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Multidimensional Evaluation of Urban Land-Use Efficiency and Innovation Capability Analysis: A Case Study in the Pearl River Delta Region, China

Yanxi Lei, Zuoji Dong, Jichang Dong and Zhi Dong *

School of Economics and Management, University of Chinese Academy of Sciences, Beijing 100190, China
* Correspondence: wlxzddx@163.com

Abstract: With China's rapid industrialization and urbanization, sustainable urban development is one of the most significant challenges that the country will face in the future, and the rational evaluation and improvement of urban land-use efficiency (ULUE) are becoming crucial for land and urban development. Existing studies rarely examine ULUE, and there is a dearth of urban land use analysis in terms of different functions, regional differences in levels of development, and innovation capacity. Therefore, we take the Pearl River Delta (PRD), China's economic and innovation center, as our research target and propose a new framework to analyze its comprehensive ULUE. First, we summarized the patterns of land-use change in the PRD region as a whole along with nine major cities from 2000 to 2020 on the basis of data from the China Land Survey. Then, we constructed a multidimensional evaluation model for ULUE and analyzed the spatial differences and causes of multidimensional performance in nine major cities. Finally, we calculated the innovation capability index of the PRD region and established a coupling coordination–evaluation model to analyze the coordination relationship between innovation capability and urban land use. The three main findings of this study are as follows. (1) The growth rate of urban land in the PRD region as a whole exhibited stage differences. (2) The comprehensive ULUE in the PRD urban agglomeration was high, and the spatial variability of functional performance in each dimension was obvious. (3) The level of coordination between innovation capability and urban land use in the PRD region was high, and the coupled coordinated development exhibited a decreasing spatial distribution pattern. Thus, the PRD region mainly relies on the cities of Shenzhen and Guangzhou to drive innovation development of the region.

Keywords: urban land-use efficiency; innovation capability; multidimensional evaluation model; coupling coordination model

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Citation: Lei, Y.; Dong, Z.; Dong, J.; Dong, Z. Multidimensional Evaluation of Urban Land-Use Efficiency and Innovation Capability Analysis: A Case Study in the Pearl River Delta Region, China. *Sustainability* **2023**, *15*, 6387. https://doi.org/10.3390/su15086387

Academic Editors: Bin Meng, Dongsheng Zhan and Ran Liu

Received: 1 March 2023
Revised: 3 April 2023
Accepted: 6 April 2023
Published: 7 April 2023

1. Introduction

Urban land is the carrier of all the social, economic, political, and cultural activities of a city and is the spatial basis on which the overall functions of a city can be realized [1–3]. In recent years, China has actively promoted the urbanization process and accomplished remarkable achievements. According to the China City Statistical Yearbook, China's urbanization rate increased from 36.2% in 2000 to 63.9% in 2020, exhibiting strong growth potential [4,5]. However, with the continuous acceleration of China's industrialization and urbanization process, the rapid expansion of construction land has resulted in the rough use and inefficient idling of urban land, resulting in corresponding socioeconomic and environmental problems, which seriously affect and constrain the sustainable development of regional socioeconomics [6–10]. Currently, China's economy has shifted from high-growth to high-quality development, and the traditional development model based on land expansion is no longer sustainable; these factors make the conflict between land resource use and economic growth increasingly prominent [11–13]. Therefore, improving the efficiency of land use in a limited geographical space is now the key to achieving sustainable urban development in China [14,15]. Furthermore, we note that China's high-quality development defines innovation as its main driver and coordination as an intrinsic characteristic [16]. Currently, with the advancement and development of science, technological innovation can effectively balance economic development, resource consumption, and environmental issues, thus promoting sustainable urban development [17,18]. Consequently, in the process of high-quality economic development in China, it is of great significance to coordinate regional urban land use and innovation capabilities.

Currently, urban land use has been studied from many theoretical perspectives, including the economy, ecology, politics, and social behavior. Jessica [19], Eric and Patrick [20], and Giuseppina [21] focused on urban-land policy. Babenko et al. [22] and Farafonova [23] studied the impact of urban land on the regional economy. Herzig et al. [24] and Mirzaei et al. [25] studied the relationship between urban land use and ecology. Auzins [26] and Storch and Schmid [27] examined urban land use in different countries and regions. By studying urban land use in Greece, Zitti et al. [28] highlighted that unsustainable urban growth has a negative impact on land-use efficiency. After studying the externalities of land use [29,30] and issues related to urban expansion, Irwin [31] and other scholars emphasized that the existence of the "dangerous" model of land has a negative impact on urban development. Nesru et al. [32] performed a case study of Ethiopia and used remote sensing data to explore the impact of land use levels on ecological and urban policies. Herold et al. studied the application of spatial measures to the process of urban land use change and used the method to evaluate urban land use [33–35]. Masini et al. [36] studied the land-use efficiency of 417 metropolitan areas in Europe, identified socioeconomic variables such as disposable income per capita and income growth as some of the predictors, and indicated that wealthier cities had higher urban land-use efficiency compared to other parts of Europe.

In China, research on land use started late, but the field of study is broader and more integrated with policy research. Liu et al. [37,38] indicated that rapid urbanization in China has indeed increased the scarcity of land for construction and that it is necessary to improve the spatial structures of urban and rural areas in the context of the "new normal" of the economy. Huang et al. [39] researched data from 2003 to 2008 in Shanghai and emphasized the need to avoid "development zone fever" and improve land-use management in development zones. Liang et al. [40] created a new analytical framework to study the relationship between economic agglomeration and land-use efficiency, indicating that economic agglomeration can significantly improve land-use efficiency. In addition, Lang [41] emphasized that urban land-use strategies are determined not only by economic forces but also by government land control. Zhou [42] and Liu et al. [43] analyzed data on prefecture-level cities in China and underscored that local governments rely heavily on land finance and that vicious competition between governments can affect ULUE and lead to rapid sprawl of land use. Yan and Zhao [44] established a system of indicators considering population, land, and industry on the basis of spatial analytic geometry to capture the urban–rural transformation mechanisms in the Beijing–Tianjin–Hebei region. Zhu [45] and Shen et al. [46] suggested that the speed of urban expansion boundaries and the scale of idle land could also be used as ULUE indicators.

Land-use efficiency is the result of a complex system composed of many natural, economic, and social factors. It is an indicator of the extent of land use and the ability to promote synergistic social, economic, and environmental development in cities [47,48]. Concerning specific methods, early studies mainly used single indicators such as gross domestic product to measure land-use efficiency [49,50]. Currently, there are three main approaches to measuring ULUE that are accepted by academics at home and abroad: parametric, nonparametric, and indicator estimation methods. Parametric methods estimate efficiency values with regression, but it is difficult to determine the exact form of the error distribution [3,51]. Nonparametric methods are also known as data envelopment analysis, but traditional data envelopment analysis models are unable to estimate long-term efficiency changes, which affects the impartiality and objectivity of efficiency evaluations [52]. In contrast, the indicator estimation method is extensively used because of its comprehensive evaluation function and high calculation accuracy [53]. The indicator estimation method is usually used to represent ULUE by first constructing an indicator evaluation system and then calculating the performance value using the coordination function, entropy method, TOPSIS model (Technique for Order Preference by Similarity to an Ideal Solution), and other methods. Currently, most of the studies on land-use efficiency using the indicator estimation method are based on the theoretical basis of FAO's "outline of sustainable land use management evaluation" [54] with the research framework of "system construction–weight determination–comprehensive evaluation", from different perspectives such as sustainable land use [55,56], intensive land use [57–59], and land-use efficiency [60–62]. Examples of estimating indicator systems include the "Intensity–Efficiency–Effectiveness" system [63], the "Economic–Social–Ecological" system [64], and the "Economic–Social–Ecological–Political–Scientific" system [65].

For this study, we took the Pearl River Delta (PRD) region as our research target, which is an important economic center and a center of scientific and technological innovation with an important position in the overall economic and social development and reform and opening up of China [66]. However, after more than 40 years of rapid development, the PRD has become increasingly saturated with land development, and new land for construction is relatively limited. Therefore, under the "new normal" of China's economy, it is crucial to alleviate the imbalance between supply and demand of urban land and to improve the level of innovative development in the PRD.

In general, the existing literature has offered valuable research results, but some drawbacks remain. (1) The existing literature has used the same criteria to evaluate regional urban land-use performance, disregarding the differences in regional development stages, and it also has limitations such as poor timeliness and effectiveness of research data. (2) Insufficient research examines the evolution of the spatial pattern of ULUE in the study area. (3) There is little literature on the coordination relationship between urban innovation capacity and urban land use at different stages of time.

This study aims to contribute to the literature in two ways. First, we have developed an innovative "five-dimensional" integrated evaluation model (comprising the economy, livelihood, ecology, society, and innovation) to calculate ULUE and analyze land-use sustainability based on the different stages of urban development in the PRD and the urban construction goals of China in the new era [1,3,41], which can enrich the theoretical framework. Secondly, we have constructed a coupled coordination model to analyze the coupled coordination relationship between urban land use and innovation capacity in nine major cities in the PRD region, which provides some insights for improving local innovation capacity and developing sustainable land-use policies.

2. Materials and Methods

2.1. Analytical Framework

This paper focuses on the PRD region, with the goal of developing a framework for assessing and analyzing ULUE and innovation capability (Figure 1), using quantitative analysis to (1) summarize the characteristics of urban land change between 2000 and 2020, (2) measure ULUE based on the regional development level index and "five-dimensional" evaluation index system with a multidimensional evaluation model, (3) analyze the coupling coordination relationship between innovation capability and urban land use based on an expanded evaluation, and (4) present proposals for improving sustainable urban land use and innovation capability in the PRD region.

2.2. Study Area

The Pearl River Delta (PRD) region, one of the largest and most developed urban agglomerations in China, is located in Guangdong province and includes 9 cities (Figure 2): Guangzhou, Shenzhen, Zhuhai, Foshan, Jiangmen, Zhaoqing, Huizhou, Dongguan, and Zhongshan. In 2021, the PRD region had a total land area of 54,769 km^2, a total population of

78.01 million, and a GDP of CNY 100,585.26 billion, accounting for about 8.8% of mainland China. The PRD region is a pioneering region in China's reform and opening up and an important economic center in China, thus making it very representative as a study region.

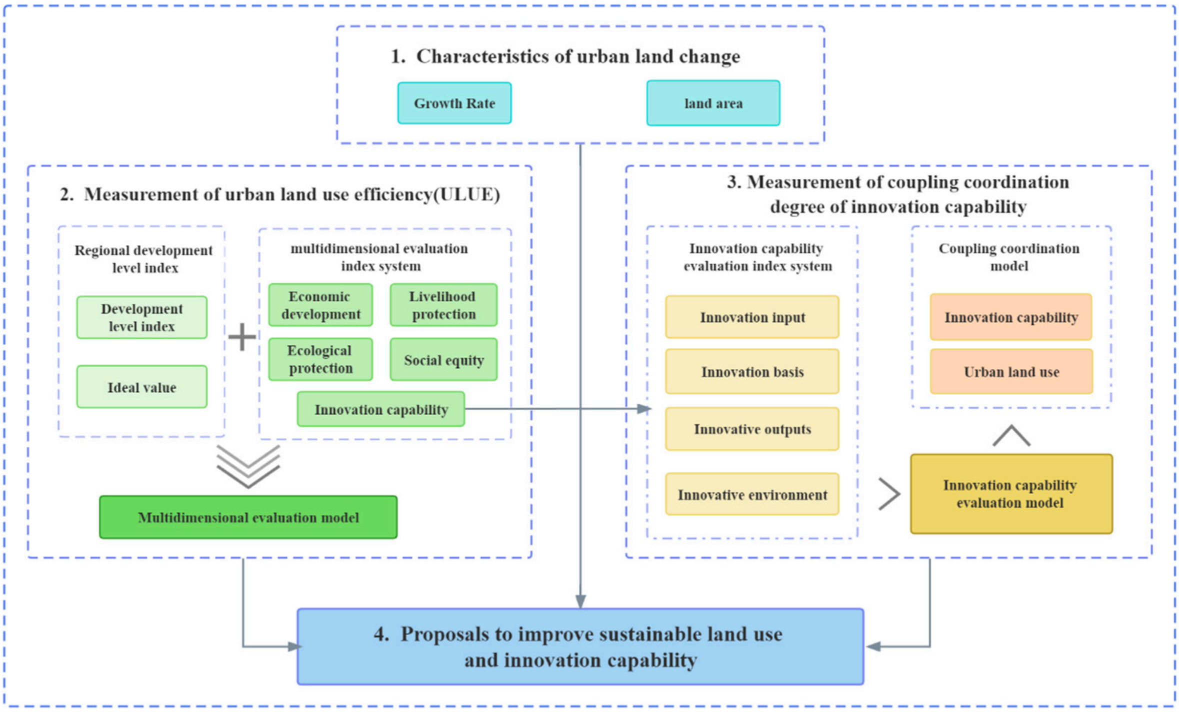

Figure 1. Research framework of this paper.

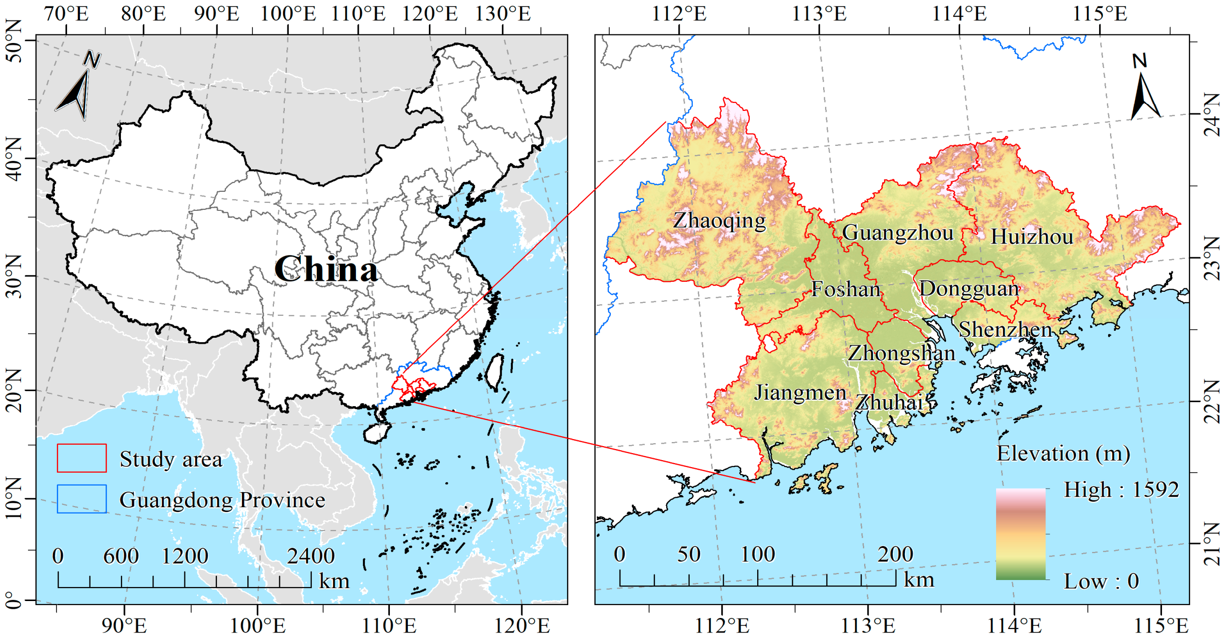

Figure 2. Spatial location of the study area.

2.3. Indicator System

2.3.1. Multidimensional Evaluation Index System

According to the basic functional values of urban land in the new era of China and the requirements of validity, systematicity, and accessibility regarding indicator selection, 18 indicators are selected in this paper from five dimensions: Economic Development, Livelihood Protection, Ecological Protection, Social Equity, and Innovation Capacity, with weights calculated using the entropy method, as shown in Table 1.

Table 1. Multidimensional evaluation index system for urban land-use efficiency (ULUE).

Classification	Specific Indicators	Indicator Interpretation	Nature of Indicator	Indicator Weights
Economic Development (M1) (0.221)	Average fixed asset investment per land area	Sum of fixed asset investment in secondary and tertiary sectors/construction land area	+	0.276
	Total social retail sales of consumer goods per land	Total social retail consumer goods/construction land area	+	0.227
	Proportion of commercial land	Land area for commercial service facilities/construction land area	+ *	0.189
	Secondary and tertiary industry output per land	Sum of output value of secondary and tertiary industries/construction land area	+	0.308
Livelihood Protection (M2)(0.190)	Proportion of residential land area	Residential land area/construction land area	+ *	0.223
	Proportion of transport infrastructure area	Transport infrastructure land area/construction land area	+	0.205
	Secondary and tertiary employees per land	Sum of employees in secondary and tertiary sectors/construction land area	+	0.363
	Financial expenditure per land	Financial expenditure/construction land area	+	0.209
Ecological Protection (M3) (0.101)	Energy consumption per land	Sum of the value of energy consumed by the secondary and tertiary sectors/construction land area	−	0.251
	Proportion of ecological land	Ecological land area/construction land area	−	0.412
	Sewage discharge per land	Industrial pollutants emissions/construction land area	−	0.337
Social Equity (M4) (0.174)	Proportion of Administrative land	Administrative office and service land area/construction land area	− *	0.424
	Construction maintenance expenses per land	Utility construction and maintenance expenses/construction land area	+	0.397
	Urban–rural gap	Per-capita disposable income of urban residents/per-capita disposable income of rural residents	−	0.179
Innovation Capability (M5) (0.314)	Innovation input per land	R&D expenses/construction land area	+	0.190
	Innovation Foundationsper land	Number of students in colleges and universities/construction land area	+	0.251
	Innovative outputs per land	Number of patents granted/construction land area	+	0.316
	Innovative environmentper land	Number of provincial-level new R&D institutions/construction land area	+	0.243

* means that the indicator is bidirectional, but as it falls within one of the single directions in the study, only unidirectionality is considered in this paper. The symbol "+" means the indicator is positive and "−" means the indicator is negative.

2.3.2. Innovation Capability Evaluation System

To better study the regional differences regarding innovation capability in the PRD region, we introduced the innovation capacity index [67,68]. The level of transformation of new knowledge into new products, processes, and services in a given location is represented by the innovation capacity index. The higher the value, the greater the ability to contribute to the regional socioeconomic system. As a result, we add new indicators to the original innovation capability indicators, which are now mainly divided into four categories: innovation input, innovation basis, innovation output, and innovation environment. Moreover, we used the entropy value method to assign weights to each indicator in the 2010–2020 PRD region innovation capability indicator system and calculate the mean value. The results are shown in Table 2.

Table 2. Innovation capability evaluation index system.

	Classification	Indicator	Nature of Indicator	Indicator Weights (Mean Value)
Innovation Capability	Innovation Input	R&D expenses	+	0.213
		Number of R&D staff	+	0.132
	Innovation Basis	Number of students in colleges and universities	+	0.151
		Number of full-time teachers in colleges and universities	+	0.113
	Innovative Outputs	Number of patents granted	+	0.167
		Number of patent applications	+	0.132
	Innovative Environment	Number of provincial-level new R&D institutions	+	0.092

The symbol "+" means the indicator is positive.

2.4. Research Methods

2.4.1. Regional Development Level Index

Based on existing studies [69,70], we selected two aggregate indicators (GDP per capita and GDP growth rate) and three structural indicators (the proportion of output value of secondary and tertiary industries, the Gini coefficient of residents' income, and the urbanization rate). Thus, we possessed a total of five indicators for measuring the regional development level index, calculated as follows:

$$Z_i = \sum\nolimits_{j=1}^{n} X_{ij} W_j. \tag{1}$$

In Equation (1), Z_i denotes the regional development index; X_{ij} denotes the great value of the jth indicator of the ith city in the PRD region; W_j denotes the weight of the jth indicator with weight calculated using the entropy method. After standardizing the above five categories of regional development index indicators and conducting hierarchical cluster analysis, we found that the range of the development index of each city in each sub-region was relatively small. Therefore, we referred to Wang et al.'s [71] study and adopted the maximum value of the development level index of each city in each sub-region as the ideal value of the development level of each sub-region. Setting the ideal value of the development level index of each sub-region as G, we obtain:

$$G = Max(Z_i). \tag{2}$$

2.4.2. Multidimensional Evaluation Model

The multidimensional evaluation of urban land-use efficiency in different regions should take into account the impact of regional development stage differences on urban land use efficiency. In this paper, the ideal value (G) of the development level of each sub-district is used to make a "sub-district correction" to the five-dimensional functional performance, and then the results are weighted and integrated to obtain the comprehensive functional performance of urban land use, calculated as follows:

$$\mathrm{F} = M_1 \times \mathrm{Q}(M_1) + M_2 \times \mathrm{Q}(M_2) + M_3 \times \mathrm{Q}(M_3) + M_4 \times \mathrm{Q}(M_4) + M_5 \times \mathrm{Q}(M_5) \quad (3)$$

$$M_y = \sum_{k=1}^{n} \frac{\alpha_{yk}\beta_{yk}}{G} \quad \mathrm{y} = 1, 2, 3, 4, 5. \quad (4)$$

In Equations (3) and (4), F denotes the comprehensive performance of urban construction land; M_1, M_2, M_3, M_4, and M_5 denote economic development, livelihood protection, ecological protection, social equity, and innovation capability performance, respectively; Q(M_1), Q(M_2), Q(M_3), Q(M_4), and Q(M_5) denote the weight of economic development, livelihood protection, ecological protection, social equity, and innovation capability performance on the comprehensive functional performance, respectively; α_{yk} denotes the maximum value and standardized value of the kth indicator of the yth functional performance; and β_{yk} denotes the weight of the kth indicator of the yth functional performance on the comprehensive functional performance.

2.4.3. Innovation Capability Evaluation Model

The Innovation Capacity Index is used to evaluate the level of a region's ability to translate new knowledge into new products, processes and services and is calculated as follows:

$$\mathrm{E} = C_1 \times \mathrm{Z}(C_1) + C_2 \times \mathrm{Z}(C_2) + C_3 \times \mathrm{Z}(C_3) + C_4 \times \mathrm{Z}(C_4) \quad (5)$$

$$C_x = \sum_{k=1}^{n} \frac{\mu_{xd}\theta_{xd}}{G} \quad \mathrm{x} = 1, 2, 3, 4. \quad (6)$$

Similar to the multidimensional evaluation model, in Equations (5) and (6), E denotes the innovation capability; C_1, C_2, C_3, and C_4 denote the innovation input, innovation base, innovation output, and innovation environment, respectively; Z(C_1), Z(C_2), Z(C_3), and Z(C_4) denote the weight of innovation input, innovation base, innovation output, and innovation environment in the overall weights in the innovation capability, respectively; μ_{xk} denotes the maximum value and standardized value of the kth indicator of the xth functional performance; and θ_{xk} denotes the weight of the kth indicator of the xth functional performance on the comprehensive functional performance.

We used a combination of absolute and relative variance measures and introduced the extreme difference (R), the coefficient of variation (CV), and the Gini coefficient (G) to measure the differences in the development of innovation capability among the nine cities in the PRD region.

$$R = E_{max} - E_{min}. \quad (7)$$

E_{max} and E_{min} are the maximum and minimum values of the city's innovation capability, respectively.

$$\mathrm{CV} = \mathrm{SD}/\overline{E}. \quad (8)$$

SD is the standard deviation of city innovation capability, and $\overline{E}$ is the mean of city innovation capability.

The Gini coefficient (*G*), originally used to measure regional income disparities, has been developed and refined and is now widely used in many fields as an important statistical indicator of disparity. The specific equation is as follows:

$$G = 1 + \frac{1}{n} - \frac{2}{n^2\overline{E}}(x_1 + 2x_2 + 3x_3 + \ldots + nx_n), \quad (9)$$

where *n* is the number of cities, $\overline{E}$ is the average value of the innovation capacity of the cities, and $x_i$denotes the value of the n cities ranked in the *i*th position after ranking them from the largest to the smallest. The value of G ranges from [0, 1] with a larger value indicating a more uneven development of innovation capacity among the nine cities in the PRD.

Based on the multidimensional performance evaluation values of urban construction land, we classify the performance levels of nine major cities into four levels, as shown in Table 3.

Table 3. Urban land-use efficiency performance value zoning.

Performance Areas	Score
Level 1 areas	$0.6 \leq$ Performance values ≤ 1
Level 2 areas	$0.5 \leq$ Performance values < 0.6
Level 3 areas	$0.4 \leq$ Performance values < 0.5
Level 4 areas	$0 \leq$ Performance values < 0.4

2.4.4. Coupling Coordination Model

We used the coordination coefficient method to study the degree of land-use coordination. This method has a wide range of applications, is simple and straightforward to calculate, and the results are intuitive and easy to compare within the time or space dimension [72]. In this study, innovation capacity and construction land were treated as two subsystems of an urban agglomeration, and the coupling degree measurement model is as follows:

$$\mathrm{C} = \{U_1 \times U_2 / [(U_1 + U_2) \times (U_1 + U_2)]\}^{\frac{1}{K}} \tag{10}$$

$$D = \sqrt{C \times T} \tag{11}$$

$$\mathrm{T}{=}\mathrm{a}U_1 + b\,U_2, \tag{12}$$

where C is the coupling degree value ($\mathrm{C} \in [0, 1]$); U_1 and U_2 represent the comprehensive scores of the PRD innovation capability level and construction-land development, respectively; k is the adjustment coefficient, which describes the system combination coordination quantity level when $U_1 \times U_2$ is at its maximum, generally taking the value of $2 \leq k \leq 5$; and the value of k in this study is 2. D is the value of the coupled coordination degree ($D \in [0, 1]$); T is the comprehensive evaluation index of the overall effectiveness of the two subsystems of innovation capacity and construction land condition; a and b are coefficients to be determined; and a + b = 1. Based on objective reality and existing research results, this study sets the influence of the level of urban innovation capacity and construction-land development on the coordination degree to the same degree, thus making a = b = 0.5.

According to the actual situation in the PRD region, we divided the coupling coordination into 3 stages and 10 levels, as shown in Table 4. The first stage is the dysfunctional decline stage. Due to irrational urban-land development and utilization, the value of its coupling coordination development with regional innovation capability is less than 0.4, implying that the improvement of the regional innovation level will be significantly limited if timely coordinated development measures are not implemented. Extreme disorder [0, 0.1], serious disorder [0.1, 0.2], moderate disorder [0.2, 0.3], and mild disorder [0.3, 0.4] are all included in this stage. The second stage is the transition-reconciliation stage with coupling coordination values ranging from 0.4 to 0.6, including the borderline disorder [0.4, 0.5) and reluctant disorder [0.5, 0.6). The third stage is the integration-coordination stage wherein the coupling coordination value between urban land efficiency and innovation capacity is higher than 0.6 and is divided into four states: primary coordination [0.6, 0.7), intermediate coordination [0.7, 0.8), good coordination [0.8, 0.9), and best coordination [0.9, 1].

Table 4. Division of coupling coordination stages.

Development Stage	**Dysfunctional Decline**				**Transition Reconciliation**		**Integration Coordination**			
Value	[0, 0.1)	[0.1, 0.2)	[0.2, 0.3)	[0.3, 0.4)	[0.4, 0.5)	[0.5, 0.6)	[0.6, 0.7)	[0.7, 0.8)	[0.8, 0.9)	[0.9, 1]
Coupling Coordination level	Extreme disorder	Serious disorder	Moderate disorder	Mild disorder	Borderline disorder	Reluctant disorder	Primary coordination	Intermediate coordination	Good coordination	Best coordination
Symbols	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10

2.5. Data Sources

The data on construction land, land for commercial and service facilities, residential land, land for transportation facilities, area of parkland, arable land, water, and forest land were all obtained from land project research and the "China City Statistical Yearbook", which is the most authoritative and comprehensive information yearbook on urban construction in China. Socioeconomic data were mainly obtained from the "National Statistical Yearbook in 2020", the statistical yearbooks of various cities in the PRD, and various statistical bulletins; innovation data were obtained from the "Guangdong Science and Technology Funding Inputs Statistical Bulletin in 2020" and the "China Science and Technology Statistical Yearbook".

3. Results

3.1. Characteristics of Urban-Land Changes

Based on data from the "China City Statistical Yearbook", we calculated the expansion rate of urban land area in the PRD region for four periods: 2000–2005, 2005–2010, 2010–2015, and 2015–2020, respectively. As can be seen from Table 5, the period of fastest growth in urban land in the PRD was 2005–2010, followed by 2000–2005. After 2010, urban land growth began to slow down with the slowest rate falling to 153.67 km^2/h in the period of 2015–2020. The results of the division of the land-expansion periods are in line with actual land construction in the PRD cities and are consistent with the findings of Yang's study [66], indicating that that the results of this paper are accurate and reasonable.

Table 5. Overall growth rate of urban land in the PRD from 2000 to 2020.

Year	**2000–2005**	**2005–2010**	**2010–2015**	**2015–2020**
Growth Rate (km^2/h)	189.14	274.78	168.79	153.67

As shown in Table 6, Dongguan had the highest proportion of construction land, accounting for more than half of Dongguan's land area in 2020, followed by Shenzhen, Foshan, and Zhongshan. Guangzhou had the largest absolute area of construction land, but its ratio of construction land area ranked fifth among the nine major cities in the PRD, ranking similarly to Zhuhai with a ratio of 25.13%. Zhaoqing had the lowest ratio with only 6.52% by 2020.

As shown in Figure 3, in terms of the different stages, between 2000 and 2005, the cities that expanded faster in descending order were Guangzhou, Jiangmen, Foshan, Zhongshan, and Zhuhai, all with urban land-growth rates greater than 15 km^2/h. Between 2005 and 2010, the expansion rate of all cities accelerated significantly with an average growth rate of 50.53 km^2/h. During the period of 2010–2015, the expansion rate of urban land in all cities showed a clear downward trend with the cities of Zhuhai, Dongguan, and Huizhou showing the most significant decrease in the growth rate. During the period of 2015–2020, the growth rate of land use in the cities of Zhaoqing, Dongguan, and Zhongshan showed an increase, while the rest of the cities remained on a downward trend.

Table 6. Urban land use in the PRD from 2000 to 2020.

City	2000–2005		2005–2010		2010–2015		2015–2020	
	Area Percentage (%)	Growth Rate (km^2/h)	Area Percentage (%)	Growth Rate (km^2/h)	Area Percentage (%)	Growth Rate (km^2/h)	Area Percentage (%)	Growth Rate (km^2/h)
Guangzhou	17.61	39.89	21.20	45.05	22.01	33.63	26.01	30.02
Shenzhen	35.84	10.92	43.18	28.38	41.28	23.96	51.52	7.64
Zhuhai	17.49	18.07	24.41	23.97	25.67	1.27	25.13	0.81
Foshan	29.80	32.90	33.68	29.47	34.98	29.21	39.86	14.77
Jiangmen	6.71	36.26	9.06	33.97	10.02	23.14	11.11	14.93
Zhaoqing	3.87	12.85	5.12	22.08	5.73	12.44	6.52	24.49
Huizhou	5.81	8.94	6.75	42.19	7.90	28.38	10.69	34.21
Dongguan	40.17	8.24	41.60	31.02	48.27	8.37	53.52	25.21
Zhongshan	28.31	21.07	34.10	18.64	36.29	8.38	38.12	1.59

Growth rate = area of regional building land growth/time span.

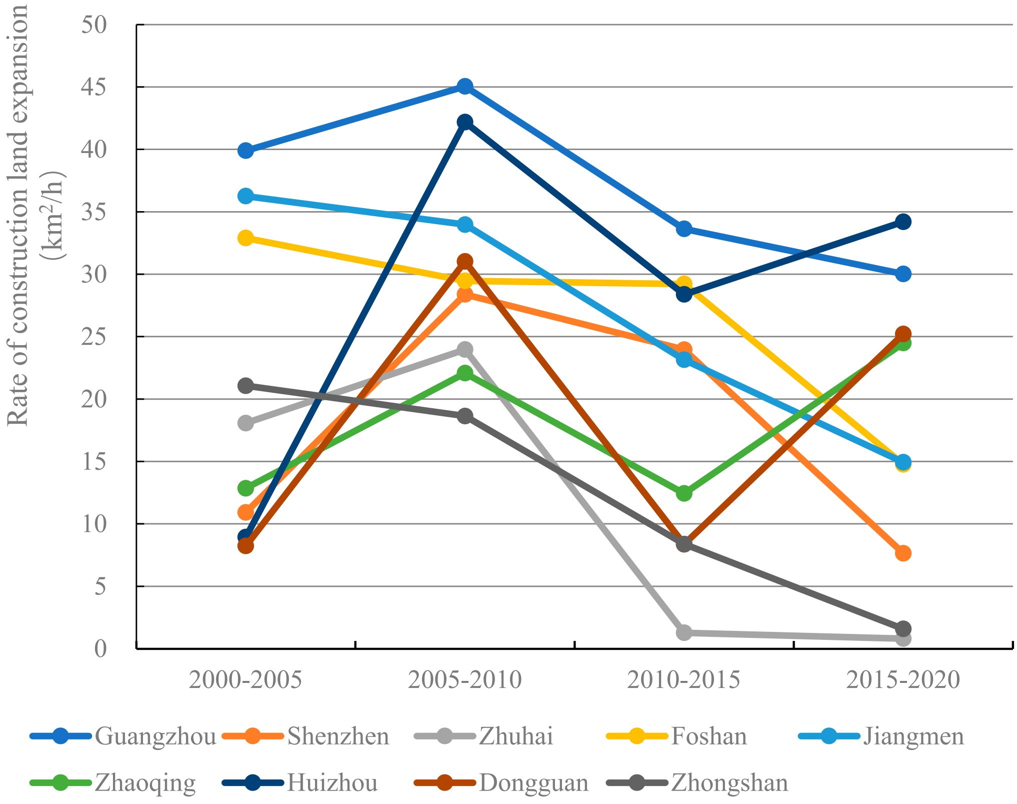

Figure 3. Rate of change in the growth of urban land in the PRD from 2000 to 2020.

Overall, the rate of expansion of construction land in the nine major cities within the PRD region was clearly differentiated, showing a degree of regional asynchrony.

3.2. Multidimensional Evaluation of Urban Land-Use Efficiency

3.2.1. Urban Development Level Index and Modeling Results

The development level indices of each city and the ideal values of each sub-district, calculated using Equations (1) and (2) in this study, are shown in Table 7. From the results, Class A divisions included Guangzhou, Shenzhen, and Zhuhai; Class B divisions included Foshan, Dongguan, and Zhongshan; and Class C divisions included Huizhou, Jiangmen, and Zhaoqing. This classification result is in line with the actual socioeconomic development of each city in the PRD and is more consistent with the classification of the development level of PRD cities according to Wang [71], indicating that the classification result of the development status of the nine cities in the PRD in this study is accurate and reasonable.

Table 7. Urban development index divisions.

Division	City	Urban Development Level Index	Ideal Value
Class A	Guangzhou Shenzhen Zhuhai	0.893 0.872 0.722	0.893
Class B	Foshan Dongguan Zhongshan	0.711 0.612 0.607	0.711
Class C	Huizhou Zhaoqing Jiangmen	0.589 0.571 0.554	0.589

Higher urban development level indices and ideal values represent a better level of regional development.

Based on the development level indices and ideal values in Table 7, we further used Equations (3) and (4) to calculate the multidimensional values of land-use efficiency (ULUE) in the PRD while considering the differences in regional development levels (Table 8) and then used the natural discontinuity point method in ArcGIS 10.2 software with the classification rules in Table 3 to map the distribution of the multidimensional levels of ULUE (Level 1 to Level 4), as shown in Figures 4 and 5.

Table 8. Multidimensional evaluation of urban land-use efficiency in the PRD.

Cities	Economic Development			Livelihood Protection			Ecological Protection			Social Equity			Innovation Capability			Comprehensive Performance		
	Value	Rank	Level	Value	Rank	Level	Value	Rank	Level	Value	Rank	Level	Value	Rank	Level	Value	Rank	Level
Guangzhou	0.793	2	L1	0.497	5	L3	0.382	9	L4	0.483	7	L3	0.727	1	L1	0.601	3	L1
Shenzhen	0.819	1	L1	0.533	4	L2	0.513	5	L2	0.546	5	L2	0.693	2	L1	0.742	1	L1
Zhuhai	0.472	5	L3	0.377	9	L2	0.394	8	L4	0.372	9	L4	0.524	4	L2	0.499	7	L3
Foshan	0.501	4	L2	0.698	1	L1	0.487	7	L3	0.549	6	L2	0.571	3	L2	0.702	2	L1
Jiangmen	0.378	7	L4	0.487	7	L3	0.601	2	L1	0.562	4	L2	0.397	7	L4	0.467	8	L3
Zhaoqing	0.309	9	L4	0.546	3	L2	0.577	3	L2	0.692	1	L1	0.397	9	L4	0.562	6	L2
Huizhou	0.456	6	L3	0.593	2	L4	0.491	6	L3	0.667	2	L1	0.481	6	L3	0.573	5	L2
Dongguan	0.537	3	L2	0.492	6	L3	0.621	1	L1	0.399	8	L4	0.483	5	L3	0.581	4	L2
Zhongshan	0.315	8	L4	0.391	8	L4	0.515	4	L2	0.583	3	L2	0.399	8	L4	0.464	9	L3

Higher evaluation values for the different dimensions represent higher land-use efficiencies accordingly.

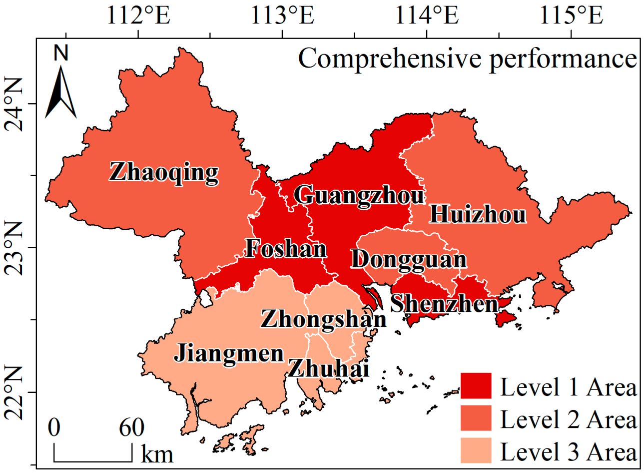

Figure 4. Spatial distribution of the comprehensive performance in the PRD.

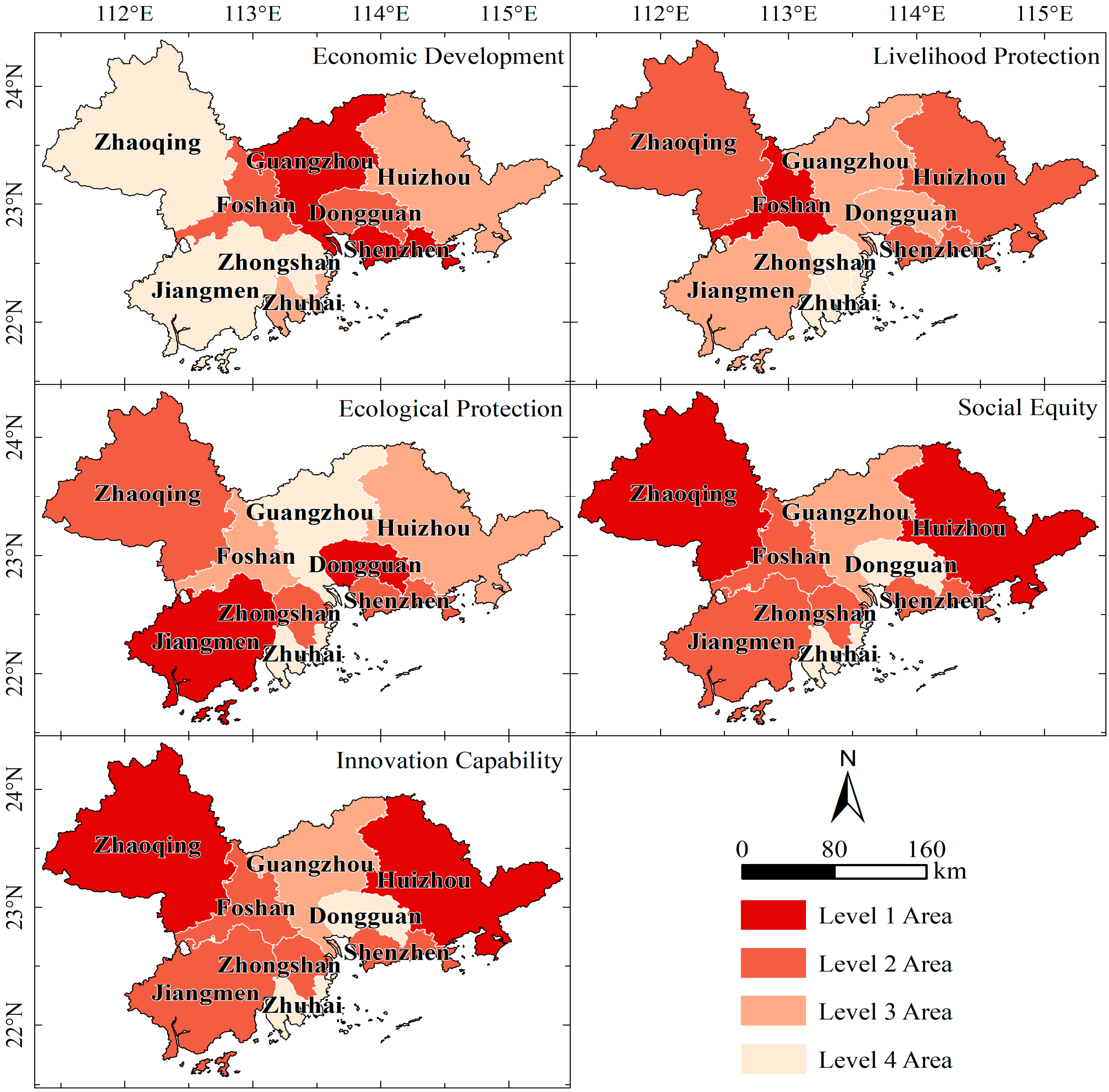

Figure 5. Spatial distribution of multidimensional performance regarding ULUE.

As shown in Table 8 and Figure 4, the comprehensive performance of urban land-use efficiency (ULUE) in the PRD was high with five cities performing at a level higher than the regional average of 0.577. Spatially, the comprehensive performance showed a spatial distribution pattern with Foshan and Shenzhen as the twin cores and other values decreasing outwards. Among them, Shenzhen, Foshan, and Guangzhou were located in the Level 1 area with values of 0.742, 0.702, and 0.601, respectively. Shenzhen and Foshan were ranked highest in all dimensions of performance evaluation regarding ULUE, making their comprehensive performance much higher than that of the other regions. Guangzhou achieved a high overall functional performance owing to its strengths in economic development, livelihood protection, and innovation capability, but it ranked low in ecological performance and political protection. Located in the Level 2 area were Zhaoqing, Huizhou, and Dongguan. Zhaoqing and Huizhou achieved more outstanding performance in social equity and livelihood protection, while Dongguan had better ecological maintenance and economic performance, boosting its overall performance strength. Jiangmen, Zhuhai, and Zhongshan were located in the Level 3 area, all with values below 0.5 and poor comprehensive performance regarding ULUE.

3.2.2. Multidimensional Evaluation

1. Economic development

As shown in Table 8 and Figure 5, the economic development performance showed a dual-core gradient with Shenzhen and Guangzhou in Level 1; Dongguan and Foshan in Level 2; Zhuhai and Huizhou in Level 3; and Zhaoqing, Jiangmen, and Zhongshan in Level 4. Shenzhen and Guangzhou showed high investment and policy support in urban construction and economic development, in addition to overseas Chinese investment and the transfer of industries and capital from Hong Kong and Macao to promote their economic development, with values of 0.819 and 0.793. Dongguan and Foshan showed relatively lower values owing to their fourth and fifth ranking in terms of regional development (Table 7), resulting in a higher functional performance rating for economic development. Zhuhai, as a coastal city, despite its geographical location, was too heavily weighted toward manufacturing development, with a lack of modern service industries and high-end innovation talent, resulting in relatively poor economic development performance (a value of 0.472 in Level 3). For a long time, peripheral cities such as Zhaoqing, Jiangmen, and Zhongshan, which mostly take over industrial transfers from central cities, have had limited urban attractiveness and investment capacity and were therefore in the fourth-tier development zone.

2. Livelihood protection

The performance of livelihood protection showed a decreasing spatial pattern outward in all directions from Foshan at the center (Figure 5). With the advancement of the Guangzhou–Foshan co-city and the sharing of resources, the demand for Foshan's infrastructure market has surged, and the city's social services are developing faster. Located in Level 2 were Huizhou, Zhaoqing, and Shenzhen. Both Huizhou and Zhaoqing were located in Zone C of the regional development level (Table 7), and the ideal value of urban development was set relatively low, putting social performance at the top after considering the difference in regional development levels. The reason for Guangzhou, Zhongshan, and Zhuhai's low rankings (values of 0.497, 0.391, and 0.377) is the mismatch between the comprehensive performance expectations set by the cities and the corresponding utility of the social services generated.

3. Ecological protection

Ecological conservation performance showed a "high south-low north" distribution pattern with Dongguan and Jiangmen in Level 1 (Figure 5). During the 13th Five-Year Plan period, Dongguan invested a significant amount of resources in promoting a new model of pollution control and was named a National Ecological Civilization Demonstration Zone by the Ministry of Ecology and Environment in 2021, achieving a milestone victory in the battle against pollution. Zhaoqing, Zhongshan, and Shenzhen were in Level 2, while Huizhou and Foshan were in Level 3, while Jiangmen and Huizhou showed inherently good ecological conditions and Zhongshan benefitted from the establishment of a forest town and the "Beautiful Zhongshan" youth charity alliance. Zhuhai and Guangzhou were in the Level 4 area with Zhuhai's ecological performance in Zone 4 being influenced by the high expectations set for its ecological performance.

4. Social Equity

Social equity performance showed a "high around—low in the middle" distribution (Figure 5). Located in Level 1 were Zhaoqing and Huizhou; the higher ranking of the two cities is due not only to the low target value set for each, but is also due to their low population densities and obvious spatial advantages regarding land, resulting in a better coordination between urban development and population growth. Located in Level 2 were Zhongshan, Jiangmen, Shenzhen, and Foshan. The only city located in Level 3 was Guangzhou, which has the largest urban–rural income gap ratio among the PRD cities, with a value of 2.15, indicating that its significant urban–rural income gap has seriously affected social equity.

5. Innovation Capability

The performance of innovation capability showed a general decreasing trend in all directions with Guangzhou and Shenzhen as the core (Figure 5). Guangzhou and Shenzhen were located in Level 1, while Foshan and Zhuhai were located in Level 2. At present, Guangzhou has more than 20 state-owned key laboratories and more than 12,000 high-tech enterprises, and a large number of highly qualified talents and R&D platforms are gathered in Guangzhou and Shenzhen. Foshan relies on the Guangzhou–Foshan Science and Technology Cooperation Zone to actively explore a new model of innovation and development. In recent years, Zhuhai's innovation capacity has been boosted by the construction of the Guangzhou–Zhuhai–Macau Science and Technology Innovation Corridor, driving its research and industrialization capacity. Huizhou and Dongguan were located in Level 3, while Jiangmen, Zhaoqing, and Zhongshan were located in Level 4. Among these, Dongguan City has built on its manufacturing strengths and was successfully established as a national innovation city in 2022. Compared to other cities in the PRD, Jiangmen, Zhaoqing, and Zhongshan have relatively weak technological innovation capabilities.

3.3. Coupling Coordination Analysis

3.3.1. Evaluation of Innovation Capability

From the above analysis, it can be seen that in the multidimensional performance evaluation of ULUE in the PRD, the innovation capability performance had the largest weighting of 0.314 compared to other dimensions of performance (Table 1). Moreover, the PRD was officially approved as a National Independent Innovation Demonstration Zone in 2015 and has now become one of the most concentrated regions in China in terms of science and technology innovation resources. Therefore, we focus on the level of innovation capacity in the PRD region from 2010 to 2020 and examine its coupled and coordinated relationship with urban land, as well as the differences in spatial distribution.

In this study, based on the innovation capability evaluation indicators (innovation input, innovation base, innovation output, and innovation environment) in Table 2, we used the science and technology innovation data from 2010 to 2020 and used Equations (2), (5), and (6) to conduct a comprehensive evaluation of the innovation capability of each city in the PRD. The results are shown in Table 9.

Table 9. Comprehensive evaluation of the innovation capabilities of cities from 2010 to 2020.

City	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Guangzhou	0.541	0.538	0.545	0.572	0.574	0.609	0.582	0.612	0.663	0.624	0.656
Shenzhen	0.556	0.579	0.597	0.587	0.591	0.614	0.662	0.674	0.683	0.679	0.671
Zhuhai	0.364	0.373	0.392	0.369	0.402	0.338	0.334	0.387	0.392	0.401	0.432
Foshan	0.299	0.305	0.313	0.319	0.321	0.325	0.366	0.378	0.381	0.401	0.414
Jiangmen	0.254	0.248	0.266	0.268	0.263	0.268	0.268	0.271	0.274	0.271	0.269
Zhaoqing	0.212	0.223	0.227	0.228	0.235	0.257	0.306	0.312	0.314	0.320	0.323
Huizhou	0.360	0.363	0.364	0.361	0.422	0.347	0.338	0.341	0.344	0.362	0.384
Dongguan	0.230	0.238	0.242	0.249	0.302	0.307	0.316	0.321	0.332	0.368	0.377
Zhongshan	0.291	0.230	0.293	0.284	0.301	0.279	0.283	0.285	0.287	0.291	0.299

According to Table 9, the cities with a continuous increase in innovation capability from 2010 to 2016 included Foshan, Dongguan, and Zhaoqing, among which Dongguan had the largest increase in the comprehensive innovation capability evaluation value. Shenzhen, Guangzhou, and Zhuhai had a relatively stable score over time with strong innovation bases and capabilities. Jiangmen and Zhaoqing had lower overall scores and relatively poorer innovation capabilities.

As shown in Table 10, in terms of the change in the extreme difference (R), although the overall gap between the cities with the highest and lowest innovation capacities within the nine major cities in the PRD region from 2010 to 2020 showed an upward trend (from 0.344 to 0.401), the gap gradually narrowed after 2017, indicating that the cities with inferior innovation capacities gradually improved their innovation capacities under the drive of the collaborative development of the Guangdong–Hong Kong–Macao Greater Bay Area. From the coefficient of variation (CV) and Gini coefficient (G), the difference in the development of innovation capacities among cities in the PRD shrank from 2010 to 2020, and the value is smaller. This indicates that the unbalanced development trend of innovation capacity in the PRD region has improved, but the change is small, indicating that the collaborative development of innovation is under great pressure.

Table 10. Regional variability in innovation capacity from 2010 to 2020.

Coefficient	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
R	0.344	0.356	0.370	0.356	0.357	0.394	0.403	0.409	0.408	0.402	0.401
G	0.345	0.367	0.345	0.350	0.323	0.354	0.343	0.343	0.359	0.327	0.322
CV	0.186	0.196	0.186	0.126	0.192	0.137	0.140	0.157	0.157	0.143	0.170

3.3.2. Analysis of the Coupling Coordination of Innovation Capability

We calculated the coupling coordination degree between the levels of innovation capacity and urban land construction in nine major cities in the PRD from 2010 to 2020 according to Equations (10–12) and divided the stages (D1 to D10) according to the criteria in Table 3. The results are shown in Table 11 and Figure 6.

Table 11. Coupling coordination values and stages from 2010 to 2020.

City	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Guangzhou	0.782	0.785	0.784	0.810	0.807	0.815	0.809	0.838	0.866	0.848	0.864
	D8			D9							
Shenzhen	0.838	0.853	0.869	0.867	0.877	0.892	0.924	0.933	0.940	0.938	0.937
	D9						D10				
Zhuhai	0.540	0.558	0.574	0.395	0.416	0.375	0.466	0.522	0.553	0.591	0.619
	D6			D4	D5	D4	D5	D6			D7
Foshan	0.378	0.360	0.373	0.410	0.397	0.409	0.475	0.441	0.427	0.438	0.455
	D4			D5	D4	D5					
Jiangmen	0.305	0.254	0.331	0.325	0.342	0.019	0.107	0.335	0.342	0.338	0.335
	D4					D2		D4			
Zhaoqing	0.144	0.150	0.197	0.193	0.213	0.277	0.338	0.344	0.349	0.357	0.365
	D2				D3		D4				
Huizhou	0.460	0.506	0.472	0.478	0.521	0.457	0.473	0.480	0.487	0.507	0.533
	D5	D6	D5		D6	D5				D6	
Dongguan	0.417	0.462	0.480	0.508	0.637	0.647	0.665	0.677	0.697	0.759	0.769
	D5			D6	D7					D8	
Zhongshan	0.291	0.253	0.311	0.305	0.330	0.312	0.318	0.333	0.346	0.349	0.351
	D3		D4								

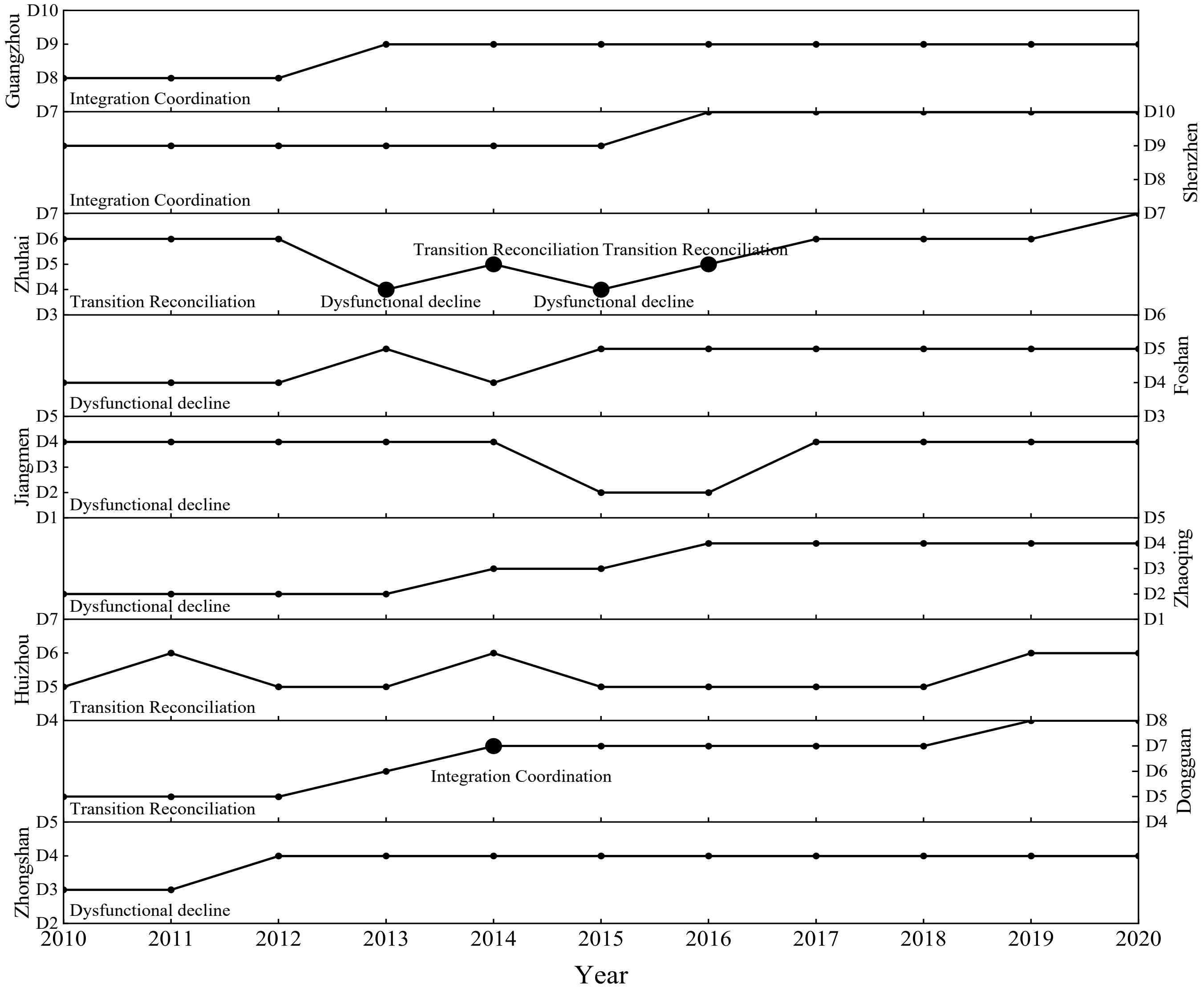

Figure 6. Coupling coordination trend from 2010 to 2020.

There was a clear upward trend in the value of coupling and coordination between innovation capacity and construction land scale for each city in the PRD between 2010 and 2020. As can be seen from Table 11 and Figure 6, the coupling coordination was in the first tier in Shenzhen and Guangzhou. Of these, Shenzhen had the best coupling coordination status with innovation capacity and urban land-use efficiency in the best coordination stage (D10) since 2017, and Guangzhou was in second place, consistently at the good coordination stage (D9) since 2013. These results indicate that the two cities are at the forefront regarding the construction of the science and technology innovation highland in the Guangdong–Hong Kong–Macao Greater Bay Area.

In the second order were Zhuhai and Dongguan, showing a clear upward trend in coupling coordination. Of these, Dongguan's coordination rose faster, developing from the verge of disorder stage (D5) in 2010 to a primary coordination stage (D7) in 2014 and entering an intermediate coordination stage (D8) in 2017. Zhuhai also rose from a barely reluctant disorder (D6) to a primary coordination stage (D7) in 2020, indicating that improvements in land-use efficiency played a certain optimizing role in the process of improving the innovation capacity of the two cities, but there is still room for further improvement in the coupling and coordination of innovation capacity and construction land. In the third order were Foshan and Huizhou, both of which were in the dysfunctional stage (D2 to D4) with low interaction between innovation capacity and construction land. However, both have improved significantly in recent years and are gradually moving toward a coordinated stage. In the fourth order, Jiangmen, Zhaoqing, and Zhongshan were in a poor state of coupling and coordination with the cities suffering from weak innovation resources, low investment in science and technology innovation, and an imbalance in the structure of land use for construction.

As shown in Figure 7, the spatial variation in the level of coordination between innovation and construction land was large from 2010 to 2020, showing a pattern of spreading around with "Shenzhen–Guangzhou" as the growth pole, indicating that a certain intensity of innovation–spatial linkage has been formed between various sub-districts within Guangzhou and Shenzhen. For the rest of the PRD, the levels of coordination were higher in Zhuhai, Foshan, and Dongguan and lower in the more-distant Jiangmen and Zhaoqing. Therefore, in the future, the PRD region should focus on guiding the transformation of dysfunctional cities into coordinated cities, cultivating more high-level coordinated cities, focusing on cultivating the "Shenzhen–Guangzhou" twin core of innovative urban growth poles, and driving up the level of coordination between regional innovation and urbanization.

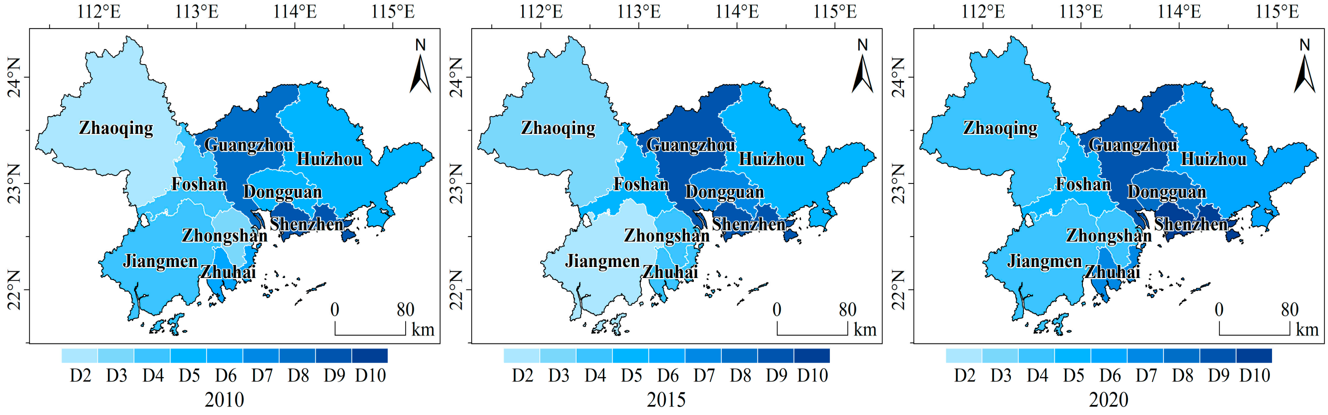

Figure 7. Spatial distribution of the coupling coordination from 2010 to 2020.

4. Conclusions

First, based on data from the Third China Land Survey, we summarized the changing characteristics of the growth rate and proportion of construction land area in the nine major cities in the PRD region. We found that the growth rate of construction land in the PRD region showed an obvious expansion in the early stage, a rapid slowdown in the middle stage, and a stabilization trend in the later stage; the expansion rate of construction land in the nine major cities was clearly differentiated, showing a certain degree of regional asynchrony. Second, we evaluated the multidimensional performance of the construction land of nine major cities in the PRD region based on the constructed multidimensional performance evaluation model. Finally, we focused on the innovation capability of the PRD region and analyzed the coupling coordination relationship between it and urban land use. The findings of this paper are as follows: (1) the overall performance of urban construction land in the PRD urban agglomeration was relatively high, showing a spatial distribution pattern, with Foshan–Shenzhen as the double core with decreasing values outward. (2) There were obvious differences in the performance of different dimensions, each with different spatial differentiation characteristics. (3) The innovation capability of the PRD region and the scale of construction land were mainly in a highly coupled stage, showing an obvious upward trend in the level of coordination. The value of coupling and coordination showed a decreasing pattern outwards spatially with "Shenzhen–Guangzhou" as the growth pole.

Based on the findings of this study, we argue that the PRD region should adopt differentiated performance enhancement measures according to the actual situation of construction land in different cities and their levels of regional development. In particular, central cities such as Guangzhou, Shenzhen, and Foshan should increase their efforts to manage ecological and environmental protections; minimize the use of land for low-efficiency, high-polluting and high-energy-consuming industries; and continue to improve levels of livelihood protection and narrow their social income gaps. Huizhou, Zhuhai, Zhongshan, and other peripheral cities should take advantage of the development policy of the Guangdong–Hong Kong–Macao Greater Bay Area and the "the Belt and Road" strategy to increase the development of their economic synergy and technological innovations and further improve their social services and populations' living standards. In addition, in the future, the PRD city cluster will need to further enhance the level of coordination between the use of construction land and regional innovation capacity, fully highlight the leading role of Shenzhen and Guangzhou as innovation hubs, accelerate the inter-regional flow of innovation factors, and improve the inter-city linkage.

Author Contributions: Conceptualization, Y.L., Z.D. (Zuoji Dong). and J.D.; methodology, Y.L. and Z.D. (Zhi Dong).; validation, Y.L.; writing—original draft preparation, Y.L.; writing—review and editing, Y.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

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

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

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