior) data platform (http://olap.epsnet.com.cn/).

3.2. Factors that Influence Eco-Efficiency in the Tobit Model

3.2.1. Model Construction

To analyze the factors that influence eco-efficiency, the eco-efficiency calculated by the super-efficiency DEA model is used as the explanatory variable. Because the efficiency index is a limited dependent variable, the panel Tobit model is used for the empirical analysis. Additionally, the level of economic development, technical level and degree of openness are used as control variables. We use the Tobit model to test the hypothesis that urban sprawl is not conducive to improving the urban ecological efficiency [48]. The econometric model is shown as follows:

$$\mathrm{eco}_{\mathrm{it}} = \begin{array}{c} \beta_0 + \beta_1 \mathrm{city}_{\mathrm{it}} + \beta_2 \mathrm{pgdp}_{\mathrm{it}} + \beta_3 \mathrm{techno}_{\mathrm{it}} + \beta_4 \mathrm{pep}_{\mathrm{it}} \\ + \beta_5 \mathrm{fdi}_{\mathrm{it}} + \beta_6 \mathrm{rgdp}_{\mathrm{it}} + \beta_7 \mathrm{perrelec}_{\mathrm{it}} + \varepsilon_{\mathrm{it}} \end{array} \quad (2)$$

where i and t denote city and year, respectively. $\mathrm{eco}_{\mathrm{it}}$ represents the ecological efficiency of city i in year t. $\mathrm{city}_{\mathrm{it}}$ represents urban sprawl of city i in year t. $\mathrm{rgdp}_{\mathrm{it}}$, $\mathrm{pgpd}_{\mathrm{it}}$, $\mathrm{techno}_{\mathrm{it}}$, $\mathrm{perrelec}_{\mathrm{it}}$, $\mathrm{pep}_{\mathrm{it}}$, and $\mathrm{fdi}_{\mathrm{it}}$ represent the growth rate of the GDP, GDP per capita, number of scientific researchers and technical service personnel, electricity consumption per unit output, year-end population, and foreign direct investment, respectively, which are the control variables of the model. $\varepsilon_{\mathrm{it}}$ is a random error term.

3.2.2. Variable Selection for the Tobit Model

Urban sprawl can be evaluated based on the population density, built-up area, land diversity, population distribution, and range of urban activities that reflect the level of urban sprawl [49–51]. Considering the frequently used indicators in the literature and the availability of the relevant data, we use the difference between the growth rate of the built-up area and the growth rate of the urban population to represent the urban sprawl level. It can keep the statistical spatial heterogeneity of land and population, and avoid the disturbance of the negative values of population growth rate [52]. Generally, urban sprawl shows that the speed of land development is faster than the speed of population growth [53]. Therefore, the larger the difference between the speed of built-up areas and population growth is, the higher the urban sprawl level. We thus obtain the situations of urban sprawl of 264 prefecture-level cities from 2003 to 2016. Economic development, the technological level, and the urban scale of cities are important factors that influence the eco-efficiency, as noted in the literature review. Therefore, the control variables are selected as follows: the GDP growth rate, which reflects the economic development level of a city; the GDP per capita, which represents the urban wealth level; the number of scientific researchers and technical service personnel; and the electricity consumption per unit output, which reflects the technology level. Furthermore, the control variables also include the year-end population and foreign direct investment, representing the city scale and the degree of city openness, respectively. Table 1 lists the variable names and explanations. The dependent variable data (i.e., $\mathrm{eco}_{\mathrm{it}}\mathrm{eco}_{\mathrm{it}}$) are obtained with the super-efficiency DEA model. The data for other variables is acquired from the China Urban Database.

Table 1. Variable explanations. DEA: data envelopment analysis.

Variable Classification	Variable Name	Variable Explanation	Data Sources
Dependent variable	eco_{it}	Eco-efficiency	DEA model results
Independent variable	$city_{it}$	Urban sprawl level	China Urban Database
Control variable	$rgdp_{it}$	Growth rate of GDP	China Regional Economic Database
	$pgpd_{it}$	GDP per capita	China Regional Economic Database
	$techno_{it}$	Number of scientific researchers and technical service personnel	China Urban Database
	$perrelec_{it}$	Electricity consumption per unit output	China Urban Database
	pep_{it}	Year-end population	China Regional Economic Database
	fdi_{it}	Foreign direct investment	China Regional Economic Database

3.3. Threshold Model Setting

To examine the effects of urban sprawl on eco-efficiency at different city scales, we establish a threshold regression model. Based on the model of Hansen et al. [54], we set the city scale as the threshold variable. Generally, there are three types of city scales in China: small cities (with urban resident population under 500,000), medium-sized cities (with urban resident population between 500,000 and 1,000,000), large cities (with urban resident population between 1,000,000 and 5,000,000), and super-large cities (with urban resident population 5,000,000) [55]. Therefore, we assume that the threshold regression model may have dual thresholds and establish the following threshold regression model:

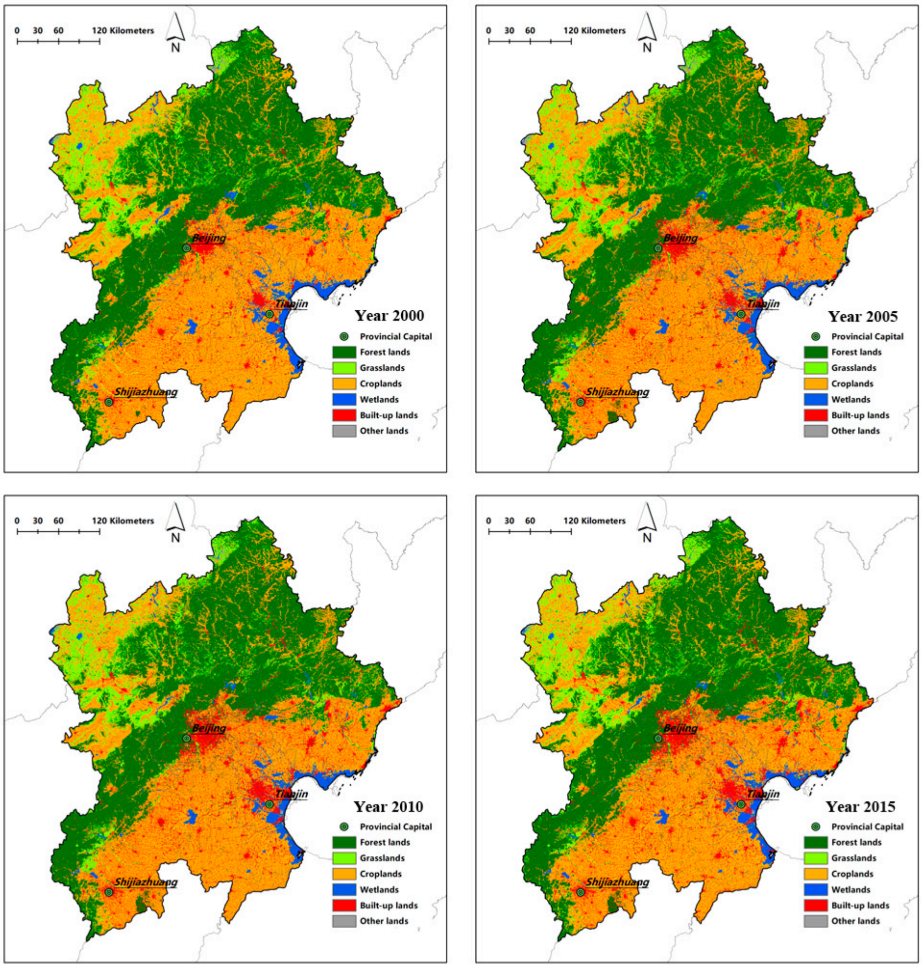
$$eco_{it} = \begin{array}{c} \beta_0 + k_1 city_{it} \cdot I(pep_{it} < R_1) + k_2 city_{it} \cdot I(R_1 \le pep_{it} < R_2) + k_3 city_{it} \cdot I(pep_{it} \ge R_2) \\ +\beta_2 pgdp_{it} + \beta_3 techno_{it} + \beta_4 pep_{it} + \beta_5 fdi_{it} + \beta_6 rgdp_{it} + \beta_7 perrelec_{it} + \varepsilon_{it} \end{array}, \quad (3)$$

where eco_{it} is the dependent variable, and $city_{it}$ is the independent variable affected by the threshold variable. pep_{it} is the threshold variable. I (·) is the indicative function. The rest of the variables are control variables. Additionally, k_1, k_2, and k_3 are the influence coefficients of the independent variables related to the dependent variable when the threshold variables satisfy $pep_{it} < R_1$, $R_1 \le pep_{it} < R_2$, and $pep_{it} \ge R_2$, respectively. ε_{it} is a random error term.

4. Results

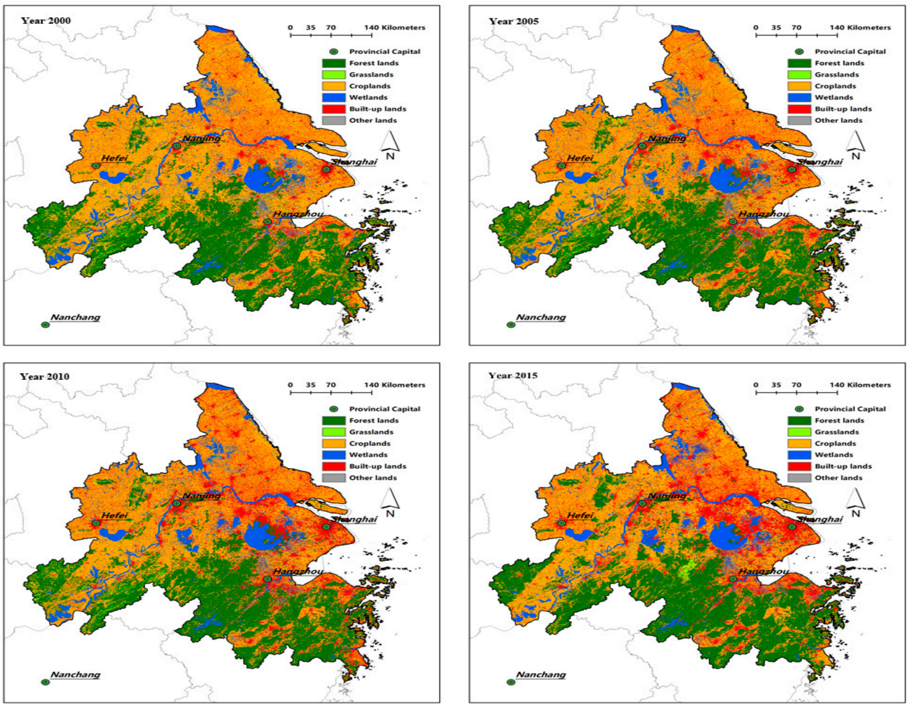
4.1. The Overall Urban Sprawl Situation in China

To show the overall urban sprawl situation in China, we present the spatial trends of urban sprawl in three major urban agglomerations based on the 30-meter spatial resolution data from China Cover [56]. (China Cover is developed by the Institute of Remote Sensing and Digital Earth (RADI) of the Chinese Academy of Sciences (CAS). The Chinese environmental satellite HJ and Landsat in the United States are the main data sources. The classification system is redefined to most suitably represent the characteristics of land cover in China according to the Land Cover Classification System of the Food and Agriculture Organization. The 2010 data have been shared by the National Earth System Science Data Center (www.geodata.cn).) As shown in Figure 1, the built-up areas in cities (represented in red) increased significantly from 2000 to 2015, reflecting the widespread urban sprawl in the major urban agglomerations in China. In particular, the Yangtze River Delta (Figure 1b) experienced the most severe urban sprawl, with an average annual growth rate of built-up areas reaching 4.4%. The annual growth rate of the Pearl River Delta averages 2.5% (Figure 1c). In the Beijing–Tianjin–Hebei agglomeration, the average annual growth rate of urban sprawl was 2%, and sprawl mainly occurred near Beijing and Tianjin. This finding illustrates that the main cities in China have been rapidly expanding.

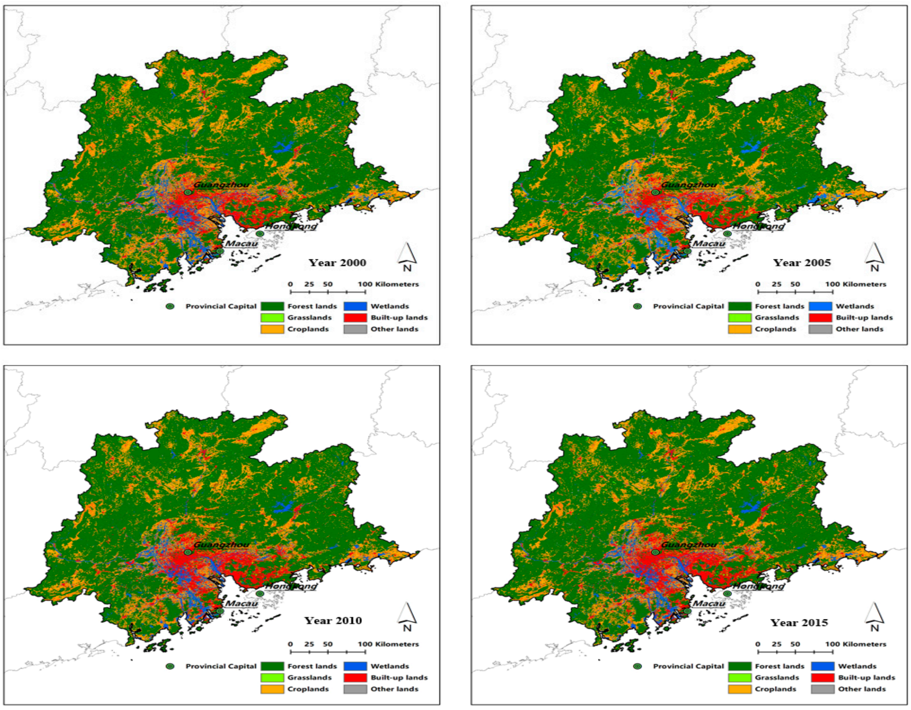


(**a**)

Figure 1. *Cont.*



(**b**)

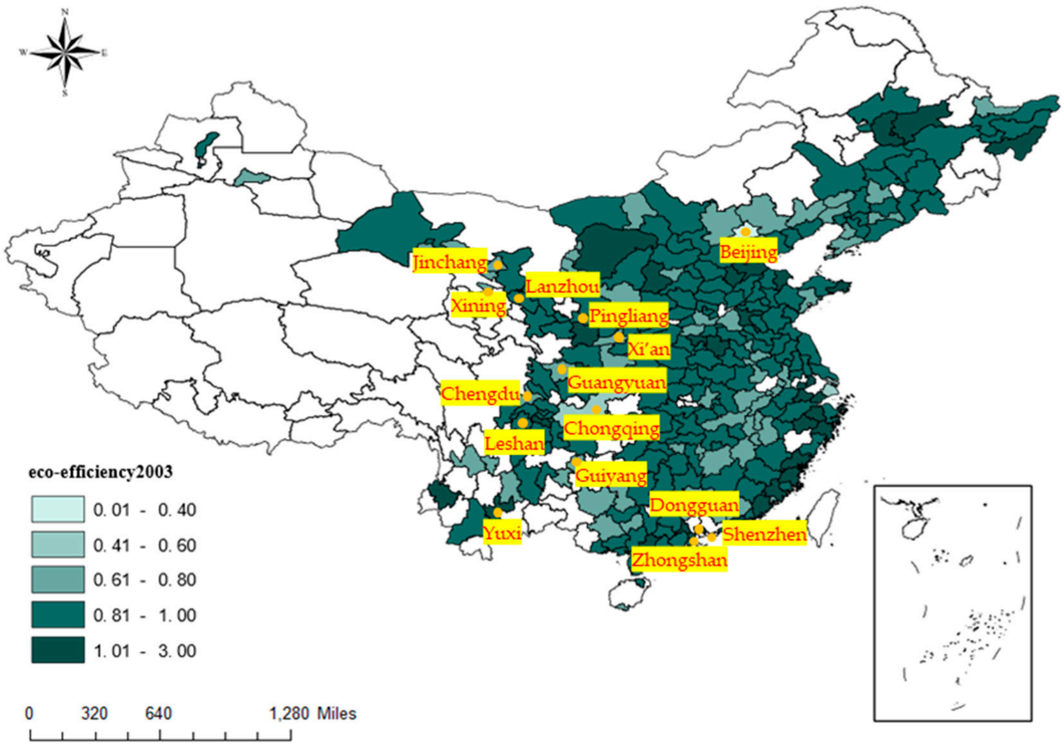


(**c**)

Figure 1. Spatial trends of urban sprawl in the Beijing–Tianjin–Hebei region (**a**), Yangtze River Delta (**b**), and Pearl River Delta (**c**) in 2000, 2005, 2010, and 2015.

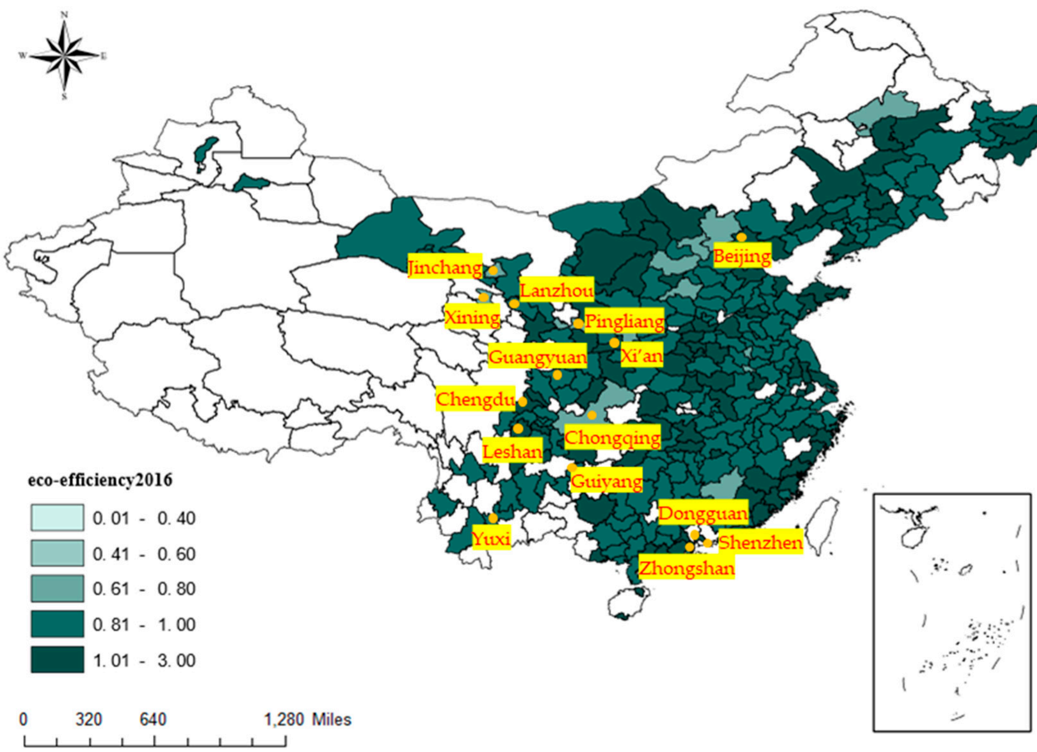
4.2. Eco-Efficiency Results

The urban eco-efficiency in 264 Chinese cities was mapped with ArcGIS 10.5 in Figure 2 to directly illustrate the regional characteristics and temporal trends of eco-efficiency. By comparing the two subfigures, we find that the level of eco-efficiency in Chinese cities has been constantly rising. In 2003, Yuxi, Zhongshan, and Dongguan ranked especially high in eco-efficiency, with values exceeding 1. In 2016, some highly economically developed cities, such as Shenzhen, and Beijing, ranked significantly higher than in 2003. At the regional level, the increase in eco-efficiency was most obvious in the eastern-central regions, especially in the cities of Eastern China. However, the eco-efficiency of several cities in Northeast China with abundant mining and energy resources have not reached the optimal level. The optimal level of eco-efficiency represents that efficiency is realized with the smallest economic inputs, the smallest undesirable outputs and the maximal desirable outputs. The eco-efficiency of some cities in Western China (e.g., Chengdu, Guangyuan, Leshan, and Xi'an) also greatly improved. Specifically, the average level of urban eco-efficiency in Eastern China has been above 0.95 since 2011, which is close to the optimal level of eco-efficiency [57]. Overall urban eco-efficiency is gradually improving. However, from a regional perspective, the level of eco-efficiency in Eastern China is much higher than that in Western and Central China. The level of eco-efficiency in Central China is generally low. Although Central China has experienced slow growth since 2010, the overall level still has a large gap with that in Eastern China and even falls below that in Western China at times. Therefore, the eco-efficiency in Western China has great potential for improvement. In addition, the eco-efficiency in Western China in 2016 is far from the optimal level of efficiency, as observed in Chongqing, Jinchang, Pingliang, Guiyang, Lanzhou, and Xining.



(a)

Figure 2. *Cont.*



(**b**)

Figure 2. Urban eco-efficiency in China in 2003 (**a**) and 2016 (**b**).

4.3. Results of the Panel Tobit Model

To test the hypothesis that urban sprawl is not conducive to improving eco-efficiency, we first establish a benchmark regression model to test the overall impact of urban sprawl on the urban eco-efficiency in China. Then, the effects of urban sprawl on the urban eco-efficiency in Eastern, Central, and Western China are compared by regression analysis.

4.3.1. Establishment of the Benchmark Regression Model

Before the empirical regression is performed, we first standardize the sample data and perform a multicollinearity test. The results show that the variance expansion factor (VIF) fluctuates between 1.03 and 2.07, and this value is much lower than 10. Therefore, there is no serious multicollinearity in the model, and regression estimation can be made. The p value of the LR test of the panel Tobit model is significant, which indicates that the model includes random effects. As a result, the random effects panel Tobit model is used for regression estimation. The results are shown in Table 2.

Model (1) in Table 2 is used to estimate the overall effect of urban sprawl on the urban eco-efficiency in China. From Model (1), the coefficient of urban sprawl (city) is significantly negative, which indicates that urban sprawl in China is not conducive to improving the urban ecological efficiency. Moreover, the eco-efficiency decreases by 0.007 units for every unit increase in urban sprawl, which verifies the above hypothesis. Other control variables also have important effects on eco-efficiency, but their effects are different. First, the per capita GDP (pgdp) of a city is positively correlated with eco-efficiency, indicating that the higher the level of economic development is in a city, the richer the city becomes. Under these conditions, the local government can provide more financial support for local pollution control, environmental quality monitoring and other projects, thus contributing to improvements in the ecological efficiency. Second, the techno coefficient is significantly positive, and the coefficient of the consumption of electricity per unit output (perelec) is significantly negative, which indicates that high numbers of scientific researchers and technical service personnel in cities are associated with high eco-efficiency. Moreover, the smaller the consumption of electricity per unit output is, the higher the technical level of the city. The possibility of improving eco-efficiency is further increased in this scenario. In addition, the inflow of foreign capital promotes the urban eco-efficiency, but the expansion of the city scale restricts eco-efficiency improvements to a certain extent.

Table 2. An empirical study of the effect of urban sprawl on urban eco-efficiency (panel Tobit model).

Model	**(1)**	**(2)**	**(3)**	**(4)**
Variables	**National Level**	**Eastern Cities**	**Central Cities**	**Western Cities**
city	−0.00701 ***	−0.0100 ***	−0.00570 *	−0.00455
	(−3.33)	(−2.63)	(−1.96)	(−1.21)
pgdp	0.0211 ***	−0.00222	0.0464 ***	0.0454 ***
	(6.87)	(−0.42)	(10.72)	(5.99)
techno	0.0995 ***	0.104 ***	0.0395 *	0.120 ***
	(15.24)	(12.18)	(1.74)	(4.74)
pep	−0.0354 ***	−0.0668 ***	0.00465	−0.0588 ***
	(−4.65)	(−4.16)	(0.47)	(−4.14)
fdi	0.0159 ***	0.00996 **	−0.00705	0.0542 ***
	(4.35)	(2.00)	(−0.77)	(5.52)
rgdp	−0.00186	−0.00810 **	0.00760 ***	−0.000480
	(−0.96)	(−2.29)	(3.18)	(−0.12)
perelec	−0.0149 ***	−0.0561 ***	−0.00948 *	−0.00578
	(−4.53)	(−4.91)	(−1.69)	(−1.41)
_cons	0.946 ***	0.966 ***	0.927 ***	0.960 ***
	(126.76)	(73.15)	(111.15)	(51.03)
N	3668	1484	1414	770

Note: *, ** and *** represent significance at the statistical levels of 10%, 5%, and 1%, respectively. The value in parentheses is t.

4.3.2. Regional Analysis of the Panel Tobit Model

The analysis of the eco-efficiency results indicated that there are obvious regional differences in urban eco-efficiency in China as shown in Figure 3. The extent of urban sprawl in China also varies depending on the specific area in which a city is located. The phenomenon of urban sprawl in China is prominent, especially in Eastern China. Therefore, urban eco-efficiency and urban sprawl in China have significant regional differences. In this section, we divide the research samples into three subgroups (i.e., eastern cities, central cities, and western cities) and then run the panel Tobit model for each sample group. Eastern China includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan. Western China includes Shanxi, Neimenggu, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. Central China includes Sichuan, Chongqing, Guizhou, Yunnan, Xizang, Shanxi, Gansu, Ningxia, Qinghai, and Xinjiang. The effects of urban sprawl on the urban eco-efficiency in different regions are further analyzed. The results of the regression are shown in Models (2), (3), and (4) in Table 2. The coefficient of urban sprawl shows that the urban sprawl of eastern cities has a significant inhibitory effect on eco-efficiency, and this result is significant at the 1% confidence level. Therefore, urban sprawl in eastern cities is not conducive to eco-efficiency improvements. However, urban sprawl has a smaller effect on urban eco-efficiency in central cities than in eastern cities. Each unit increase in urban sprawl leads to a 0.0057-unit decrease in eco-efficiency, which is only significant at the 10% confidence level. Compared with that in the eastern and western cities, the effect of urban sprawl on eco-efficiency in western cities is relatively weak. Although the coefficient is negative in these cities, the effect of urban sprawl on eco-efficiency is not significant.

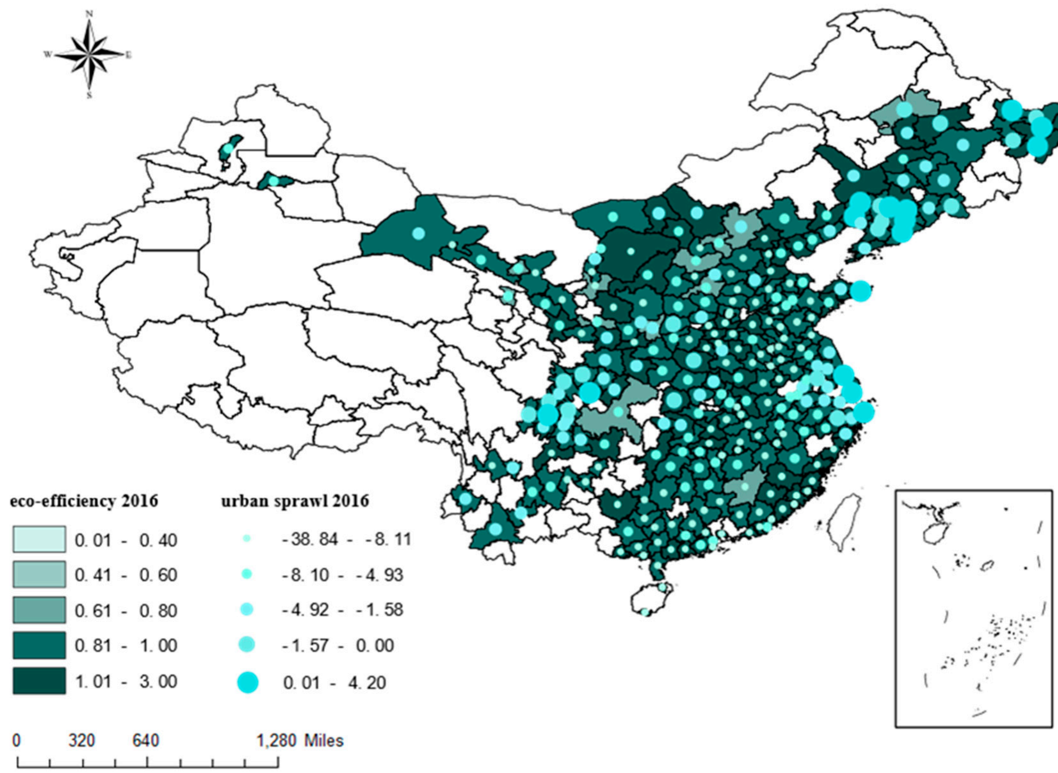


Figure 3. Urban eco-efficiency and urban sprawl in China in 2016.

4.4. Threshold Regression Analysis

The above analysis shows that there are regional differences in the effect of urban sprawl on urban eco-efficiency. The different degrees of urban sprawl in eastern cities, central cities and western cities have different effects on urban eco-efficiency. In addition, large cities are concentrated in Eastern China, and smaller cities are concentrated in the central and western regions. The literature shows that there may be relation between the urban scale and urban spatial structure [58]. Therefore, we hypothesize that there may be specific ranges of urban scales that reflect the different impacts of urban sprawl on eco-efficiency. The threshold regression model is used to explore this issue.

Before threshold regression analysis, we first test the threshold effect, including the threshold values and the number of thresholds, to determine the specific form of the threshold regression model. The single threshold effect and the double threshold effect are estimated by using STATA15.0 (Stata Corp. LLC, College Station, TX, USA, 2017), and the F value is calculated by the Bootstrap method with 300 repetitions. The corresponding p values and critical values are shown in Table 3. The urban scale passes the double threshold test at the 1% significance level and the single threshold test at the 5% significance level, which suggests that a city scale threshold effect does exist. We select the double threshold regression model according to the significance level. R_1 and R_2 are the estimated threshold values of the double threshold regression model and are equal to 142.102 and 1029.368, respectively. The regression results of the model are shown in Table 3.

Table 3. Threshold effect test.

			Critical Value		
	***F* Value**	***P* Value**	**1%**	**5%**	**10%**
Single threshold test	8.646 **	0.017	10.489	5.522	3.266
Double threshold test	29.963 ***	0.000	10.753	6.674	4.645

Note: ** and *** represent significance at the statistical levels of 5%, and 1%, respectively.

Table 4 shows that the influence of the urban scale on urban sprawl has a double threshold effect. The urban scale can be divided into three ranges: cities with a population of less than 1.42 million, cities with a population between 1.42 million and 10.29 million, and cities with a population of more than 10.29 million. The coefficients of urban sprawl all pass the 1% significance test at the three different city scales with negative signs. This finding indicates that urban sprawl has a negative impact on urban eco-efficiency, even if there are differences in the urban scale, which further supports the conclusion of the empirical analysis in the previous section. Moreover, the different city scales can reflect the degree of urban sprawl and the corresponding negative effect on eco-efficiency. Specifically, when the scale of a city is less than 1.42 million people, the eco-efficiency decreases by 0.04 units per a unit increase in urban sprawl. When the city scale fluctuates between 1.42 million and 10.29 million people, the coefficient decreases to −0.00846, indicating that the negative impact of urban sprawl tends to be weak. When the scale of a city exceeds 10.29 million people, the negative impact of urban sprawl on eco-efficiency will be further aggravated. For every unit increase in urban sprawl, eco-efficiency will decrease by nearly 0.075 units. This result supports the results in Section 2; notably, urban sprawl has a greater negative impact on the eco-efficiency of small cities than on larger cities. However, with the further expansion of the urban scale, the inhibition of urban sprawl on urban ecological efficiency is remarkably highlighted.

Table 4. Estimation results of the threshold regression model.

Variables		Results
	K1	−0.0408 *** (−3.60)
City	K2	−0.00846 *** (−3.56)
	K3	−0.0747 *** (−5.34)
pgdp		0.0215 *** (6.77)
techno		0.0442 *** (6.66)
fdi		−0.000746 (−0.19)
rgdp		−0.00202 (−0.91)
Perelec		−0.0311 *** (−11.38)
pep		−0.0273 *** (−7.58)
_cons		0.945 *** (485.44)

Note: *** are significant at the statistical levels of 1%, respectively. The value in parentheses is t.

5. Discussion

This study calculates the eco-efficiency of 264 prefecture-level cities in China from 2003 to 2016 using the super-efficiency DEA model. The results show that the urban eco-efficiency in China is increasing, with obvious regional differences. Among them, the eco-efficiency level in eastern cities is close to the optimal frontier of eco-efficiency, and the eco-efficiency of central cities is far behind that of eastern and even western cities. This situation may be attributed to the carrying capacity of urban resources and the environment. Eastern cities with developed economies and advanced technologies can provide substantial financial and technical support for pollution control and environmental protection. Therefore, eastern cities can balance environmental protection and economic growth. Although the central cities are relatively rich in natural resources, they have not been fully utilized due to the pattern of urbanization, especially in the cities in the Shanxi and Henan Provinces, which are rich in energy and mineral resources (e.g., coal and non-ferrous metals,). However, the extensive development pattern in these cities has not only led to the blind exploitation of natural resources but also seriously damaged the local ecological environment, resulting in a low level of eco-efficiency in central cities. The low level of urban economic development in western cities has limited the regional economy. In addition, the overexploitation of coal and other natural resources has damaged the local environment, resulting in a low level of eco-efficiency. Therefore, urbanization planning in China should focus on cultivating urban agglomerations in the central and western regions in the future to improve the overall eco-efficiency.

The results of the panel Tobit model suggest that urban sprawl is not conducive to eco-efficiency improvements in China. Moreover, urban sprawl has a significant inhibitory effect on the ecological efficiency in eastern cities. Compared with eastern cities, urban sprawl has a smaller negative impact on urban eco-efficiency in central cities and has no significant effect on urban eco-efficiency in western cities. At the present stage of development, the overexpansion mode of urbanization in China is characterized by low-density and inefficient expansion, which has seriously restricted the coordinated development of economic activities and the environment. Moreover, the large-scale construction of homesteads and development zones require large quantities of land, water, and other essential resources, increasing the pressure on the environment and resources [59]. This approach restricts urban eco-efficiency improvements. Generally, urban sprawl occurs in large and medium-sized cities, such as Shanghai, Jinzhou, Benxi, Tieling, and Weihai. These cities have the highest levels of urban sprawl and are concentrated in Eastern China. Therefore, urban sprawl has the most significant impact on eco-efficiency in these areas. For instance, Shanghai is a city with concentrated industry, a high population and a highly developed infrastructure, which put enormous pressure on the urban environment and resource utilization. Therefore, the Master Plan of Shanghai (2016–2040) proposed a 4-fold strategy for urbanization, with a focus on the population scale, land resources, the ecological environment, and urban safety, to achieve the "negative growth" of built-up areas by 2040. The total scale of construction land should be strictly reduced, and the proportions of public service facilities and ecological lands should be greatly increased.

The effect of urban sprawl on eco-efficiency is not only related to the geographical location of a city but also the urban scale. When the urban scale is very small, urban sprawl seriously hinders eco-efficiency improvements. With the gradual expansion of the urban scale, the negative effect of urban sprawl on eco-efficiency first decreases and then increases, and the inhibitory effect gradually increases. The combined status of the urban eco-efficiency, urban scale and urban sprawl in China is visualized in Figure 4. When cities are small, urban sprawl can not only reduce the allocation efficiency of urban resources but also restrict the positive effect of economic agglomeration [60]. Additionally, sprawl can increase the operating and ecological costs of the urban economy and have a negative impact on urban eco-efficiency [61]. Therefore, these small-scale cities are best suited for a compact development model that focuses on protecting green spaces, improving energy efficiency and encouraging the use of public transport. For example, small cities, such as Jiuquan, Shizuishan, Tongchuan, Yangquan, and Panzhihua, have been experiencing urban sprawl. These cities should focus on the concept of compact urban development and clearly understand the boundaries of urban development to control urban sprawl.

As the population scale and urban scale increase, moderate urban sprawl can alleviate the pressure on city centers and weaken the restraining effect on eco-efficiency. For instance, in 2019, China published the Guiding Opinions on Fostering and Developing the Modern Metropolitan Areas. The plan states that the restrictions on the scale of urban residence will be gradually reduced (except in megacities). This policy aims to eliminate the barriers between urban and rural areas and accelerate the population mobility and distribution. Moreover, this approach is beneficial for attracting more talent to cities and promoting the high-tech growth and productivity of cities. In megacities (e.g., Beijing, Shanghai, and Chengdu), the high pressures on resource utilization and the environment in central urban areas have caused cities to expand to the suburbs. However, the suburbs cannot effectively undergo population and industry shifts. Therefore, urban sprawl decreases the eco-efficiency of these large-scale cities and hinders the sustainable development of the urban economy [62]. For example, Beijing is relocating non-essential capital functions to suburban districts (e.g., Daxing district and Changping district). Due to the lag in public services and the job-housing imbalance, excessive commuting and traffic congestion have occurred, which have increased vehicle emissions and smog.

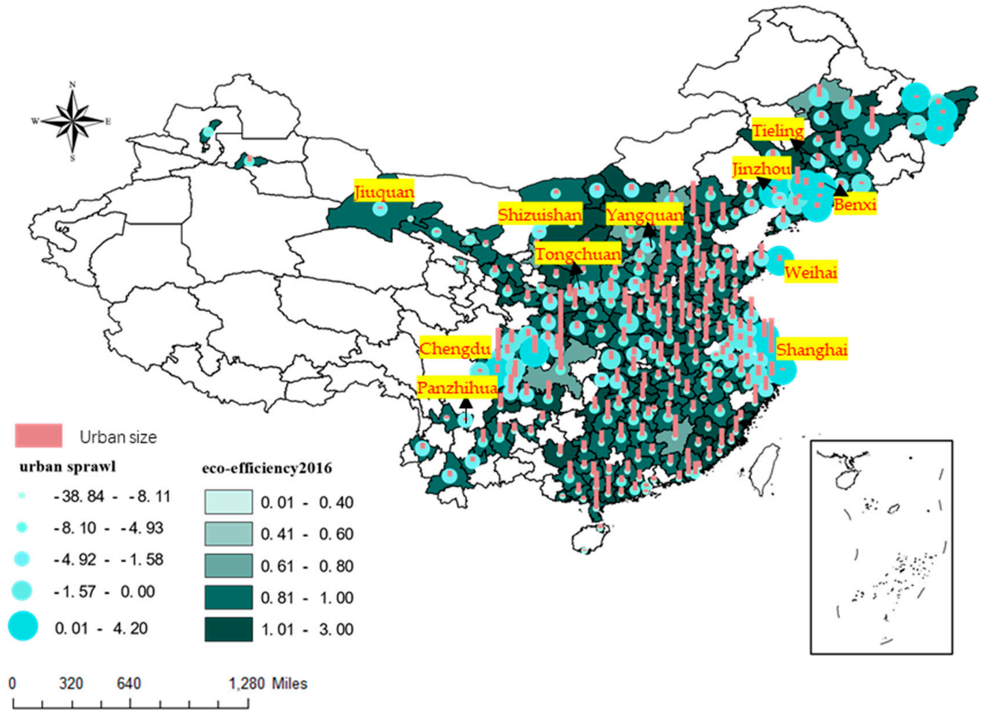


Figure 4. The urban scale, eco-efficiency, and urban sprawl in China in 2016.

6. Conclusions

This study measured the eco-efficiency of 264 prefecture-level cities in China from 2003 to 2016 by using the super-efficiency DEA model with undesired outputs. A panel Tobit model was employed to assess the effect of urban sprawl on urban eco-efficiency. Then, a threshold regression model was applied to check the threshold effect of urban sprawl on the urban eco-efficiency. The results show that urban eco-efficiency has increased, with obvious regional differences. The eco-efficiency of eastern cities has approached the optimal frontier, but the eco-efficiency of central cities lags behind that of eastern and even western cities. The results of the Tobit model indicate that urban sprawl has an inhibiting effect on eco-efficiency, which supports our assumption. Such an inhibitory effect is most obvious in Eastern China but relatively weak or even insignificant in Central and Western China. Furthermore, the threshold effect of urban sprawl on eco-efficiency is highlighted by the threshold regression model. When the city scale is sufficiently small, urban sprawl seriously hinders eco-efficiency improvements. With the gradual expansion of the city scale, the negative effect of urban sprawl on eco-efficiency first decreases and then increases, and the restraining effect is gradually strengthened.

Based on the above analysis, we propose the following suggestions. First, urban development should emphasize the economic output and environmental impact per unit area rather than the blind expansion of urban built-up areas. Second, the cities in Central China should focus on the environmental impacts of urban development to improve the overall eco-efficiency. Third, due to the inhibiting effect of urban sprawl on the eco-efficiency, the cities in Eastern China should optimize the urban spatial structure and improve resource utilization during urban expansion to reduce the effect of urban sprawl. Fourth, cities should consider the threshold effect of the city scale when establishing eco-efficiency goals to balance the tradeoff between the urban economy and environment. The contribution of this study is to determine the impact of urban sprawl on eco-efficiency and verify the threshold effect of urban scale. There are still limitations in our study. First, we divided the research samples into three groups based on geographical locations (i.e., eastern cities, central cities, and western cities) to test the impacts of urban sprawl on eco-efficiency. Further study can consider more types of geographical characteristics of cities to supplement the mechanisms of urban sprawl on eco-efficiency. Second, due to lacking data, the undesired outputs for measuring eco-efficiency were concentrated on industrial pollution. Other undesired outputs (e.g., vehicle exhaust) were not taken into account. More comprehensive indicators can be integrated into the eco-efficiency assessment in future studies.

Author Contributions: Q.Z. is the key author and did most of the writing in this contribution. C.Y. edited the text and solidified the argument. B.C. gave review suggestions for the manuscript during the whole writing process. D.Z. and Y.Y. assisted the visualization and calculation of eco-efficiency. H.Z. mainly did the data processing and collection.

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