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An Empirical Study on the Mismatch Phenomenon in Utilizing Urban Land Resources in China

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Abstract: Effective land use contributes to sustainable urban development. However, there are various reports suggesting that urban land resources used mismatch to different extents in many Chinese cities. This study measures the degree of the mismatch phenomenon in utilizing urban land resources from a supply–demand perspective, and a mismatching coefficient, namely land resource mismatch (LRM), is adopted as the measurement. The data used for the empirical analysis are from a sample of 35 cities in China. The empirical study shows the effectiveness of employing the mismatching coefficient LRM model in evaluating the degree of the mismatch phenomenon in utilizing urban land resources. The research findings suggest the following: (1) Overall, the mismatch phenomenon in utilizing urban land resources is significant in China in the form of either supply shortage or over-supply. (2) The degree of the mismatch phenomenon is different between different types of land, with the land for administration and public services showing more serious mismatching and the land for commercial and business facilities showing less mismatching. (3) There are significant differences both in the type and the degree of land use mismatch among different cities, which are contributed largely by the intensity of local government's controlling and planning role on land resources and the maturity of applying market mechanisms. The results from this study can inform the government of the importance and necessity of adopting effective policy measures for mitigating the mismatch phenomenon in utilizing urban land resources. The research method applied in this study can be applied in a larger context internationally for understanding the effectiveness of utilizing urban land resources.

Keywords: mismatch phenomenon; urban land resources; supply–demand perspective; sustainable development; China

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Citation: Shen, L.; Zhang, L.; Bao, H.; Wong, S.; Du, X.; Wei, X. An Empirical Study on the Mismatch Phenomenon in Utilizing Urban Land Resources in China. *Land* **2023**, *12*, 1196. https://doi.org/10.3390/land12061196

Academic Editor: Brian D. Fath

Received: 9 May 2023
Revised: 28 May 2023
Accepted: 3 June 2023
Published: 7 June 2023

1. Introduction

It is commonly appreciated that one of the major strategies for driving sustainable urbanization development is the full tapping of the value of urban land resources [1], Proper utilization of urban land resources in cities is a prerequisite for achieving sustainable urban development. However, various cases are reported in which urban land resources have not been utilized effectively or in a sustainable way in the process of urbanization, typically characterized by the mismatch in the use of urban land resources [2,3]. There are various specifications for the mismatch of urban land resources. Zhang and Zhang [4] considered that land resource mismatch (LRM) is mainly caused by the deviation from the optimal allocation of land resources. Du and Li [5] found that the actual price for industrial land in many Chinese cities is much lower than the market value, and they pointed out that the difference in land price can indicate that there is a mismatch in utilizing urban land resources.

The mismatch phenomenon in utilizing urban land resources has become one of the biggest challenges in achieving the goal of sustainable urban development [6]. Batunova and Gunko [7] pointed out that the mismatch in utilizing urban land resources is one of the most important challenges in urban planning. Other studies also argue that the mismatch in utilizing urban land resources can lead to various types of social, economic and environmental problems, such as increases in pollution emissions [5], degradation of urban land resources [8], difficulty in upgrading industrial structure and the poor quality of economic growth [9]. It is considered very important to understand how and to what extent the mismatch phenomenon happens in utilizing urban land resources so that proper action measures can be taken to mitigate the phenomenon, which in turn contributes to achieving sustainable land use [10]. Midrigan and Xu [11] also opined that an accurate understanding of the mismatch phenomenon in utilizing urban land resources is of great significance for achieving sustainable urban development. However, to gain this understanding, there is a need for a proper method to help assess whether there is a mismatch phenomenon.

It seems that the mismatch in utilizing urban land resources is particularly prominent in developing countries such as China, where urbanization has been a major development scheme over the past few decades. According to the China Statistical Yearbook Report (National Statistics Bureau of China, 2021), the urbanization rate reached a record of 63.89% in 2021, increasing from 17.92% in 1978. This rapid urbanization has positioned China as the country with the fastest economic development in the world during the past 30 years. However, the rapid urbanization process has been accompanied not only by the demand increase for urban land resources, but also by the mismatch in using urban land resources. In studying the impact of the urbanization process on land in referring to Chongqing city in China, Zong and Cai [12] found that most counties in Chongqing display a greater level of demand for land resources in the process of urbanization, but the supply of land is a limitation. Ruan [13] argued that there are two types of mismatch phenomena in land use, namely supply shortage and over-supply. Either of these two phenomena will have negative impacts on the sustainable development of cities and society [14].

On the other hand, China's current land use planning is controlled by the government in terms of land supply and demand. However, this government-led land planning system often causes mismatches between supply and demand [15]. Biitir et al. [16] opined that under the circumstance of over-centralization of land administration, especially in developing countries, local residents' needs or demands for urban land resources are largely defined by administration considerations instead of by considering market practice. The land for the real estate market in the Chinese context is controlled by the government. Real estate has been a major economic sector for the last few decades in China [17]. China's housing economy accounted for an average of 17.5% of GDP from 2013 to 2021 [18]. The government has introduced a series of regulations and policies to maintain the stability of housing prices in order to address the economic fluctuations of market demand [19]. Such a government-led land planning system gives more consideration to local residents' demands than to marketing factors.

Urbanization in China will continue in the coming future, and it will have a huge impact on the sustainable urban development of the country. It is a pressing issue to understand how and to what extent the mismatch phenomenon happens in utilizing urban land resources in the urbanization process of China. As pointed out by Xu [20], further urbanization progress in China might involve more mismatch phenomena in the utilization of urban land resources, which in turn will affect the healthy development of urbanization if proper measures are not taken.

2. Literature Review

The concept of mismatch has been introduced in utilizing resources across different aspects, such as water, food and environmental systems [21–23]. The problems caused by the mismatch in utilizing urban land resources have been attracting attention among both researchers and decision-makers around the world in the past few years. For example, Alam and Banerjee [24] analyzed the LRM brought by urbanization in the South Bengal region of India and found that the population and building density of core cities increased greatly at the cost of reducing green space area. In referring to Chinese large cities, Xie et al. [25] introduced the concept of mismatch in their study on urban green total factor productivity (TFP) and opined that land resource mismatch can directly reduce the green TFP. In examining the problem of mismatch of urban land resources in the United States, Hasse and Lathrop [26] pointed out that urban expansion is one of the major forces leading to the mismatch problem, which is accompanied by land consumption and inefficient use. In China, according to the study by Zhang and Pan [27], urban development mainly occurs through urban sprawl. This sprawl process is accompanied by various land use mismatch phenomena, which are mainly characterized by the imbalance between land supply and demand.

Scholars have conducted studies to address the problem of the mismatch in utilizing land resources in various circumstances [28,29]. Some scholars explain land use mismatch from the perspective of land supply, in which land area and land price are used as indicators to reflect the mismatch. For example, Li et al. [30] measured the mismatch phenomenon in using industrial land by the proportion of the agreed land area for industrial function to the total land area, arguing that a larger value of this proportion value signifies a more serious mismatch situation. This conclusion was extended in the study by Du and Li [5] who found that LRM can even cause environmental problems and pointed out that the higher the degree of LRM is, the greater pollution emissions will be. Some other scholars measured the mismatch phenomenon in utilizing land resources by the proportion of the land for industry, mining and storage to the total land area [31,32].

Nevertheless, criticism has been received in measuring the land use mismatch phenomenon by the proportion of different kinds of land areas. Instead, Yu et al. [33] pointed out that land price is a better measurement than land area in analyzing the land use mismatch phenomenon as the price has a greater influence on the allocation of land resources. For example, the government usually controls land resource allocation by adjusting land price, and enterprises consider land price as the most important factor in making business development decisions. In line with this development, several scholars suggested using the ratio of the price of industrial land to the price of commercial land in measuring the mismatch degree of land resource utilization. For example, Lai [34] used the ratio of the average price between commercial and industrial land to measure the mismatch degree of land resource use. Others use the price difference between different types of industrial land to measure the mismatch in utilizing industrial land resources [35].

However, it appears that the methods introduced in previous studies for measuring LRM mainly focus on industrial land [36]. In fact, urban land consists of various types of land, such as industrial land, residential land and land for administration and public services. Proper examination of the mismatch phenomenon of urban land use should consider all types of urban land. Furthermore, some scholars suggest measuring the mismatch phenomenon in land use from the perspective of land demand. Zhang et al. [37] opined that the demand for land from different groups of stakeholders varies significantly, and it is the demand difference that leads to the problem of mismatch in land use. In examining the impacts of land use change on ecosystems, Laliberte and Tylianakis [38] commented that the demand difference among different groups of stakeholders often causes not only land use change but also the mismatch of land resource utilization, which in turn causes biodiversity change and serious damage to ecosystem functions.

The above discussion demonstrates that previous studies have introduced a methodology for examining the mismatch phenomenon in utilizing urban land resources from either a land supply or land demand perspective. However, it is considered that both supply and demand should be taken into account collectively where the mismatch phenomenon is examined [39]. The lack of an integrative perspective between supply and demand prevents an adequate analysis of the reason behind the mismatch phenomenon; therefore, effective measures cannot be taken to correct the problems. The implication of mismatch means that there is a deviation of what is supplied from what is demanded. This supply–demand perspective in understanding land use mismatch has been echoed in other studies. Zhang et al. [40] pointed out that the mismatch of land resources can be appreciated by comparing the demand (the planned supply) scale for land with what is actually supplied. In studying the strategic measures for promoting high-quality urban development in China, He et al. [41] emphasized the importance of examining the mismatch phenomenon of land resource utilization from a supply–demand perspective and pointed out that addressing the problem of mismatch between supply and demand for land is the key to promoting high-quality urbanization in Chinese cities. Sun et al. [42] adopted supply and demand as key variables in analyzing the mismatch phenomenon of school land space, and they found that the mismatch problems of school land over-supply and supply shortage are significant in some cities in China, and the developed cities have supply-shortage school clusters, while the underdeveloped cities are over-supplied school clustering areas.

Furthermore, in measuring the mismatch phenomenon in land use from a supply–demand perspective, previous studies mainly refer to either economic demands or functional demands as the demand variable [37,43,44]. Restuccia and Rogersom [10] also proposed that the definition of LRM is essentially the contradiction between the distribution of land resources and the needs of economic development. However, both economic and functional demands are the responses to residents' demands such as living conditions, work environment, education and medical benefits. Virtually, urbanization and urban development are for residents, and land use in the process of urbanization serves not for meeting the economic or functional demands per se, but for meeting residents' demands. Therefore, residents' demands should be considered as the criterion for measuring LRM. People are the core variable in pursuing the effectiveness and sustainability of land use. Li et al. [45] also opined that land supply for development should be based on the demands imposed by residents, who are the masters of urbanization and sustainable urban development. As commented by Wang et al. [46], residents' demands are the determinant for urban land use planning. In investigating the problem of land idle status in China. Qu et al. [47] pointed out that residents' demands have not been properly taken into account in planning the utilization of urban land resources in a significant number of cities. These discussions demonstrate the importance of considering residents' demands in analyzing the variable of demand when the land use mismatch phenomenon is measured. Urbanization and sustainable urban development will be sabotaged if residents' demands cannot be met in the process of utilizing urban land resources.

Therefore, the aim of this study is to assess the mismatch phenomenon in utilizing urban land resources from the integrative supply–demand perspective in the context of China by employing a mismatching coefficient model, in which the demand for land is counted by referring to human demands. In building up the mismatch coefficient model, all types of urban land resources will be taken into account, including residential land, land for administration and public services, land for commercial and business facilities, land for industry and manufacturing, land for logistics and warehousing, land for roads, streets and transportation, land for municipal utilities, and land for green space and squares. The remainder of this paper is organized as follows: Section 3 presents the methodology of this research. Section 4 presents the results of an empirical study on the mismatch phenomenon in utilizing urban land resources referring to 35 sample cities in China. Section 5 provides a discussion and the policy implications of the study, followed by the conclusions in Section 6.

3. Research Methodology

The methodology for conducting this study includes 4 research procedures: (1) comprehending the implication of LRM from the "supply–demand" perspective by conducting a literature review; (2) selecting the indicators for measuring the supply and demand of land resources; (3) developing an LRM coefficient for measuring the degree of the mismatch phenomenon; and (4) presenting a demonstration of the application of the LRM model in the context of China. Research data were collected for 35 sample Chinese cities during 2015–2019.

3.1. Supply–Demand Perspective on the Concept of LRM

The concept of LRM has been addressed comprehensively in previous studies. Match or mismatch is a relative concept. Jiang [48] suggested that, in the real world, the match between urban land supply and demand is a dynamic equilibrium state that moves from one equilibrium stage to another. Zhang and Zhang [4] described the mismatch phenomenon in using urban land resources as a deviation from the effective land allocation state. In line with these theoretical references, the measurement for the mismatch phenomenon of urban land resources is defined as a relative coefficient index in this study, which can specify the dynamic state of the match between the supply and the demand. This index is called the land resource mismatch (LRM) index, which can be written as follows:

$$\mathrm{LRM} = \frac{S - D}{D} \tag{1}$$

where S is the supply of land resources and D is the demand for land resources. The measurement LRM reflects the relative deviation degree of land supply in meeting the demand imposed by residents' needs in their social and economic activities.

There are two scenarios in referring to the value of LRM in formula (1): (a) LRM assumes a positive value when supply is greater than demand, representing an over-supply mismatch phenomenon where there is an over-supply of land resources and indicating that some land resources are in an idle state; (b) LRM assumes a negative value when demand is greater than supply, representing a supply shortage mismatch phenomenon, indicating that there is a shortage of land supply in meeting residents' demands and that residents' living environment may not be of good quality. Both the two types of mismatch phenomena in utilizing urban land resources should be mitigated in order to promote residents' living quality and thus promote sustainable urban development.

3.2. Indicators for Measuring LRM

In applying LRM model (1), there is a need to establish the indicators for measuring the variables S and D. There are various types of urban land for the development of urbanization. According to the Code for Classification of Urban Land Use and Planning Standards of Land Development (Ministry of Housing and Urban-Rural Development, China, 2012), there are eight types of urban land: (1) residential land, (2) land for administration and public services, (3) land for commercial and business facilities, (4) land for industry and manufacturing, (5) land for logistics and warehousing, (6) land for roads, streets and transportation, (7) land for municipal utilities, and (8) land for green space and squares. Therefore, specific indicators for the two variables S and D across these eight types of urban land need to be defined.

In referring to the variable D, the per capita land area specified in the national standard is adopted as the indicator, which reflects the importance of residents' demands. As we have discussed, the land use planning system in China is government-led, and it has difficulty in adapting to the market demand. Residents' demands for land resources are decided by administration considerations in order to respond to local residents' demands. For the variable S, the per capita available land area available is adopted as the indicator. Accordingly, all the indicators across eight types of urban land can be shown in Table 1. The data for these indicators are available from China Urban Construction Statistical Yearbook.

Table 1. Indicators for measuring mismatch phenomenon across eight types of urban land.

Type of Urban Land	Supply Indicator	Demand Indicator
T_1: Residential land	S_1: Per capita available residential land area	D_1: Specified per capita residential land area in national standard
T_2: Land for administration and public services	S_2: Per capita available land area for administration and public services	D_2: Specified per capita land area for administration and public services in national standard
T_3: Land for commercial and business facilities	S_3: Per capita available land area for commercial and business facilities	D_3: Referring to existing average supply quota as no specified criterion
T_4: Land for industry and manufacturing	S_4: Per capita available land area for industrial and manufacturing	D_4: Referring to existing average supply quota as no specified criterion
T_5: Land for logistics and warehouses	S_5: Per capita available land area for logistics and warehouses	D_5: Referring to existing average supply quota as no specified criterion
T_6: Land for roads, streets and transportation	S_6: Per capita available land area for roads, streets and transportation	D_6: Specified per capita land area for roads, streets and transportation in national standard
T_7: Land for municipal utilities	S_7: Per capita available land area for municipal utilities	D_7: Referring to existing average supply quota as no specified criterion
T_8: Land for green space and squares	S_8: Per capita available land area for green space and squares	D_8: Specified per capita land area for green space and squares in national standard

In referring to Table 1, the supply indicator for each type of urban land is denoted as follows:

$$S_i = \frac{A_i}{P} \tag{2}$$

where S_i denotes the per capita supply for the type i urban land, A_i denotes the total area of type i land in a concerned city, and P is the total urban population in the concerned city.

Therefore, the LRM model (1) can be rewritten as follows:

$$LRM = \frac{{A_i}/{P} - D_i}{D_i} \tag{3}$$

For the demand indicator D_i in Table 1, this study adopts the national standards specified in "Code for Classification of Urban Land Use and Planning Standards of Land Development" (Ministry of Housing and Urban-Rural Development, China, 2012). In the Chinese land planning system, there are no specific demand standards defined officially for different cities; the demands for land resources are defined in national standards, which cannot fully follow the law of economic development and accordingly cannot be measured from the perspective of the market mechanism. It is considered that national standards have implications for both functional and economic demands as they are closely associated with residents' demands; therefore, this study adopts the same thresholds for all the sample cities at this stage. The land demand values are specified in the national document Code, which is applicable to all cities. However, the values for D_3, D_4, D_5 and D_7 are not available in the Code. As an alternative, these values are obtained by referring to the existing average supply quota for a group of sample cities, as suggested in the study by Zhang et al. [49].

3.3. Mismatch Measurements for Different Types of Land Resources

In referring to LRM model (3), the mismatch measurements for the eight types of urban land among a sample of cities can be established as follows:

$$lrm_{i,j} = \frac{S_{i,j} - D_{i,j}}{D_{i,j}} = \frac{{A_{i,j}}/{P_j} - D_{i,j}}{D_{i.j}} \tag{4}$$

where $\mathrm{lrm}_{i,j}$ represents the mismatch coefficient in utilizing type i urban land in city j; i represents a specific type of urban land (i = 1, 2, . . . , 8), j represents a specific sample city, and $S_{i,j}$ and $D_{i,j}$ refer to land supply and land demand for type i urban land in city j, respectively.

3.3.1. Normalization

To eliminate the influence of different magnitudes across different indicators in model (4), the results of $\mathrm{lrm}_{i,j}$ need to be normalized in order to conduct a comparative analysis between cities. The normalized value of $\mathrm{lrm}_{i,j}$ is calculated according to the following equations:

$$\mathrm{lrm}'_{i,j} = \frac{\mathrm{lrm}_{i,j} - \min(\mathrm{lrm}_{i,j})}{\max(\mathrm{lrm}_{i,j}) - \min(\mathrm{lrm}_{i,j})}, (\mathrm{lrm}_{i,j} > 0) \quad (5)$$

$$\mathrm{lrm}'_{i,j} = \frac{\mathrm{lrm}_{i,j} - \min(\mathrm{lrm}_{i,j})}{\max(\mathrm{lrm}_{i,j}) - \min(\mathrm{lrm}_{i,j})}, (\mathrm{lrm}_{i,j} < 0) \quad (6)$$

where $\mathrm{lrm}'_{i,j}$ is the normalized value of the result $\mathrm{lrm}_{i,j}$. Equation (5) is applicable to normalize the positive indexes, where a larger value reflects a larger degree of the mismatch phenomenon in utilizing urban land resources, and the normalized values lie in the range of [0, 1]. Equation (6) is used to normalize the negative indexes, where a smaller value reflects a larger degree of mismatch in using urban land resources, and the normalized values lie in the range of [−1, 0].

3.3.2. Mismatch Coefficients under Two Scenarios

The mismatch coefficient $\mathrm{lrm}'_{i,j}$ reflects the degree of deviation between supply and demand, namely the degree of deviation of land supply from residents' demands. It is appreciated, nevertheless, that there will be no perfect match in reality between supply and demand. Thus, a mismatch phenomenon in utilizing urban land resources always exists, but to different degrees. The degree of the mismatch can be described in three grades, namely acceptable level of mismatch, considerable mismatch and severe mismatch.

As discussed previously, there are two mismatch scenarios according to the value of the mismatch coefficient: Scenario A: $\mathrm{lrm}'_{i,j} < 0$; Scenario B: $\mathrm{lrm}'_{i,j} > 0$. Scenario A means that the demand for land resources is greater than the supply. The smaller the value of $\mathrm{lrm}'_{i,j}$, the more serious the mismatch. Scenario B indicates that the supply of land resources is greater than the demand. The larger the value of $\mathrm{lrm}'_{i,j}$, the more serious the mismatch.

The classifications of three grades of the mismatch phenomenon under two scenarios are summarized in Table 2, in which the criteria for the classifications are defined. The values for the parameters a_1, a_2, b_1 and b_2 which define the classification criteria in Table 2 need to be established. For this, the natural breakpoint method is adopted. The natural breakpoint method is also called the Jenks natural breakpoint classification method, introduced by Jenks [50]. By using this method, data values are classified into different classes according to the breaks or gaps that naturally exist in the dataset [51]. When the number of classifications is determined, the data breakpoints between classes are identified in a way that minimizes the differences within the classes and maximizes the differences between the classes. This way can help group the similar values in the data most appropriately. It is well appreciated that the natural breakpoint method can better maintain the statistical characteristics of the data [52].

By further analyzing the classifications in Table 2, it can be seen that there are five mismatch zones, as described in Table 3.

Table 2. Classification of mismatch grades under two scenarios.

Mismatch Scenario	Mismatch Grade		
	Acceptable Mismatch	Considerable Mismatch	Severe Mismatch
A ($S < D$)	$S \approx D$ ($a_2 \leq$ lrm < 0)	$S < D$ ($a_1 \leq$ lrm $< a_2$)	$S << D$ ($-1 \leq$ lrm $< a_1$)
B ($S > D$)	$S \approx D$ ($0 <$ lrm $\leq b_1$)	$S > D$ ($b_1 <$ lrm $\leq b_2$)	$S >> D$ ($b_2 <$ lrm ≤ 1)

Table 3. The classification of five mismatch zones.

Mismatch Zone	Specification	Criterion
Zone I	Severe $S < D$ mismatch	($-1 \leq$ lrm $< a_1$)
Zone II	Considerable $S < D$ mismatch	($a_1 \leq$ lrm $< a_2$)
Zone III	Acceptable mismatch ($S \approx D$)	($a_2 \leq$ lrm $\leq b_1$)
Zone IV	Considerable $S > D$ mismatch	($b_1 <$ lrm $\leq b_2$)
Zone V	Severe $S > D$ mismatch	($b_2 <$ lrm ≤ 1)

4. Empirical Study

This section presents an empirical study of the mismatch phenomenon in the Chinese context, applying the LRM coefficient models developed in the previous section.

4.1. Study Area

The empirical study was conducted in reference to 35 large cities in China, which are either municipal cities, provincial capitals or large economically developed cities. These cities have been experiencing a dramatic process of urbanization in the last few decades, which has attracted a huge number of residents from rural areas and small towns. In line with the population growth, these large cities have been under the pressure of providing living and working conditions for the massive inflow population. Therefore, the investigation on whether or not these cities have a significant mismatch phenomenon in utilizing urban land resources is considered particularly important. The locations of the 35 sample cities are displayed in Figure 1.

4.2. Research Data and Calculations

In referring to the indicators in Table 1, the data for these indicators were collected for 35 sample cities for the period from 2015 to 2019. The data for processing the values of supply (S) indicators were collected from China Urban Construction Statistical Yearbook [53] (Ministry of Housing and Urban-Rural Development, China, 2016–2020). The values of supply indicators were calculated accordingly, as presented in Appendix A.

The data for demand (D) indicators were collected from Code for Classification of Urban Land Use and Planning Standards of Land Development [54] (Ministry of Housing and Urban-Rural Development, China, 2012), and the values for D_3, D_4, D_5 and D_7 were calculated by referring to the existing average supply quotas for each type of urban land between the sample cities. As a result, the data for all the demand indicators were obtained, as shown in Appendix B. The values in Appendix B are applicable to all sample cities, as discussed in the methodology section. By applying the data in Appendices A and B to the calculation model (4), the values of mismatch coefficient $\text{lrm}_{i,j}$ were obtained, as shown in Appendix C.

4.3. Normalization

The normalization for the values of $\text{lrm}_{i,j}$ in Appendix C was conducted by referring to calculation models (5) and (6), and the normalized values of $\text{lrm}'_{i,j}$ are shown in Appendix D.

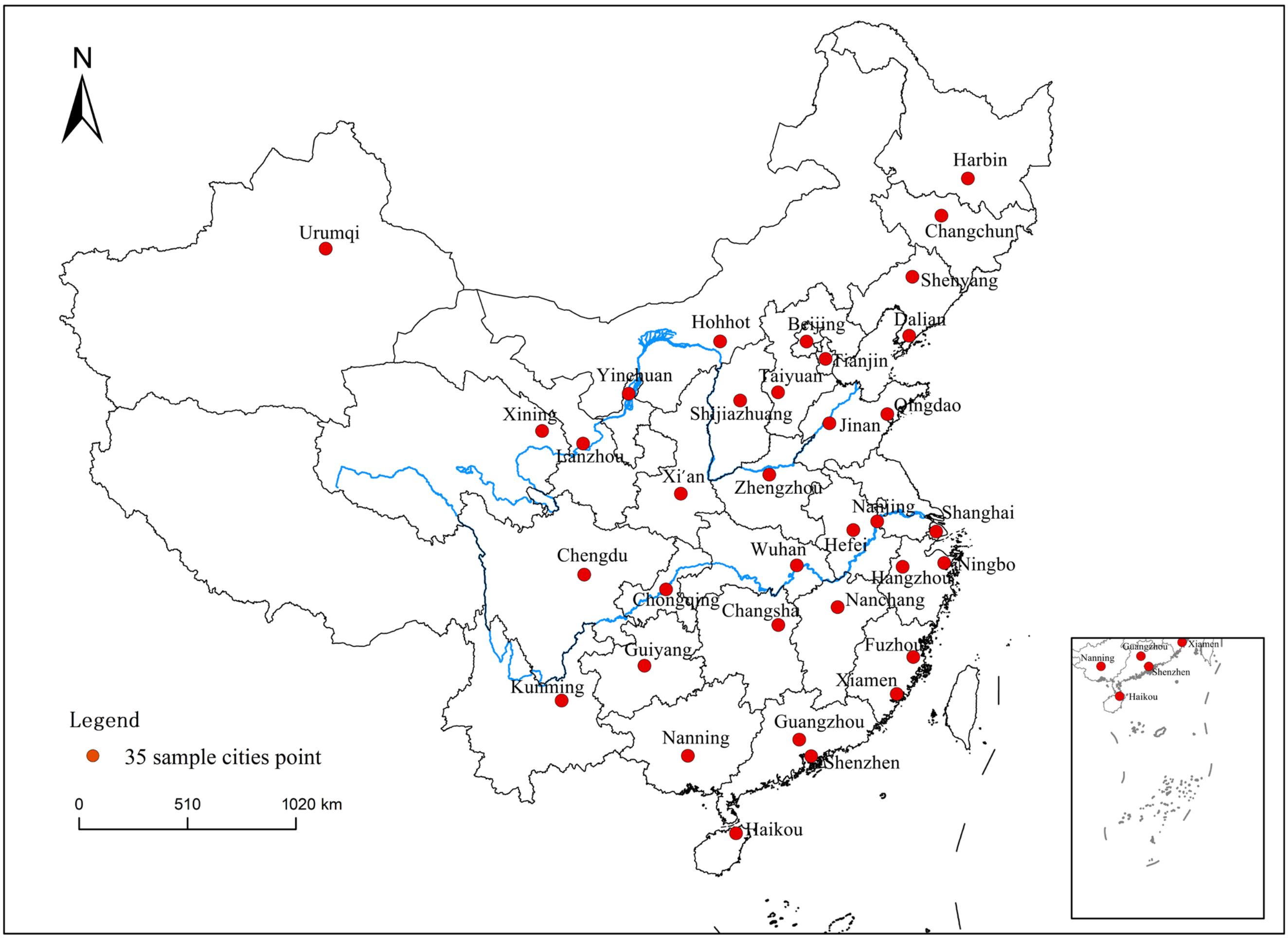

Figure 1. The locations of the 35 sample cities in China.

4.4. Establishment of Classification Criteria

Referring to the classification framework in Table 3, the values for the parameters a_1, a_2, b_1 and b_2 were derived by applying natural breaks method in ArcGIS 10.8 software. As a result, the following values of the parameters were obtained: $a_1 = -0.5813$, $a_2 = -0.2724$, $b_1 = 0.1715$ and $b_2 = 0.3969$. Accordingly, the classification criteria for LRM zones were established, as shown in Table 4.

Table 4. The classification criteria for LRM zones.

Title 1	Title 2	Title 3
Zone I	Severe $S < D$ mismatch	$[-1, -0.5813)$
Zone II	Considerable $S < D$ mismatch	$[-0.5813, -0.2724)$
Zone III	Acceptable mismatch ($S \approx D$)	$[-0.2724, 0.1715]$
Zone IV	Considerable $S > D$ mismatch	$(0.1715, 0.3969]$
Zone V	Severe $S > D$ mismatch	$(0.3969, 1]$

4.5. Results

Based on the classification criteria in Table 4, the empirical analysis results in Appendix D could be presented for the different LRM zones, as shown in Figure 2.

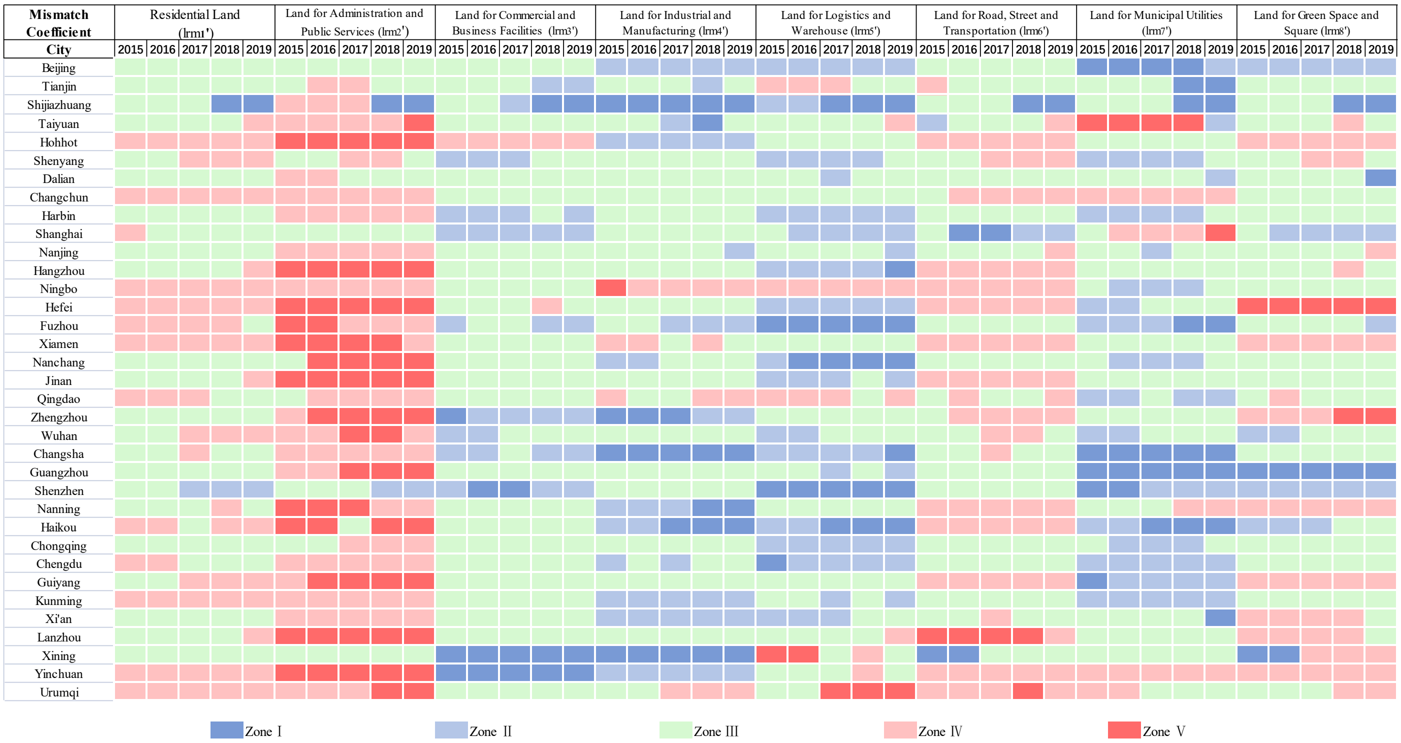

Figure 2. Distribution of mismatch phenomenon in utilizing urban land resources in 35 sample cities (2015–2019).

By referring to the data in Figure 2, the changes in the proportion of cities with different mismatch zones across eight types of urban land during the surveyed period (2015–2019) can be observed, as presented graphically in Figure 3.

According to Figure 3, most sample cities have been in a state of over-supply mismatch in utilizing the land for administration and public services (T_2) during the whole surveyed period, evidenced by the fact that most cities are positioned in Zones IV and V. Almost all the sample cities are located in Zones III and IV, suggesting that they are in the state of either acceptable or considerable $S > D$ mismatch in utilizing T_1 (residential land), T_6 (land for roads, streets and transportation) and T_8 (land for green space and squares).

Nevertheless, in referring to the utilization of the land types T_3 (land for commercial and business facilities), T_4 (land for industry and manufacturing), T_5 (land for logistics and warehouses) and T_7 (land for municipal utilities), majority of the sample cities are in the state of Zone III, suggesting an acceptable level of mismatch. In particular, a state of acceptable mismatch is presented in utilizing T_3-type land, although few cities demonstrated considerable $S < D$ mismatch in the position of Zones I and II.

From the perspective of sample cities, the data in Figure 2 show that different cities have different degrees of the land mismatch phenomenon across all eight types of urban land. This can be appreciated as the structure of land resources is different in different cities. Several typical cases can be noted. For example, the city of Shijiazhuang presents mainly the state of severe $S < D$ mismatch for all types of land, but the city of Urumqi is in the opposite situation, namely in a state of severe $S > D$ mismatch across almost all types of land. Other cases such as Chongqing and Nanjing have no serious land mismatch phenomenon across all types of land.

Figure 3. The proportion of cities with different mismatch zones across eight types of urban land resources (2015–2019).

5. Discussion and Policy Implications

The mismatch coefficient model LRM established in this study allows for the consideration of not only land supply (*S*) and demand (*D*) but also the relation between the two variables when measuring the mismatch phenomenon in the process of utilizing various types of urban land resources. This "supply–demand" perspective method is innovative, and it is distinguished from the existing mismatch analysis methods by taking into account the demand from the perspective of residents' demands. The effectiveness and applicability of this method are supported by the empirical study.

The results from the empirical study on a sample of 35 cities in China provide important references to further investigate the weak performances in utilizing urban land resources in different cities. Based on these results, decision-makers and urban planners can formulate better measures and policy instruments to alleviate the mismatch phenomenon and optimize land allocation for the mission of sustainable urban development. In particular, policy measures should be taken to ensure that master plans are fully complied with in practice.

5.1. Mismatch Phenomenon between Different Types of Urban Land

The results from the empirical study show that, overall, the mismatch phenomenon in utilizing urban land resources in China is significant. There are various factors for this; one of the major reasons is that the existing local urban plans are not compliant with master plans which are considered properly made. Nevertheless, the degree of mismatch varies between different types of land. This is because the attributes determining supply and demand are different when different types of land are concerned. For example, as shown in Figure 3, the type T_2 land (land for administration and public services) shows a severe $S > D$ mismatch phenomenon. The local governments in general want to build more public service facilities; thus, more supplies for this type of land have been provided in recent years across almost all over the country. Consequently, the supply of this type of land is much higher than the demand specified in relevant standards. Li [9] pointed out that land for administration is controlled and decided by governmental planning action, and the use of this type of land is largely influenced by government planning behaviors. However, the planned action by the government can easily divert from reality, as appreciated in previous studies [55]. Wang et al. [56] opined that the existing planning methods for the land for administration and public services mainly consider macroscopic indicators such as population and GDP but ignore the demand factors such as accessibility and traffic conditions.

The T_1 (residential land), T_6 (land for roads, streets and transportation) and T_8 (land for green space and squares) land types show an $S > D$ mismatch phenomenon. The land types T_3 (land for commercial and business facilities), T_4 (land for industry and manufacturing), T_5 (land for logistics and warehouses) and T_7 (land for municipal utilities) present a significant $S < D$ mismatch phenomenon. However, the degree of the mismatch problem in these land types is not as serious as that presented in T_2-type land. This is because the supplies for these types of land are subject to both governmental decisions and the function of market mechanisms. In particular, the market has significant impacts on the supply of these land types. The use of these types of land will be subject to more market influence. As market action is much closer to reality, the mismatch phenomenon will be less serious as a result [57,58]. In other words, the mismatch degree can be reduced by adopting a market mechanism. For example, as it is well appreciated that the supply for the land type T_1 (residential land) is primarily determined by market demand in China [59], there seems to be no serious mismatch problem for this type of land, according to the results presented in the previous section. This further proves that the market does play a role in the adjustment of the mismatch phenomenon.

The above discussion shows that the allocation of land resources among various types of land is determined by both governmental macro-control measures and market interference. However, the land under more governmental planning action will present a more serious mismatch phenomenon, such as T_2 (land for administration and public services), whereas those land types subject to more market influence will have a less serious mismatch phenomenon, such as T_1 (residential land) and T_3 (land for commercial and business facilities). It is interesting to note that this type of mismatch problem was reported in the early 20th century in Mexico [60]. In addressing such mismatch problems, governments are not able to resolve all the problems without the participation of public communities. Therefore, it is necessary to promote public–private partnerships integrating market functions with government regulation. This partnership practice can help in making better decisions on the planning and management of various types of urban land resources, which will in turn lead to the mitigation of the land use mismatch phenomenon. This action would ensure that various types of urban land resources are provided in a balanced way not only for avoiding the waste of urban land resources but also, more importantly, for satisfying the demands of residents and achieving the mission of sustainable urban development.

5.2. Mismatch Phenomenon between Different Cities

As shown in Figure 2, some cities such as Shijiazhuang present a severe $S < D$ mismatch phenomenon across all types of land. Those cities with a severe $S < D$ mismatch phenomenon are major cities or relatively developed cities. They generally enjoy more important political and economic status and have a large inflow population [61]. However, whilst they have a strong ability in attracting population inflows, they have limited land resources to accommodate this large number of inflow population members, which consequently brings the problem of the $S < D$ mismatch phenomenon. For this type of city, the city government should consider controlling the inflow population and at the same time introducing flexible land control policies such as utilizing idle and inefficiently used land to increase land supply to meet residents' demands.

Some other cities present a severe $S > D$ mismatch phenomenon; examples include Urumqi, Lanzhou and Hefei. They are in the state of Zone IV and Zone V across almost all types of land. These cities have relatively more land resources to offer, and on the other hand, they have a smaller scale of population as the result of net population outflows. The local governments in these cities should formulate relevant policies to attract more population inflow and restrain the scale of the land supply in accordance with the demands of the actual populations.

There are still other cities where both $S > D$ and $S < D$ mismatch phenomena exist. One of the main reasons for this is considered that the land plan for urban development does not match their resource endowment. For example, the planning of Kunming aims to develop the cultural and tourism industries [62]; thus, the priority is given to the development of the tertiary industry, which expects more supply for commercial service land (T_3) than for industrial land (T_4). Nevertheless, the market demand for T_3 is not large as as expected, and the demand for T_4 is not as small as expected. Consequently, Kunming presents the $S > D$ mismatch phenomenon for T_3-type land and $S < D$ mismatch phenomenon for T_4-type land. This indicates that tailor-made policies should be adopted to plan urban land use by considering the different natural endowments in each city, and optimizing the structure of land use to ensure that land supply matches with demand for all types of economic development patterns, so as to reduce the mismatch phenomenon in utilizing urban land resources.

Furthermore, some cities, such as Chongqing and Nanjing, demonstrate a less severe mismatch phenomenon in utilizing urban land resources. The good experiences of these cities should be reviewed and taken as a reference for promotion in other cities [63]; thus, the overall mismatch phenomenon can be mitigated at the national level.

It is interesting to note that, in general, developed cities such as Beijing, Nanjing and Chongqing demonstrate a less severe mismatch phenomenon in utilizing land resources. This may be because the market mechanism plays a significant role in determining land use in these developed cities, together with their advantages of having high-quality resources, both naturally and socially [45]. On the other hand, the less developed cities present more serious mismatch phenomena in land use. This may be because the administrative measure is the major factor determining land planning in those cities. For example, according to the study by Ma et al. [64], there is a severe problem of $S > D$ mismatch for urban land resources in Yinchuan City, where the land plan for urban development is primarily formulated by the local government. Other similar cases include Hohhot and Urumqi [65], which might continue to present a severe mismatch phenomenon in utilizing urban land resources.

In summary, developed cities have better market practices, and the market can respond more effectively to the changes in demands in reality. Thus, market interference can significantly adjust the mismatch phenomenon in land use. On the other hand, the market mechanism is less effective in less developed cities, and they rely more on governmental planning. However, governmental planning behavior cannot be easily changed to respond to reality; thus, a more severe mismatch phenomenon happens in these cities where governmental planning has a greater influence. Therefore, local governments not only need to implement different policy measures to alleviate the mismatch according to different mismatch phenomena, but also need to promote market practice for adjusting the mismatch phenomenon of land resources in the process of use at the same time.

5.3. Mismatch Phenomenon between Different Surveyed Years

The changes in LRM during the survey period are of interest. As shown in Figure 2, the temporal evolution is mainly manifested in three forms of change. Firstly, some mismatch phenomena remain unchanged in the same state throughout the five-year study period. For example, almost all types of land resources in Beijing show a stable development trend, among which T_1 (residential land), T_2 (land for administration and public services), T_3 (land for commercial and business facilities) and T_6 (land for roads, streets and transportation) are in an acceptable mismatch state; T_4 (land for industry and manufacturing), T_5 (land for logistics and warehouses) and T_8 (land for green space and squares) are in a slight $S < D$ mismatch state; and T_7 (land for municipal utilities) is in the state of serious $S < D$ mismatch except for the degree of the mismatch being reduced for the year of 2019. This shows that Beijing, the capital of the country, has effectively implemented the master planning for various land resources and can meet the residents' demands in a stable and orderly manner.

The second form of LRM change is an improving change trend, which is specifically manifested as the change from Zone I ($S << D$) to Zone III ($S \approx D$) or from Zone V ($S >> D$) to Zone III ($S \approx D$) during the surveyed period. In other words, either the change from $S < D$ to $S \approx D$ or the change from $S > D$ to $S \approx D$ is an improvement of the mismatch phenomenon. For example, the three land use types T_3 (land for commercial and business facilities), T_5 (land for logistics and warehouses) and T_7 (land for municipal utilities) in Shenyang changed from a slight $S < D$ mismatch state to an acceptable mismatch state, whilst the two land use types T_2 (land for administration and public services) and T_8 (land for green space and squares) improved from a slight $S > D$ mismatch to an acceptable mismatch state. This suggests that Shenyang has made effective improvements in reducing land use mismatch.

The third form of LRM change is a deterioration change trend from the existing mismatch state to either Zone I ($S << D$) or Zone V (serious $S >> D$), For example, almost all types of land resources in Shijiazhuang experienced significant changes from the originally acceptable mismatch or slight mismatch to the serious $S < D$ mismatch in 2018. It was also shown that Shijiazhuang, a city close to Beijing, had attracted a large number of people flowing out of Beijing, presenting great land supply pressure and resulting in the situation of land resources being in short supply.

The results show the various dynamic changes in the mismatch phenomenon in utilizing urban land resources, and there is no obvious change of deterioration or improvement. These findings show that the improvement and optimization of urban land resource mismatch is a long-term process. It will be difficult to achieve sustainable development of urban land resources if the supply and demand of land resources are not balanced. Land use management divorced from residents' demands should be avoided.

6. Conclusions

This study introduces a land resource mismatch (LRM) coefficient model for evaluating the degree of the mismatch phenomenon in using urban land resources. The model is developed from a "supply–demand" perspective, and it emphasizes the consideration of residents' demands. In using the LRM model, the LRM phenomena are classified into five zones, namely severe $S < D$ mismatch, considerable $S < D$ mismatch, acceptable mismatch, considerable $S > D$ mismatch and severe $S > D$ mismatch. These five zones are used to describe the mismatch degree in utilizing urban land resources. The application of the LRM model can help understand the degree of the mismatch phenomenon in utilizing different types of land.

The effectiveness of the proposed LRM method is proven by an empirical case study that includes 35 sample cities in China. The research findings suggest the following: (1) The degree of the mismatch phenomenon is different between different types of urban land, where the land for administration and public services is subject to the most severe $S > D$ mismatch. (2) The mismatch phenomenon is more serious where administrative planning plays a leading role, and the phenomenon is less serious if there is effective market participation. (3) There are significant differences in the degree of land use mismatch between different cities. The mismatch problem is less serious in developed cities where the market plays a more active role in the process of utilizing land resources. However, the problem is more serious in relatively less developed cities where there is a strong administrative role in manipulating land resources. (4) Overall, the mismatch phenomenon in utilizing urban land resources is significant in China in the form of either supply shortage or over-supply. The causes for the mismatch phenomenon in utilizing urban land resources are multiple, but the major cause is the non-compliance with the urban master plans.

Policy implications from this study can be highlighted by drawing on the research findings. Either over-supply mismatch or supply-shortage mismatch will affect the sustainability of urban development. However, the policy measures for addressing the two different scenarios should be different in order to meet human demands and contribute to sustainable urban development. Firstly, the government-led spatial planning system in China has limitations in dynamically meeting the balance between the supply and demand of urban land resources. However, market-oriented spatial planning has the weakness of the lack of consideration of the sustainability of urban land resources. Therefore, the functions between the market mechanism and the administration role should be integrated into the process of decision making in the planning and management of various types of urban land resources. Secondly, different policy measures should be adopted in responding to different types of mismatch phenomena in order to alleviate the overall mismatch. Thirdly, relevant policies should be introduced to promote the function of the market mechanism in mitigating the mismatch phenomenon of land resources. The practice of the market mechanism can help local government to design specific urban planning policies to balance dynamically between the supply and demand of urban land resources.

The LRM model provides a new methodological tool for understanding the mismatch phenomenon in utilizing urban land resources. This method is complementary to the existing methods for studying the mismatch phenomenon in utilizing urban land resources, and it contributes to the development of the literature in this discipline. The method can be used for investigating LRM in a larger context globally. Practically, the application of the method can help decision-makers in a city understand whether the supply of urban land resources can match the demand from its residents. The mismatch degree can be evaluated and judged according to the value of the mismatch coefficient, and the evaluation results can further help poor performers learn from the experience of better performers. The empirical findings provide references for the local governments in China to formulate tailor-made land policies for mitigating the mismatch phenomenon in utilizing urban land resources.

The limitations of this study at its current stage are implicit as only big cities in the Chinese context were selected as the sample cities for the demonstration. It is recommended for future studies to apply the LRM model in evaluating the mismatch phenomenon in different types of cities or even in a wider context internationally. Furthermore, different scenarios could be designed for different cities or regions. Thus, comparison can be conducted more scientifically at regional and international levels, and the experiences and lessons can be captured and shared in promoting land use efficiency whilst meeting residents' demands, which is the mission of sustainable urban development.

Author Contributions: Conceptualization, L.S. and L.Z.; methodology, L.S. and L.Z.; software, L.Z.; formal analysis, L.S. and L.Z.; writing—original draft preparation, L.S., L.Z., S.W. and H.B.; all authors participated in writing—review and editing; visualization, L.Z., X.D. and X.W.; funding acquisition, L.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Social Science Foundation of China (Grant No. "17ZDA062") and the Fundamental Research Funds for the Central University (Grant No. "2021CDJSKZD03").

Data Availability Statement: The data presented in this study are available on request from the author.

Acknowledgments: The authors wish to express their sincere gratitude to the National Social Science Foundation of China (Grant No. "17ZDA062") and the Fundamental Research Funds for the Central University (Grant No. "2021CDJSKZD03") for funding this research project. Appreciation is also due to all members of the research team for their invaluable contributions.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. The values for *S* "supply" indicators (m^2/person).

	S_1					S_2					S_3					S_4				
City	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**
Beijing	22.2171	22.3936	22.5615	22.9645	22.9448	9.2374	9.3041	9.1879	9.2916	9.2836	7.1071	7.1893	7.2631	7.3661	7.3598	14.0358	14.0094	14.0195	14.1188	14.1067
Tianjin	32.8497	35.9497	40.5272	19.1447	20.1957	9.5931	10.901	11.3216	5.4896	5.8151	6.9618	9.6357	11.2398	6.0942	6.0981	30.8625	32.1482	35.4045	17.1482	18.2315
Shijiazhuang	36.3349	36.5127	37.2038	6.868	5.8107	10.1765	10.1817	9.919	1.54	1.2759	6.7679	6.9216	5.9627	1.0848	0.8997	6.1059	6.1113	6.0271	2.5039	2.0522
Taiyuan	22.0815	21.9355	35.0585	34.0762	55.1042	13.9633	14.1935	14.5788	11.0202	20.8671	8.4429	8.3871	7.6365	6.4745	11.2123	25.9782	26.129	18.0499	6.8152	22.5579
Hohhot	56.2424	57.5477	56.9668	50.1925	55.8643	17.0455	17.8531	20.7854	18.4187	20.5	19.3333	19.5244	19.2339	16.8399	18.7429	14.0606	14.2825	14.3196	12.4246	13.8286
Shenyang	33.4581	37.6115	42.1773	41.9203	47.2376	9.3572	9.6593	11.8161	11.6227	5.3744	4.5438	6.121	6.6596	6.6009	7.9392	21.521	31.8877	37.0208	36.7	30.8539
Dalian	35.7494	37.1519	36.6332	35.574	35.4635	9.9114	9.959	9.7749	9.4923	8.2635	7.1007	7.1892	7.0103	6.8076	8.4414	32.8075	35.6124	35.438	34.4133	32.5673
Changchun	42.3705	49.3222	45.9281	41.8048	43.6839	13.3678	15.4634	14.7941	13.514	13.6984	7.8762	8.9263	8.5126	7.9824	8.17	31.1524	38.8714	37.1112	34.223	35.5111
Harbin	30.2919	31.7123	31.9025	32.7598	33.8528	12.4413	12.4944	12.4706	12.6958	12.939	5.606	6.041	5.998	6.3574	6.5297	21.2191	22.4529	22.2582	22.7978	23.2598
Shanghai	43.8415	22.5445	22.5978	22.7657	22.6416	6.6961	6.245	6.2568	6.2312	6.3089	5.6946	4.7977	4.8608	4.8482	5.134	30.3531	22.9677	22.7674	22.5895	22.1462
Nanjing	35.1259	36.297	35.6413	34.6891	35.2561	14.8165	15.3471	14.9798	14.639	10.1427	8.7854	9.4057	9.8009	9.4655	9.415	27.4684	26.8981	26.8164	26.187	14.7864
Hangzhou	37.8964	41.0364	39.7482	38.9646	47.568	20.2686	20.8169	19.8431	19.6208	18.853	13.7824	14.6166	14.1436	13.8843	9.1223	22.8281	24.4894	24.111	22.9255	31.3956
Ningbo	44.3644	48.057	46.2466	42.7085	42.63	14.2064	13.6819	13.3098	14.1739	14.5283	12.8776	10.4501	9.9122	10.4814	10.6469	71.8979	64.8197	61.2915	64.5401	62.1171
Hefei	54.9121	58.8324	58.5004	58.8395	61.3528	19.6864	20.091	19.9609	19.3952	20.2064	14.9197	15.6605	15.2549	14.971	15.2934	37.037	37.4574	36.1706	35.8804	36.1737
Fuzhou	52.5107	52.8019	50.7396	41.454	40.7908	15.7115	16.0409	15.2264	10.5078	10.3623	5.7939	6.6259	7.212	5.6727	5.5506	18.7911	17.9773	18.225	13.6415	13.3733
Xiamen	50.9097	49.9357	45.8935	50.1864	46.0378	16.8807	15.9096	16.0004	15.9849	14.8577	13.9256	12.958	11.8103	11.9427	10.973	48.7692	45.1039	42.9346	43.2977	39.7106
Nanchang	36.3877	35.7881	38.5881	38.366	37.5015	8.1211	17.0551	18.2786	18.2419	17.7382	13.9307	8.2301	8.8549	8.9908	9.1203	16.974	17.0181	24.7776	24.4694	23.7938
Jinan	35.23	36.0163	37.1373	38.7895	47.1636	19.9467	22.4487	22.7284	22.554	21.3159	7.8033	8.7899	9.5385	10.1974	13.7239	25.18	26.306	26.1745	26.4821	31.1463
Qingdao	44.5475	49.4313	46.9146	40.0493	39.0361	9.8474	12.27	13.0289	11.1798	12.5063	6.6743	9.0386	9.4198	9.0345	11.506	52.8116	41.5468	44.6445	43.3867	45.8037
Zhengzhou	26.3419	30.4613	33.3423	35.3669	35.0105	15.0283	17.3774	19.0214	20.3663	19.8738	3.7983	4.3922	4.8075	5.2159	5.1528	9.1974	10.634	11.6387	12.1989	11.5572
Wuhan	33.8324	35.5643	45.6721	44.7781	43.3916	13.9766	14.1949	16.3339	15.7897	15.3008	5.4679	5.8587	7.3922	7.3096	7.0833	21.2813	21.6461	36.9055	36.0844	34.9671
Changsha	32.2784	31.9422	45.5317	34.9518	31.9558	11.4287	11.0466	14.4591	11.0461	10.1001	5.5583	5.1862	7.2419	5.7047	5.2164	7.8959	7.7608	11.689	8.9843	8.2157
Guangzhou	33.1653	33.9531	33.9143	33.1606	32.6697	12.3899	12.2694	17.175	16.7185	16.351	8.5628	9.6138	8.7457	8.7048	8.5517	29.3302	29.7431	29.495	28.8607	28.448
Shenzhen	21.2859	17.5179	16.9017	16.3458	15.8444	5.2545	5.0091	4.7916	2.8956	2.8068	4.4547	3.0004	2.9741	4.6559	4.5131	27.7804	22.9603	21.8018	20.9894	20.3456
Nanning	41.1466	40.0846	39.4302	42.5179	41.1107	19.2612	19.0966	18.8386	14.9342	14.772	7.4838	9.2345	9.1257	9.8313	9.583	14.32	14.9132	14.7673	8.2738	7.9637

Table A1. *Cont.*

			S_1					S_2					S_3					S_4		
City	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**
Haikou	50.463	49.2273	35.085	45.1366	44.8675	24.0833	20.0091	9.5216	21.6522	21.5232	12.3796	12.1545	8.2471	8.3278	8.2781	11.3981	11.1909	8.1363	7.6616	7.6159
Chongqing	33.9686	33.6356	33.1458	34.5053	34.7908	9.5271	9.6853	9.9499	9.999	9.962	6.7856	6.7852	6.9052	7.1515	7.0673	22.8504	22.3841	21.806	21.9588	22.1517
Chengdu	43.915	41.6846	40.5668	39.9296	40.2964	12.433	13.5029	12.9968	11.1305	11.0128	10.9302	11.734	11.3872	9.5743	9.8295	16.4216	18.5794	17.7262	19.2858	18.4865
Guiyang	37.3687	40.2822	46.5749	45.212	44.486	15.3034	17.2624	18.913	18.3596	18.0648	11.9327	12.396	13.2029	12.8165	12.6107	23.5033	22.8168	29.0193	28.1701	27.7178
Kunming	46.1821	46.1523	46.2348	47.5991	47.4984	11.5277	11.436	11.5051	11.987	11.7286	9.1953	9.3233	9.4896	10.1901	9.9466	13.7652	13.4747	13.5741	13.89	13.8114
Xi'an	28.1373	28.7893	29.2667	26.7171	39.3848	15.047	14.9095	14.4387	13.0325	14.1195	9.7816	9.6117	10.2754	9.6174	8.9323	14.2388	14.3339	15.9028	13.8372	17.5621
Lanzhou	35.7327	37.1067	38.0367	37.8892	42.9788	16.3576	17.7508	17.9977	17.8799	17.7493	10.328	11.2671	11.1457	11.0461	15.4905	24.724	26.168	26.4585	26.2059	39.3535
Xining	36.4835	36.7742	23.0466	22.8817	21.7511	4.4019	4.4263	4.7075	4.7259	4.6891	1.9481	1.9355	1.9554	2.0447	2.0411	3.4817	3.4545	3.4441	3.4052	3.3888
Yinchuan	46.6899	47.1524	48.5443	53.4915	53.3418	25.443	25.8995	26.9661	30.8539	30.1355	2.5158	2.6487	2.8582	3.5294	3.601	14.5166	15.0515	15.5068	16.6603	16.5772
Urumqi	56.1292	56.7636	56.9384	58.2173	56.5603	11.112	11.2154	15.3221	15.8632	17.6043	10.0573	10.1854	14.2277	9.9318	14.2448	30.1911	30.5943	47.7349	48.6543	44.586
			S_5					S_6					S_7					S_8		
City	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**
Beijing	2.7502	2.7405	2.7347	2.7305	2.7282	14.3292	14.41	14.4538	14.5766	14.5641	1.7069	1.6871	1.6898	1.6958	1.6944	6.0883	6.1439	6.1723	6.2381	6.2327
Tianjin	9.2725	9.1783	8.7792	4.0229	4.2352	22.7572	19.1922	19.6598	10.9399	11.6517	3.4499	3.6805	3.0593	1.5338	1.5462	12.8184	13.0256	15.3096	8.9257	8.781
Shijiazhuang	2.1913	2.2226	1.927	0.4873	0.3852	15.6623	15.6153	16.9948	3.4109	2.967	5.6037	5.5926	5.1299	0.8465	0.7282	17.4313	17.3911	17.468	3.5603	3.0122
Taiyuan	3.8967	3.871	4.1654	3.4076	8.1307	7.4687	16.129	13.8845	21.0352	32.1694	14.288	14.1935	12.4961	12.2674	1.6908	11.3655	11.2903	11.8019	20.4219	7.8072
Hohhot	6.3258	6.4271	6.3173	5.455	6.0714	32.5152	32.6065	31.9204	27.6665	30.7929	3.5152	3.525	3.4964	3.4848	3.8786	25.1364	25.207	24.653	21.3195	23.7286
Shenyang	2.1542	2.9543	2.613	2.5492	4.6355	11.0386	15.3364	22.6888	22.5371	24.6463	2.4495	2.7037	2.0441	2.0078	5.1273	14.9535	17.6727	18.3462	18.1876	15.6762
Dalian	3.2699	3.3574	3.1296	3.0391	3.9613	17.7862	17.3869	17.4179	16.9143	14.3846	3.6077	3.5778	3.458	3.358	2.1351	15.3362	14.6447	15.1338	14.6962	3.3608
Changchun	4.0967	5.4709	5.2243	4.7884	5.0161	20.6978	25.872	25.0154	22.9526	23.7641	8.0318	9.7812	9.2563	8.4356	8.6432	10.4458	11.5821	11.0172	10.6902	11.0817
Harbin	2.385	2.6306	2.6078	2.7243	2.7675	12.5396	12.9257	12.9147	13.2772	13.558	2.6309	2.569	2.5468	2.6009	2.6422	9.7121	9.5225	9.4845	9.7318	9.9114
Shanghai	3.5416	2.4197	2.3582	2.3092	2.1543	17.3422	5.5259	5.6196	5.6763	5.7266	5.394	8.797	8.7817	8.1806	10.1922	7.8505	5.7743	5.7684	5.7497	5.797
Nanjing	3.0396	3.1036	3.4882	3.3767	3.1063	18.2464	19.1974	20.5284	19.9891	25.7892	3.2339	3.8232	2.9838	2.8966	2.963	15.6967	16.2953	13.4649	13.0943	24.9464
Hangzhou	2.7944	2.7456	2.7554	2.5666	1.5902	22.0663	25.8372	24.5558	27.2869	32.2412	3.3605	3.6284	4.0171	3.9495	2.6731	15.3633	15.8613	15.9446	18.6963	11.0256
Ningbo	9.3541	8.9405	8.3849	9.2691	9.1273	30.753	31.7752	31.0458	31.4795	31.1127	2.9946	2.5217	2.3949	2.8136	2.7241	10.1805	10.5451	10.4057	14.2395	13.8697
Hefei	2.3833	2.4403	2.4326	2.4052	2.158	32.175	32.5199	31.8874	31.6362	28.3734	2.9077	3.0326	3.1374	3.1074	3.2497	36.2458	36.5618	35.4476	34.5418	30.8939
Fuzhou	0.8456	0.8218	0.8875	1.3411	1.3123	17.0634	16.8473	16.2976	16.454	16.019	2.5733	2.5682	2.8373	1.467	1.4439	11.3686	11.3	10.8158	8.0469	6.7015

Table A1. *Cont.*

	S_5					S_6					S_7					S_8				
City	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**
Xiamen	4.5665	4.1783	4.8386	4.6667	4.3317	28.19	32.6923	28.7531	27.9131	29.9589	4.4536	7.4298	3.9469	4.5505	4.2211	20.8527	19.9861	22.2577	19.5527	19.3222
Nanchang	2.3073	1.5098	1.6451	1.7421	1.694	17.2552	18.1259	19.4971	19.4433	18.9065	3.1674	2.5847	2.7215	2.7433	2.6675	12.7026	12.5421	12.9981	13.2359	12.8704
Jinan	2.8033	3.0282	3.012	3.0985	2.6906	23.3267	22.0781	22.4786	22.4528	24.9684	4.61	4.5256	4.6206	4.6536	4.0198	12.0767	12.3314	12.167	12.1138	16.1574
Qingdao	7.7721	8.3896	9.4317	4.9975	8.5936	18.1584	22.1817	16.3761	20.1872	22.5022	2.8284	2.9304	4.7873	2.1305	2.1203	14.4899	19.2681	10.2321	13.7044	13.7674
Zhengzhou	4.1279	4.772	5.2224	5.3977	5.3333	19.0044	21.9755	24.0538	26.0928	24.8411	4.1331	4.7778	5.2305	5.673	5.6054	21.2514	24.5731	26.8965	31.0493	31.7873
Wuhan	2.7941	2.7499	4.4284	4.3311	4.197	13.188	13.9921	21.9426	22.1871	21.5001	1.9717	2.0212	4.8825	4.6871	4.542	5.0736	5.6074	8.0664	7.9669	7.7202
Changsha	2.3317	2.0426	2.6746	2.1152	1.9337	14.0931	15.2201	21.7257	16.7107	15.2775	1.2336	1.1948	1.4682	1.1698	1.0708	9.4209	9.8319	14.9119	11.4254	10.4457
Guangzhou	3.071	3.1583	3.1044	3.1204	3.0843	12.624	12.4258	12.1788	11.8658	11.5965	1.1397	1.1251	1.1025	1.0742	1.0496	4.3375	4.2611	4.1511	4.0384	3.9465
Shenzhen	1.5995	1.7064	1.6092	1.5537	1.5061	11.5679	19.3074	18.7719	18.2611	17.701	1.7902	1.9406	1.8973	1.8424	1.7859	4.9495	5.9361	5.7175	5.5786	5.4075
Nanning	3.3629	3.3556	3.2971	3.3302	3.2054	25.8671	25.6609	25.211	21.8656	22.0897	4.3512	4.0676	3.9887	8.0716	7.7732	20.8731	19.5861	19.2605	24.9892	24.0527
Haikou	2.6389	2.5909	0.5449	0.4997	0.4967	24.0741	24.0909	24.4736	22.485	28.9735	2.287	2.2455	0.7296	0.6579	0.654	6.1574	6.0455	7.3883	10.9094	17.3841
Chongqing	2.5062	2.6372	2.763	2.83	2.6535	18.6504	19.3806	20.7405	21.1948	21.1387	3.0117	3.0017	2.7095	2.8361	2.8171	10.7667	9.4613	10.1434	10.0894	10.684
Chengdu	1.2297	2.8849	2.7648	2.1452	2.2621	20.2383	20.6172	20.6685	20.2974	21.2163	2.1015	2.6841	2.6099	1.8043	1.7234	14.9107	13.166	13.1412	13.2909	12.9921
Guiyang	3.4472	4.5743	4.5942	4.4598	4.3882	25.7471	25.802	29.2464	28.3905	27.9347	1.8154	2.3465	2.57	2.4948	2.4548	20.7802	21.3614	22.5266	21.8674	21.5162
Kunming	3.1187	3.0848	3.0934	3.1288	2.8781	10.9551	11.5151	11.6098	12.917	13.3019	2.1266	2.0872	2.1202	2.2341	2.12	12.3061	12.6352	12.7491	12.682	12.4444
Xi'an	2.3349	2.3737	2.8634	3.755	3.2602	20.0265	20.3564	23.0877	19.7776	16.6515	4.1925	4.1259	4.8528	4.4245	1.4068	23.491	23.2209	26.1194	22.9621	10.8273
Lanzhou	4.0465	4.1795	4.299	4.3521	9.5503	33.9693	34.9084	35.7422	35.5215	27.5953	5.2364	5.3025	5.6968	5.6733	3.61	26.096	26.6977	28.0093	27.5789	8.1022
Xining	11.7798	11.6292	6.8399	6.9775	6.6751	5.3635	5.3655	10.4611	13.1832	13.4053	2.9263	3.1523	3.1705	3.1665	3.0814	4.4765	4.4426	18.5322	19.3333	19.4972
Yinchuan	6.5375	6.7167	6.6306	7.1063	6.9292	25.0758	24.7333	26.0962	28.3871	29.1079	8.3463	8.4343	8.3703	9.0038	9.3116	24.0474	23.6756	23.6908	25.3226	24.2703
Urumqi	6.645	6.714	14.7079	14.9737	13.4821	25.7585	26.1692	30.9166	34.7129	31.4523	8.2499	8.3543	4.8903	4.9267	4.8937	16.1521	16.3272	17.5525	19.3566	18.3229

Appendix B

Table A2. The data for demand indicators for the survey period (2015–2019) (m^2/person).

	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8
2019	23	5.5	8.8	23.89	4.19	12	3.38	10
2018	23	5.5	8.31	23.42	3.86	12	3.78	10
2017	23	5.5	8.87	24.95	4.18	12	3.99	10
2016	23	5.5	8.74	23.77	4.05	12	4.17	10
2015	23	5.5	8.55	23.85	3.92	12	3.88	10

Appendix C

Table A3. The values of $\mathrm{lrm}_{i,j}$ for 35 sample cities during the surveyed period (2015–2019).

	Residential (lrm_1)					Land for Administration and Public Services (lrm_2)					Land for Commercial and Business Facilities (lrm_3)					Land for Industry and Manufacturing (lrm_4)				
City	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**
Beijing	−0.0340	−0.0264	−0.0191	−0.0015	−0.0024	0.6795	0.6917	0.6705	0.6894	0.6879	−0.1688	−0.1774	−0.1812	−0.1136	−0.1637	−0.4115	−0.4106	−0.4381	−0.3971	−0.4095
Tianjin	0.4282	0.5630	0.7621	−0.1676	−0.1219	0.7442	0.9820	1.0585	−0.0019	0.0573	−0.1858	0.1025	0.2672	−0.2666	−0.3070	0.2940	0.3525	0.4190	−0.2678	−0.2369
Shijiazhuang	0.5798	0.5875	0.6176	−0.7014	−0.7474	0.8503	0.8512	0.8035	−0.7200	−0.7680	−0.2084	−0.2081	−0.3278	−0.8695	−0.8978	−0.7440	−0.7429	−0.7584	−0.8931	−0.8931
Taiyuan	−0.0399	−0.0463	0.5243	0.4816	1.3958	1.5388	1.5806	1.6507	1.0037	2.7940	−0.0125	−0.0404	−0.1391	−0.2209	0.2741	0.0892	0.0992	−0.2766	−0.7090	−0.0558
Hohhot	1.4453	1.5021	1.4768	1.1823	1.4289	2.0992	2.2460	2.7792	2.3489	2.7273	1.2612	1.2339	1.1684	1.0265	1.1299	−0.4105	−0.3991	−0.4261	−0.4695	−0.4212
Shenyang	0.4547	0.6353	0.8338	0.8226	1.0538	0.7013	0.7562	1.1484	1.1132	−0.0228	−0.4686	−0.2997	−0.2492	−0.2057	−0.0978	−0.0977	0.3415	0.4838	0.5670	0.2915
Dalian	0.5543	0.6153	0.5927	0.5467	0.5419	0.8021	0.8107	0.7773	0.7259	0.5025	−0.1695	−0.1774	−0.2097	−0.1808	−0.0407	0.3756	0.4982	0.4204	0.4694	0.3632
Changchun	0.8422	1.1444	0.9969	0.8176	0.8993	1.4305	1.8115	1.6898	1.4571	1.4906	−0.0788	0.0213	−0.0403	−0.0394	−0.0716	0.3062	0.6353	0.4874	0.4613	0.4864
Harbin	0.3170	0.3788	0.3871	0.4243	0.4719	1.2621	1.2717	1.2674	1.3083	1.3525	−0.3443	−0.3088	−0.3238	−0.2350	−0.2580	−0.1103	−0.0554	−0.1079	−0.0266	−0.0264
Shanghai	0.9062	−0.0198	−0.0175	−0.0102	−0.0156	0.2175	0.1355	0.1376	0.1329	0.1471	−0.3340	−0.4511	−0.4520	−0.4166	−0.4166	0.2727	−0.0338	−0.0875	−0.0355	−0.0730
Nanjing	0.5272	0.5781	0.5496	0.5082	0.5329	1.6939	1.7904	1.7236	1.6616	0.8441	0.0275	0.0762	0.1049	0.1390	0.0699	0.1517	0.1316	0.0748	0.1181	−0.3811
Hangzhou	0.6477	0.7842	0.7282	0.6941	1.0682	2.6852	2.7849	2.6078	2.5674	2.4278	0.6120	0.6724	0.5945	0.6708	0.0366	−0.0428	0.0303	−0.0336	−0.0211	0.3142
Ningbo	0.9289	1.0894	1.0107	0.8569	0.8535	1.5830	1.4876	1.4200	1.5771	1.6415	0.5062	0.1957	0.1175	0.2613	0.2099	2.0146	1.7270	1.4566	1.7558	1.6001

Table A3. *Cont.*

	Residential (lrm_1)					Land for Administration and Public Services (lrm_2)					Land for Commercial and Business Facilities (lrm_3)					Land for Industry and Manufacturing (lrm_4)				
City	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**
Hefei	1.3875	1.5579	1.5435	1.5582	1.6675	2.5793	2.6529	2.6293	2.5264	2.6739	0.7450	0.7918	0.7198	0.8016	0.7379	0.5529	0.5758	0.4497	0.5320	0.5142
Fuzhou	1.2831	1.2957	1.2061	0.8023	0.7735	1.8566	1.9165	1.7684	0.9105	0.8840	−0.3223	−0.2419	−0.1869	−0.3174	−0.3692	−0.2121	−0.2437	−0.2695	−0.4175	−0.4402
Xiamen	1.2135	1.1711	0.9954	1.1820	1.0016	2.0692	1.8927	1.9092	1.9063	1.7014	0.6287	0.4826	0.3315	0.4371	0.2469	1.0448	0.8975	0.7208	0.8487	0.6622
Nanchang	0.5821	0.5560	0.6777	0.6681	0.6305	0.4766	2.1009	2.3234	2.3167	2.2251	0.6293	−0.0583	−0.0017	0.0819	0.0364	−0.2883	−0.2840	−0.0069	0.0448	−0.0040
Jinan	0.5317	0.5659	0.6147	0.6865	1.0506	2.6267	3.0816	3.1324	3.1007	2.8756	−0.0873	0.0057	0.0754	0.2271	0.5595	0.0558	0.1067	0.0491	0.1307	0.3037
Qingdao	0.9368	1.1492	1.0398	0.7413	0.6972	0.7904	1.2309	1.3689	1.0327	1.2739	−0.2194	0.0342	0.0620	0.0872	0.3075	1.2143	0.7479	0.7894	0.8525	0.9173
Zhengzhou	0.1453	0.3244	0.4497	0.5377	0.5222	1.7324	2.1595	2.4584	2.7030	2.6134	−0.5558	−0.4975	−0.4580	−0.3723	−0.4145	−0.6144	−0.5526	−0.5335	−0.4791	−0.5162
Wuhan	0.4710	0.5463	0.9857	0.9469	0.8866	1.5412	1.5809	1.9698	1.8709	1.7820	−0.3605	−0.3297	−0.1666	−0.1204	−0.1951	−0.1077	−0.0894	0.4792	0.5408	0.4637
Changsha	0.4034	0.3888	0.9796	0.5196	0.3894	1.0780	1.0085	1.6289	1.0084	0.8364	−0.3499	−0.4066	−0.1835	−0.3135	−0.4072	−0.6689	−0.6735	−0.6164	−0.6164	−0.6561
Guangzhou	0.4420	0.4762	0.4745	0.4418	0.4204	1.2527	1.2308	2.1227	2.0397	1.9729	0.0015	0.1000	−0.0140	0.0475	−0.0282	0.2298	0.2513	0.1822	0.2323	0.1908
Shenzhen	−0.0745	−0.2384	−0.2651	−0.2893	−0.3111	−0.0446	−0.0893	−0.1288	−0.4735	−0.4897	−0.4790	−0.6567	−0.6647	−0.4397	−0.4872	0.1648	−0.0341	−0.1262	−0.1038	−0.1484
Nanning	0.7890	0.7428	0.7144	0.8486	0.7874	2.5020	2.4721	2.4252	1.7153	1.6858	−0.1247	0.0566	0.0288	0.1831	0.0890	−0.3996	−0.3726	−0.4081	−0.6467	−0.6667
Haikou	1.1940	1.1403	0.5254	0.9625	0.9508	3.3788	2.6380	0.7312	2.9368	2.9133	0.4479	0.3907	−0.0702	0.0021	−0.0593	−0.5221	−0.5292	−0.6739	−0.6729	−0.6812
Chongqing	0.4769	0.4624	0.4411	0.5002	0.5126	0.7322	0.7610	0.8091	0.8180	0.8113	−0.2064	−0.2237	−0.2215	−0.1394	−0.1969	−0.0419	−0.0583	−0.1260	−0.0624	−0.0728
Chengdu	0.9093	0.8124	0.7638	0.7361	0.7520	1.2605	1.4551	1.3631	1.0237	1.0023	0.2784	0.3426	0.2838	0.1521	0.1170	−0.3115	−0.2184	−0.2895	−0.1765	−0.2262
Guiyang	0.6247	0.7514	1.0250	0.9657	0.9342	1.7824	2.1386	2.4387	2.3381	2.2845	0.3956	0.4183	0.4885	0.5423	0.4330	−0.0145	−0.0401	0.1631	0.2028	0.1602
Kunming	1.0079	1.0066	1.0102	1.0695	1.0651	1.0959	1.0793	1.0918	1.1794	1.1325	0.0755	0.0667	0.0699	0.2262	0.1303	−0.4228	−0.4331	−0.4559	−0.4069	−0.4219
Xi'an	0.2234	0.2517	0.2725	0.1616	0.7124	1.7358	1.7108	1.6252	1.3695	1.5672	0.1441	0.0997	0.1584	0.1573	0.0150	−0.4030	−0.3970	−0.3626	−0.4092	−0.2649
Lanzhou	0.5536	0.6133	0.6538	0.6474	0.8686	1.9741	2.2274	2.2723	2.2509	2.2272	0.2080	0.2891	0.2566	0.3292	0.7603	0.0366	0.1009	0.0605	0.1190	0.6473
Xining	0.5862	0.5989	0.0020	−0.0051	−0.0543	−0.1997	−0.1952	−0.1441	−0.1407	−0.1474	−0.7722	−0.7785	−0.7795	−0.7539	−0.7681	−0.8540	−0.8547	−0.8620	−0.8546	−0.8582
Yinchuan	1.0300	1.0501	1.1106	1.3257	1.3192	3.6260	3.7090	3.9029	4.6098	4.4792	−0.7057	−0.6969	−0.6778	−0.5753	−0.5908	−0.3913	−0.3668	−0.3785	−0.2886	−0.3061
Urumqi	1.4404	1.4680	1.4756	1.5312	1.4591	1.0204	1.0392	1.7858	1.8842	2.2008	0.1763	0.1654	0.6040	0.1952	0.6187	0.2659	0.2871	0.9132	1.0775	0.8663
	Land for Logistics and Warehouses (lrm_5)					**Land for Roads, Streets and Transportation (lrm_6)**					**Land for Municipal Utilities (lrm_7)**					**Land for Green Space and Squares (lrm_8)**				
City	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**
Beijing	−0.2984	−0.3233	−0.3458	−0.2926	−0.3489	0.1941	0.2008	0.2045	0.2147	0.2137	−0.5601	−0.5954	−0.5765	−0.5514	−0.4987	−0.3912	−0.3856	−0.3828	−0.3762	−0.3767

Table A3. *Cont.*

	Land for Logistics and Warehouses (lrm_5)					Land for Roads, Streets and Transportation (lrm_6)					Land for Municipal Utilities (lrm_7)					Land for Green Space and Squares (lrm_8)				
City	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**
Tianjin	1.3654	1.2662	1.1003	0.0422	0.0108	0.8964	0.5993	0.6383	−0.0883	−0.0290	−0.1109	−0.1174	−0.2333	−0.5942	−0.5425	0.2818	0.3026	0.5310	−0.1074	−0.1219
Shijiazhuang	−0.4410	−0.4512	−0.5390	−0.8738	−0.9081	0.3052	0.3013	0.4162	−0.7158	−0.7527	0.4443	0.3411	0.2857	−0.7761	−0.7846	0.7431	0.7391	0.7468	−0.6440	−0.6988
Taiyuan	−0.0059	−0.0442	−0.0035	−0.1172	0.9405	−0.3776	0.3441	0.1570	0.7529	1.6808	2.6825	2.4037	2.1319	2.2454	−0.4997	0.1365	0.1290	0.1802	1.0422	−0.2193
Hohhot	0.6137	0.5869	0.5113	0.4132	0.4490	1.7096	1.7172	1.6600	1.3055	1.5661	−0.0940	−0.1547	−0.1237	−0.0781	0.1475	1.5136	1.5207	1.4653	1.1319	1.3729
Shenyang	−0.4504	−0.2705	−0.3749	−0.3396	0.1063	−0.0801	0.2780	0.8907	0.8781	1.0539	−0.3687	−0.3516	−0.4877	−0.4688	0.5170	0.4953	0.7673	0.8346	0.8188	0.5676
Dalian	−0.1658	−0.1710	−0.2513	−0.2127	−0.0546	0.4822	0.4489	0.4515	0.4095	0.1987	−0.0702	−0.1420	−0.1333	−0.1116	−0.3683	0.5336	0.4645	0.5134	0.4696	−0.6639
Changchun	0.0451	0.3508	0.2498	0.2405	0.1972	0.7248	1.1560	1.0846	0.9127	0.9803	1.0701	1.3456	1.3199	1.2316	1.5572	0.0446	0.1582	0.1017	0.0690	0.1082
Harbin	−0.3916	−0.3505	−0.3761	−0.2942	−0.3395	0.0450	0.0771	0.0762	0.1064	0.1298	−0.3219	−0.3839	−0.3617	−0.3119	−0.2183	−0.0288	−0.0478	−0.0515	−0.0268	−0.0089
Shanghai	−0.0965	−0.4025	−0.4358	−0.4018	−0.4858	0.4452	−0.5395	−0.5317	−0.5270	−0.5228	0.3902	1.1096	1.2009	1.1642	2.0154	−0.2150	−0.4226	−0.4232	−0.4250	−0.4203
Nanjing	−0.2246	−0.2337	−0.1655	−0.1252	−0.2586	0.5205	0.5998	0.7107	0.6658	1.1491	−0.1665	−0.0832	−0.2522	−0.2337	−0.1234	0.5697	0.6295	0.3465	0.3094	1.4946
Hangzhou	−0.2871	−0.3221	−0.3408	−0.3351	−0.6205	0.8389	1.1531	1.0463	1.2739	1.6868	−0.1339	−0.1299	0.0068	0.0449	−0.2091	0.5363	0.5861	0.5945	0.8696	0.1026
Ningbo	1.3863	1.2075	1.0059	1.4013	1.1783	1.5627	1.6479	1.5871	1.6233	1.5927	−0.2282	−0.3953	−0.3998	−0.2557	−0.1941	0.0180	0.0545	0.0406	0.4240	0.3870
Hefei	−0.3920	−0.3975	−0.4180	−0.3769	−0.4850	1.6813	1.7100	1.6573	1.6364	1.3645	−0.2506	−0.2728	−0.2137	−0.1779	−0.0385	2.6246	2.6562	2.5448	2.4542	2.0894
Fuzhou	−0.7843	−0.7971	−0.7877	−0.6526	−0.6868	0.4219	0.4039	0.3581	0.3712	0.3349	−0.3368	−0.3841	−0.2889	−0.6119	−0.5728	0.1369	0.1300	0.0816	−0.1953	−0.3299
Xiamen	0.1649	0.0317	0.1576	0.2090	0.0338	1.3492	1.7244	1.3961	1.3261	1.4966	0.1478	0.7817	−0.0108	0.2038	0.2488	1.0853	0.9986	1.2258	0.9553	0.9322
Nanchang	−0.4114	−0.6272	−0.6064	−0.5487	−0.5957	0.4379	0.5105	0.6248	0.6203	0.5755	−0.1837	−0.3802	−0.3179	−0.2743	−0.2108	0.2703	0.2542	0.2998	0.3236	0.2870
Jinan	−0.2849	−0.2523	−0.2794	−0.1973	−0.3579	0.9439	0.8398	0.8732	0.8711	1.0807	0.1881	0.0853	0.1580	0.2311	0.1893	0.2077	0.2331	0.2167	0.2114	0.6157
Qingdao	0.9827	1.0715	1.2564	0.2947	1.0510	0.5132	0.8485	0.3647	0.6823	0.8752	−0.2710	−0.2973	0.1998	−0.4364	−0.3727	0.4490	0.9268	0.0232	0.3704	0.3767
Zhengzhou	0.0530	0.1783	0.2494	0.3984	0.2729	0.5837	0.8313	1.0045	1.1744	1.0701	0.0652	0.1458	0.3109	0.5008	0.6584	1.1251	1.4573	1.6897	2.1049	2.1787
Wuhan	−0.2872	−0.3210	0.0594	0.1221	0.0017	0.0990	0.1660	0.8285	0.8489	0.7917	−0.4918	−0.5153	0.2237	0.2400	0.3438	−0.4926	−0.4393	−0.1934	−0.2033	−0.2280
Changsha	−0.4052	−0.4957	−0.3601	−0.4520	−0.5385	0.1744	0.2683	0.8105	0.3926	0.2731	−0.6821	−0.7135	−0.6320	−0.6905	−0.6832	−0.0579	−0.0168	0.4912	0.1425	0.0446
Guangzhou	−0.2166	−0.2202	−0.2573	−0.1916	−0.2639	0.0520	0.0355	0.0149	−0.0112	−0.0336	−0.7063	−0.7302	−0.7237	−0.7158	−0.6895	−0.5662	−0.5739	−0.5849	−0.5962	−0.6054
Shenzhen	−0.5920	−0.5787	−0.6150	−0.5975	−0.6406	−0.0360	0.6089	0.5643	0.5218	0.4751	−0.5386	−0.5346	−0.5245	−0.5126	−0.4716	−0.5050	−0.4064	−0.4283	−0.4421	−0.4593
Nanning	−0.1421	−0.1715	−0.2112	−0.1373	−0.2350	1.1556	1.1384	1.1009	0.8221	0.8408	0.1214	−0.0245	−0.0003	1.1353	1.2998	1.0873	0.9586	0.9261	1.4989	1.4053
Haikou	−0.3268	−0.3603	−0.8696	−0.8706	−0.8815	1.0062	1.0076	1.0395	0.8738	1.4145	−0.4106	−0.4615	−0.8171	−0.8260	−0.8065	−0.3843	−0.3955	−0.2612	0.0909	0.7384
Chongqing	−0.3607	−0.3488	−0.3390	−0.2668	−0.3667	0.5542	0.6151	0.7284	0.7662	0.7616	−0.2238	−0.2802	−0.3209	−0.2497	−0.1665	0.0767	−0.0539	0.0143	0.0089	0.0684

Table A3. *Cont.*

	Land for Logistics and Warehouses (lrm_5)					Land for Roads, Streets and Transportation (lrm_6)					Land for Municipal Utilities (lrm_7)					Land for Green Space and Squares (lrm_8)				
City	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**
Chengdu	−0.6863	−0.2877	−0.3386	−0.4443	−0.4601	0.6865	0.7181	0.7224	0.6914	0.7680	−0.4584	−0.3563	−0.3459	−0.5227	−0.4901	0.4911	0.3166	0.3141	0.3291	0.2992
Guiyang	−0.1206	0.1294	0.0991	0.1554	0.0473	1.1456	1.1502	1.4372	1.3659	1.3279	−0.5321	−0.4373	−0.3559	−0.3400	−0.2737	1.0780	1.1361	1.2527	1.1867	1.1516
Kunming	−0.2044	−0.2383	−0.2600	−0.1894	−0.3131	−0.0871	−0.0404	−0.0325	0.0764	0.1085	−0.4519	−0.4995	−0.4686	−0.4090	−0.3728	0.2306	0.2635	0.2749	0.2682	0.2444
Xi'an	−0.4044	−0.4139	−0.3150	−0.0272	−0.2219	0.6689	0.6964	0.9240	0.6481	0.3876	0.0805	−0.0106	0.2162	0.1705	−0.5838	1.3491	1.3221	1.6119	1.2962	0.0827
Lanzhou	0.0323	0.0320	0.0285	0.1275	1.2793	1.8308	1.9090	1.9785	1.9601	1.2996	0.3496	0.2716	0.4278	0.5009	0.0681	1.6096	1.6698	1.8009	1.7579	−0.1898
Xining	2.0051	1.8714	0.6364	0.8076	0.5931	−0.5530	−0.5529	−0.1282	0.0986	0.1171	−0.2458	−0.2441	−0.2054	−0.1623	−0.0883	−0.5524	−0.5557	0.8532	0.9333	0.9497
Yinchuan	0.6677	0.6584	0.5863	0.8410	0.6537	1.0896	1.0611	1.1747	1.3656	1.4257	1.1511	1.0226	1.0978	1.3820	1.7549	1.4047	1.3676	1.3691	1.5323	1.4270
Urumqi	0.6952	0.6578	2.5186	2.8792	2.2177	1.1465	1.1808	1.5764	1.8927	1.6210	1.1263	1.0034	0.2256	0.3034	0.4479	0.6152	0.6327	0.7553	0.9357	0.8323

Appendix D

Table A4. The normalized values $lrm_{i,j}'$.

	Residential Land (lrm_1')					Land for Administration and Public Services (lrm_2')					Land for Commercial and Business Facilities (lrm_3')					Land for Industry and Manufacturing (lrm_4')				
City	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**
Beijing	−0.0369	−0.0285	−0.0205	−0.0013	−0.0023	0.1471	0.1498	0.1452	0.1493	0.1490	−0.1843	−0.1938	−0.1979	−0.1239	−0.1787	−0.4500	−0.4490	−0.4791	−0.4343	−0.4478
Tianjin	0.0926	0.1219	0.1650	−0.1831	−0.1331	0.1612	0.2128	0.2294	−0.0017	0.0121	−0.2029	0.0219	0.0576	−0.2914	−0.3356	0.0635	0.0762	0.0906	−0.2927	−0.2588
Shijiazhuang	0.1255	0.1272	0.1337	−0.7672	−0.8175	0.1842	0.1844	0.1740	−0.7876	−0.8401	−0.2277	−0.2273	−0.3583	−0.9511	−0.9821	−0.8138	−0.8126	−0.8296	−0.9770	- 1.0000
Taiyuan	−0.0433	−0.0503	0.1134	0.1042	0.3026	0.3336	0.3427	0.3579	0.2175	0.6060	−0.0133	−0.0438	−0.1518	−0.2414	0.0592	0.0190	0.0212	−0.3023	−0.7755	−0.0607
Hohhot	0.3133	0.3256	0.3201	0.2562	0.3097	0.4552	0.4871	0.6028	0.5094	0.5915	0.2734	0.2674	0.2532	0.2224	0.2449	−0.4488	−0.4364	−0.4659	−0.5134	−0.4605
Shenyang	0.0983	0.1375	0.1806	0.1782	0.2284	0.1519	0.1638	0.2489	0.2412	−0.0246	−0.5124	−0.3276	−0.2724	−0.2247	−0.1067	−0.1065	0.0738	0.1047	0.1227	0.0629
Dalian	0.1200	0.1332	0.1283	0.1183	0.1173	0.1737	0.1756	0.1683	0.1572	0.1087	−0.1851	−0.1938	−0.2291	−0.1975	−0.0442	0.0812	0.1078	0.0909	0.1015	0.0785
Changchun	0.1824	0.2480	0.2160	0.1771	0.1948	0.3101	0.3928	0.3664	0.3159	0.3231	−0.0859	0.0043	−0.0437	−0.0428	−0.0780	0.0661	0.1375	0.1054	0.0998	0.1052
Harbin	0.0685	0.0819	0.0837	0.0918	0.1021	0.2735	0.2756	0.2747	0.2836	0.2932	−0.3765	−0.3376	−0.3540	−0.2568	−0.2820	−0.1204	−0.0603	−0.1177	−0.0287	−0.0285
Shanghai	0.1963	−0.0213	−0.0188	−0.0108	−0.0167	0.0469	0.0291	0.0295	0.0285	0.0316	−0.3651	−0.4933	−0.4943	−0.4555	−0.4555	0.0588	−0.0366	−0.0954	−0.0384	−0.0795

Table A4. *Cont.*

	Residential Land (lrm_1')					Land for Administration and Public Services (lrm_2')					Land for Commercial and Business Facilities (lrm_3')					Land for Industry and Manufacturing (lrm_4')				
City	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**
Nanjing	0.1141	0.1251	0.1189	0.1100	0.1153	0.3673	0.3882	0.3737	0.3602	0.1829	0.0056	0.0162	0.0224	0.0298	0.0148	0.0326	0.0282	0.0159	0.0253	−0.4167
Hangzhou	0.1402	0.1698	0.1577	0.1503	0.2315	0.5824	0.6040	0.5656	0.5568	0.5265	0.1325	0.1456	0.1287	0.1452	0.0076	−0.0465	0.0062	−0.0364	−0.0227	0.0678
Ningbo	0.2012	0.2361	0.2190	0.1856	0.1849	0.3432	0.3225	0.3078	0.3419	0.3559	0.1095	0.0421	0.0252	0.0564	0.0452	0.4368	0.3744	0.3158	0.3807	0.3469
Hefei	0.3008	0.3377	0.3346	0.3378	0.3615	0.5594	0.5754	0.5702	0.5479	0.5799	0.1613	0.1715	0.1559	0.1736	0.1598	0.1197	0.1246	0.0973	0.1151	0.1113
Fuzhou	0.2781	0.2808	0.2614	0.1738	0.1675	0.4026	0.4156	0.3834	0.1973	0.1915	−0.3524	−0.2644	−0.2042	−0.3469	−0.4037	−0.2318	−0.2663	−0.2946	−0.4566	−0.4814
Xiamen	0.2630	0.2538	0.2157	0.2562	0.2170	0.4487	0.4104	0.4140	0.4134	0.3689	0.1361	0.1044	0.0716	0.0945	0.0533	0.2264	0.1944	0.1561	0.1839	0.1434
Nanchang	0.1260	0.1203	0.1467	0.1446	0.1365	0.1031	0.4556	0.5038	0.5024	0.4825	0.1362	−0.0635	−0.0015	0.0175	0.0076	−0.3151	−0.3105	−0.0072	0.0094	−0.0040
Jinan	0.1151	0.1225	0.1331	0.1486	0.2277	0.5697	0.6684	0.6794	0.6725	0.6237	−0.0952	0.0009	0.0160	0.0490	0.1211	0.0118	0.0228	0.0103	0.0280	0.0656
Qingdao	0.2030	0.2490	0.2253	0.1605	0.1510	0.1712	0.2668	0.2967	0.2238	0.2761	−0.2397	0.0071	0.0131	0.0186	0.0664	0.2632	0.1620	0.1710	0.1847	0.1987
Zhengzhou	0.0312	0.0701	0.0973	0.1164	0.1130	0.3756	0.4683	0.5332	0.5862	0.5668	−0.6078	−0.5440	−0.5009	−0.4071	−0.4532	−0.6720	−0.6044	−0.5835	−0.5240	−0.5646
Wuhan	0.1019	0.1182	0.2136	0.2051	0.1921	0.3341	0.3427	0.4271	0.4057	0.3864	−0.3941	−0.3604	−0.1820	−0.1314	−0.2131	−0.1175	−0.0974	0.1037	0.1170	0.1003
Changsha	0.0872	0.0840	0.2123	0.1124	0.0842	0.2336	0.2185	0.3532	0.2185	0.1812	−0.3826	−0.4446	−0.2005	−0.3427	−0.4453	−0.7317	−0.7367	−0.5813	−0.6742	−0.7177
Guangzhou	0.0956	0.1030	0.1026	0.0955	0.0909	0.2715	0.2668	0.4603	0.4423	0.4278	0.0000	0.0214	−0.0150	0.0100	−0.0305	0.0495	0.0542	0.0392	0.0501	0.0411
Shenzhen	−0.0812	−0.2605	−0.2898	−0.3163	−0.3401	−0.0485	−0.0973	−0.1406	−0.5178	−0.5355	−0.5238	−0.7183	−0.7271	−0.4809	−0.5328	0.0354	−0.0369	−0.1377	−0.1132	−0.1620
Nanning	0.1709	0.1609	0.1547	0.1838	0.1705	0.5426	0.5361	0.5259	0.3719	0.3655	−0.1361	0.0120	0.0059	0.0394	0.0190	−0.4369	−0.4074	−0.4463	−0.7074	−0.7292
Haikou	0.2588	0.2471	0.1137	0.2085	0.2060	0.7329	0.5721	0.1583	0.6370	0.6319	0.0969	0.0845	−0.0765	0.0001	−0.0645	−0.5710	−0.5788	−0.7371	−0.7360	−0.7451
Chongqing	0.1032	0.1000	0.0954	0.1082	0.1109	0.1586	0.1648	0.1752	0.1772	0.1757	−0.2255	−0.2444	−0.2421	−0.1522	−0.2151	−0.0455	−0.0634	−0.1375	−0.0679	−0.0793
Chengdu	0.1970	0.1760	0.1654	0.1594	0.1629	0.2732	0.3154	0.2955	0.2218	0.2172	0.0601	0.0740	0.0613	0.0327	0.0251	−0.3405	−0.2386	−0.3165	−0.1928	−0.2472
Guiyang	0.1352	0.1627	0.2221	0.2092	0.2024	0.3865	0.4638	0.5289	0.5070	0.4954	0.0855	0.0904	0.1057	0.1174	0.0936	−0.0155	−0.0435	0.0351	0.0437	0.0344
Kunming	0.2184	0.2181	0.2189	0.2318	0.2308	0.2375	0.2339	0.2366	0.2556	0.2454	0.0161	0.0142	0.0148	0.0488	0.0279	−0.4624	−0.4736	−0.4986	−0.4450	−0.4613
Xi’an	0.0481	0.0543	0.0588	0.0347	0.1543	0.3763	0.3709	0.3523	0.2969	0.3398	0.0309	0.0213	0.0341	0.0338	0.0029	−0.4407	−0.4341	−0.3965	−0.4474	−0.2895
Lanzhou	0.1198	0.1328	0.1415	0.1402	0.1882	0.4281	0.4830	0.4928	0.4881	0.4830	0.0448	0.0624	0.0553	0.0711	0.1647	0.0076	0.0216	0.0128	0.0255	0.1401
Xining	0.1269	0.1296	0.0001	−0.0053	−0.0591	−0.2181	−0.2133	−0.1573	−0.1537	−0.1610	−0.8447	−0.8517	−0.8527	−0.8247	−0.8402	−0.9342	−0.9350	−0.9429	−0.9349	−0.9388
Yinchuan	0.2232	0.2275	0.2407	0.2874	0.2859	0.7865	0.8045	0.8466	1.0000	0.9717	−0.7720	−0.7624	−0.7414	−0.6292	−0.6462	−0.4279	−0.4010	−0.4138	−0.3155	−0.3346
Urumqi	0.3122	0.3182	0.3199	0.3319	0.3163	0.2211	0.2252	0.3872	0.4085	0.4772	0.0379	0.0356	0.1307	0.0420	0.1339	0.0574	0.0620	0.1978	0.2335	0.1877
Average	0.1430	0.1432	0.1480	0.1067	0.1196	0.3107	0.3336	0.3476	0.2936	0.2888	−0.1543	−0.1392	−0.1341	−0.1399	−0.1446	−0.1771	−0.1702	−0.1792	−0.1993	−0.1950

Table A4. *Cont.*

	Land for Logistics and Warehouses (lrm_5')					Land for Roads, Streets and Transportation (lrm_6')					Land for Municipal Utilities (lrm_7')					Land for Green Space and Squares (lrm_8')				
City	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**
Beijing	−0.3262	−0.3535	−0.3780	−0.3199	−0.3815	0.0418	0.0433	0.0440	0.0463	0.0460	−0.6126	−0.6513	−0.6305	−0.6030	−0.5454	−0.4277	−0.4216	−0.4185	−0.4113	−0.4119
Tianjin	0.2960	0.2744	0.2384	0.0088	0.0020	0.1942	0.1297	0.1382	−0.0963	−0.0314	−0.1210	−0.1281	−0.2549	−0.6500	−0.5934	0.0608	0.0653	0.1149	−0.1172	−0.1330
Shijiazhuang	−0.4823	−0.4934	−0.5895	−0.9559	−0.9934	0.0659	0.0651	0.0900	−0.7829	−0.8234	0.0961	0.0737	0.0617	−0.8489	−0.8582	0.1609	0.1601	0.1617	−0.7044	−0.7644
Taiyuan	−0.0061	−0.0480	−0.0035	−0.1279	0.2038	−0.4129	0.0743	0.0338	0.1631	0.3644	0.5818	0.5213	0.4623	0.4869	−0.5465	0.0293	0.0277	0.0388	0.2258	−0.2396
Hohhot	0.1329	0.1270	0.1106	0.0893	0.0971	0.3707	0.3723	0.3599	0.2830	0.3395	−0.1025	−0.1689	−0.1350	−0.0851	0.0317	0.3281	0.3297	0.3176	0.2453	0.2976
Shenyang	−0.4926	−0.2957	−0.4099	−0.3713	0.0227	−0.0873	0.0600	0.1930	0.1902	0.2284	−0.4031	−0.3845	−0.5334	−0.5127	0.1119	0.1072	0.1662	0.1808	0.1773	0.1228
Dalian	−0.1811	−0.1868	−0.2747	−0.2324	−0.0594	0.1043	0.0971	0.0976	0.0885	0.0428	−0.0764	−0.1551	−0.1455	−0.1218	−0.4027	0.1155	0.1005	0.1111	0.1016	−0.7262
Changchun	0.0095	0.0758	0.0539	0.0519	0.0425	0.1570	0.2505	0.2350	0.1977	0.2124	0.2319	0.2917	0.2861	0.2669	0.3376	0.0093	0.0340	0.0217	0.0147	0.0231
Harbin	−0.4282	−0.3832	−0.4112	−0.3216	−0.3712	0.0094	0.0164	0.0162	0.0228	0.0278	−0.3520	−0.4198	−0.3955	−0.3410	−0.2385	−0.0311	−0.0519	−0.0560	−0.0290	−0.0093
Shanghai	−0.1053	−0.4402	−0.4766	−0.4393	−0.5313	0.0963	−0.5901	−0.5815	−0.5763	−0.5718	0.0843	0.2405	0.2603	0.2523	0.4370	−0.2349	−0.4621	−0.4627	−0.4648	−0.4596
Nanjing	−0.2454	−0.2554	−0.1808	−0.1367	−0.2827	0.1126	0.1298	0.1539	0.1441	0.2490	−0.1819	−0.0906	−0.2756	−0.2554	−0.1347	0.1233	0.1363	0.0749	0.0668	0.3240
Hangzhou	−0.3139	−0.3521	−0.3726	−0.3663	−0.6787	0.1817	0.2499	0.2267	0.2761	0.3657	−0.1462	−0.1418	0.0012	0.0094	−0.2285	0.1161	0.1269	0.1287	0.1884	0.0219
Ningbo	0.3005	0.2617	0.2180	0.3038	0.2554	0.3388	0.3573	0.3441	0.3519	0.3453	−0.2494	−0.4322	−0.4371	−0.2794	−0.2120	0.0036	0.0115	0.0085	0.0917	0.0836
Hefei	−0.4286	−0.4346	−0.4571	−0.4121	−0.5304	0.3645	0.3707	0.3593	0.3548	0.2958	−0.2739	−0.2981	−0.2335	−0.1944	−0.0418	0.5692	0.5761	0.5519	0.5322	0.4531
Fuzhou	−0.8579	−0.8719	−0.8617	−0.7138	−0.7513	0.0912	0.0873	0.0774	0.0802	0.0724	−0.3682	−0.4200	−0.3158	−0.6693	−0.6265	0.0294	0.0279	0.0174	−0.2134	−0.3606
Xiamen	0.0355	0.0065	0.0339	0.0450	0.0070	0.2924	0.3739	0.3026	0.2874	0.3244	0.0318	0.1693	−0.0115	0.0439	0.0537	0.2352	0.2164	0.2657	0.2070	0.2020
Nanchang	−0.4499	−0.6860	−0.6633	−0.6001	−0.6516	0.0947	0.1105	0.1352	0.1343	0.1246	−0.2006	−0.4157	−0.3476	−0.2998	−0.2303	0.0583	0.0548	0.0647	0.0699	0.0620
Jinan	−0.3114	−0.2757	−0.3054	−0.2155	−0.3913	0.2045	0.1819	0.1892	0.1887	0.2342	0.0405	0.0182	0.0340	0.0498	0.0408	0.0447	0.0503	0.0467	0.0455	0.1333
Qingdao	0.2129	0.2322	0.2723	0.0636	0.2277	0.1110	0.1838	0.0788	0.1477	0.1896	−0.2963	−0.3250	0.0430	−0.4772	−0.4075	0.0971	0.2008	0.0047	0.0801	0.0814
Zhengzhou	0.0112	0.0384	0.0538	0.0861	0.0589	0.1263	0.1801	0.2176	0.2545	0.2319	0.0138	0.0313	0.0671	0.1083	0.1426	0.2438	0.3159	0.3663	0.4564	0.4725
Wuhan	−0.3140	−0.3510	0.0126	0.0262	0.0000	0.0212	0.0357	0.1795	0.1839	0.1715	−0.5379	−0.5636	0.0482	0.0517	0.0743	−0.5388	−0.4803	−0.2112	−0.2221	−0.2491
Changsha	−0.4431	−0.5421	−0.3938	−0.4943	−0.5889	0.0375	0.0579	0.1755	0.0849	0.0589	−0.7461	−0.7804	−0.6913	−0.7553	−0.7473	−0.0630	−0.0180	0.1063	0.0306	0.0093
Guangzhou	−0.2366	−0.2406	−0.2812	−0.2093	−0.2884	0.0110	0.0074	0.0029	−0.0119	−0.0364	−0.7726	−0.7987	−0.7916	−0.7830	−0.7542	−0.6193	−0.6277	−0.6397	−0.6521	−0.6621
Shenzhen	−0.6475	−0.6329	−0.6727	−0.6535	−0.7006	−0.0390	0.1318	0.1221	0.1129	0.1028	−0.5891	−0.5847	−0.5736	−0.5606	−0.5158	−0.5523	−0.4444	−0.4683	−0.4835	−0.5022

Table A4. *Cont.*

	Land for Logistics and Warehouses ($lrm_5{}'$)					Land for Roads, Streets and Transportation ($lrm_6{}'$)					Land for Municipal Utilities ($lrm_7{}'$)					Land for Green Space and Squares ($lrm_8{}'$)				
City	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**	**2015**	**2016**	**2017**	**2018**	**2019**
Nanning	−0.1552	−0.1873	−0.2308	−0.1499	−0.2568	0.2504	0.2467	0.2386	0.1781	0.1821	0.0260	−0.0265	0.0000	0.2460	0.2817	0.2356	0.2077	0.2006	0.3249	0.3046
Haikou	−0.3573	−0.3939	−0.9513	−0.9523	−0.9643	0.2180	0.2183	0.2252	0.1893	0.3066	−0.4489	−0.5047	−0.8939	−0.9035	−0.8823	−0.4202	−0.4324	−0.2855	0.0194	0.1599
Chongqing	−0.3943	−0.3814	−0.3706	−0.2917	−0.4009	0.1199	0.1331	0.1577	0.1659	0.1649	−0.2445	−0.3062	−0.3509	−0.2729	−0.1819	0.0163	−0.0586	0.0028	0.0016	0.0145
Chengdu	−0.7507	−0.3145	−0.3701	−0.4858	−0.5032	0.1486	0.1555	0.1564	0.1497	0.1663	−0.5013	−0.3896	−0.3782	−0.5716	−0.5360	0.1062	0.0684	0.0678	0.0711	0.0646
Guiyang	−0.1316	0.0278	0.0212	0.0334	0.0099	0.2483	0.2493	0.3115	0.2961	0.2878	−0.5820	−0.4782	−0.3891	−0.3717	−0.2992	0.2336	0.2462	0.2715	0.2572	0.2496
Kunming	−0.2233	−0.2604	−0.2841	−0.2069	−0.3423	−0.0949	−0.0439	−0.0352	0.0163	0.0232	−0.4942	−0.5463	−0.5125	−0.4472	−0.4076	0.0497	0.0569	0.0593	0.0579	0.0527
Xi'an	−0.4422	−0.4526	−0.3443	−0.0294	−0.2425	0.1448	0.1508	0.2002	0.1403	0.0838	0.0171	−0.0112	0.0466	0.0367	−0.6385	0.2924	0.2866	0.3495	0.2810	0.0176
Lanzhou	0.0067	0.0066	0.0059	0.0273	0.2773	0.3970	0.4139	0.4290	0.4250	0.2817	0.0755	0.0586	0.0925	0.1084	0.0144	0.3490	0.3620	0.3905	0.3811	−0.2073
Xining	0.4348	0.4058	0.1378	0.1749	0.1284	−0.6049	−0.6047	−0.1400	0.0211	0.0251	−0.2686	−0.2667	−0.2244	−0.1773	−0.0963	−0.6041	−0.6078	0.1848	0.2022	0.2058
Yinchuan	0.1446	0.1426	0.1269	0.1822	0.1415	0.2361	0.2299	0.2546	0.2960	0.3090	0.2495	0.2216	0.2379	0.2996	0.3805	0.3045	0.2964	0.2968	0.3322	0.3093
Urumqi	0.1505	0.1424	0.5462	0.6245	0.4809	0.2485	0.2559	0.3418	0.4104	0.3514	0.2441	0.2174	0.0486	0.0655	0.0969	0.1332	0.1370	0.1636	0.2027	0.1803
Average	−0.1997	−0.2026	−0.2129	−0.1991	−0.2273	0.1086	0.1252	0.1523	0.1261	0.1356	−0.1965	−0.2127	−0.1952	−0.2330	−0.2321	0.0160	0.0188	0.0579	0.0391	−0.0251

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