ISEIS

Journal of Environmental Informatics Letters 3(1) 49-58 (2020)

Journal of Environmental Informatics Letters

www.iseis.org/jeil

Land-Use Variations in Regions with Rapid Economic Development - A Case Study in the Pearl River Delta

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Received 29 February 2020; revised 09 March 2020; accepted 12 March 2020; published online 31 March 2020

ABSTRACT. This study evaluates land use/cover changes (LUCC), urban expansion, and landscape patterns in the Pearl River Delta (PRD) from 1995 to 2015. Specifically, by analyzing the spatial-temporal process and transfer direction of LUCC, as well as landscape pattern change, human activity and sustainable urban development can be better understood. The results show that forestland has the largest area (occupying more than 50%) in all landscape types. The forest coverage rate of the PRD is relatively high; meanwhile, forestland presents a spatially distributed form of aggregation. Urban-land expansion is primarily driven by population growth and economic development. The LUCC is imbalanced and shows a one-way transition; the proportion of built-up land increased from 7.91% in 1995 to 14.34% in 2015 (urban expansion has nearly doubled in size). Foshan, Guangzhou, Shenzhen, and Dongguan have seen the most significant expansion of built-up land, primarily through the occupation of large amounts of forest and cropland. The landscape tends to be more fragmented and diversified. Human activities, as the main driving force, need to avoid the acceleration of the urbanization process to occupy a large amount of ecological land in future development.

Keywords: land use/cover change, landscape pattern, landscape heterogeneity, Pearl River Delta

1. Introduction

Land use has generally been considered a local environmental issue; however, it is becoming a force of global importance (Foley et al., 2005; Cai et al., 2007). Land use/cover change (LUCC) has essential impacts on regional ecological security and natural succession of ecosystems (Salazar et al., 2015; Yu et al., 2018; Hu et al., 2019). Therefore, studying of LUCC is desired for sustainable social-ecological systems.

Previously, there were several types of research on LUCC, which could be classified into four categories: exploring (1) the spatial-temporal analysis of LUCC (Jiao et al., 2019); (2) the effects of LUCC (economic impacts, environmental effects, ecological effects, etc.) (Du and Huang, 2017; Gong et al., 2020); (3) the driving mechanism of LUCC (Hasselmann et al., 2010; Li et al., 2020); and (4) the scenario prediction of LUCC (Dang and Kaisaki, 2017; Gomes et al., 2019). However, the amount of research on the spatial-temporal analysis of LUCC is the most due to it directly reflects the effects of climate change and human activities on the natural environment. Dewan and Yamaguchi (2009) evaluated LUCC and urban expansion in Greater Dhaka using satellite images and socio-economic data, which found that the land-use maps will contribute to both the development of sustainable urban land-use planning decisions and also for forecasting possible future changes. Velázquez et al. (2003) found that Oaxaca has lost over half a million hectares of forested areas during 1980 ~ 2001; the core results may contribute to the understanding of how LUCC and GIS methods can provide more targeted information that may help to improve conservation policies and land use planning strategies.

Tremendous efforts have been made in studying the spatial-temporal analysis of LUCC. However, there is a limited report in analyzing changes in landscape patterns brought by LUCC and their interrelationships. Moreover, from a China perspective, there has been a crucial demand for scientific bases to dealing with economic development and land-use protection. This is especially true for Pearl River Delta (PRD) as located in the south of the country and with the highest GDP as well as rapid urban expansion.

Therefore, as an extension of the previous efforts, the objective of this study is to explore the LUCC and landscape change in the PRD using the multivariate methods and variables. Specifically, the purpose entails analyzing the spatial-temporal pattern on LUCC, the landscape distribution on a class level, the landscape heterogeneity, and LUCC impact on landscape pattern. Moreover, this study could provide a targeted suggestion that may help to improve environmental conservation policies and land use planning strategies.

2. Overview of the Study Area

The study area is the whole PRD region, which is an ag-

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ISSN: 2663-6859 print/2663-6867 online
 doi:10.3808/jeil.202000024.

glomeration located in Guangdong, southern China (Figure 1), and covers approximately 54,000 km^2 with a subtropical climate. The PRD is one of the most densely urbanized regions in the world and consists of nine municipals, which are Guangzhou (GZ), Shenzhen (SZ), Foshan (FS), Dongguan (DG), Huizhou (HZ), Zhongshan (ZS), Zhuhai (ZH), Jiangmen (JM) and Zhaoqing (ZQ). The report released by the World Bank Group (2015) showed that the Pearl River Delta had become the most significant urban agglomeration in the world with the largest surface area and population. The PRD became a research hot spot due to the dramatic growth of economy, the rapid expansion of cities, and the location neighbored with Hong Kong and Macao (Hu and Xia, 2019). And it is being planned to be a world-class Grand Bay Area by China's government.

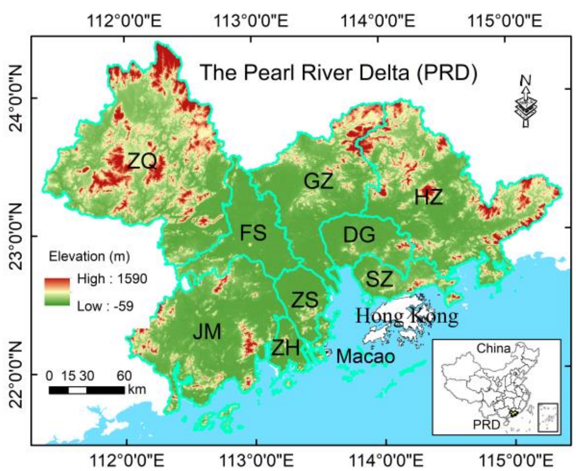

Figure 1. Location of the PRD.

3. Methods

3.1. Data Resource

Five land use/cover maps of PRD in 1995, 2000, 2005, 2010 and 2015 were downloaded from the Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) (http://www.resdc.cn). The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) global digital elevation model (GDEM) with a resolution of 30 m, which was used to obtain elevation (http://www.gscloud.cn/). The GDP and population data were collected from the Guangdong Statistical Yearbook (from 1996 to 2016).

3.2. Land-Use Transition Matrix

Firstly, this study attempted to employ a quantitative approach in exploring the spatial and temporal distribution of land use in the PRD. Moreover, ArcGIS 10.2 is used to measure the land-use transfer matrix (the application of Markov model to LUCC). The Markov model can not only quantitatively indicate the conversion between different land-use types, but also reveal the transfer rate between LUCC. Therefore, the characteristics of the transfer structure and direction of the regional LUCC can state entirely. The land-use transition matrix can be calculated as (Muller and Middleton, 1994):

$$M_{LC} \cdot M_t = M_{t+1} \tag{1}$$

The Markov chain equation is constricted using the land-use distributions at the beginning (M_t) and at the end (M_{t+1}) of a discrete time period as well as a transition matrix (M_{LC}) representing the land-use changes that occurred during that period. It reflects the actual transition process of a system from time t to time t + 1, revealing the specific process of LUCC.

3.3. Class Distribution Statistics

A primary goal of landscape ecology is to understand the development of spatial heterogeneity. Landscape pattern index is a quantitative indicator that can highly condense the information of land use. Choosing a suitable index is very important for the rationality of landscape pattern analysis. Based on the research objectives and the ecological implications of each indicator, this study screened eight landscape indexes at the level of class metrics (Table 1). Class metrics are computed for every patch type/class in the landscape. Using ArcGIS 10.2 software, the land use data of the PRD from 1995 to 2015 are converted into raster data in BIL format. The pixel size (resolution) is set to 500 m × 500 m. Furthermore, the landscape pattern analysis of various selected indexes is performed based on the Fragstats 4.2 software. For details, refer to the tutorial of FRAGSTATS software(http://www.umass.edu/landeco/research/fragstats/documents/fragstats.help.4.2.pdf)

3.4. Detection of Landscape Heterogeneity

Landscape heterogeneity controls the regional consequences of processes occurring in ecosystems. Furthermore, it reflects the heterogeneity and complexity of land use and plays an essential role in controlling the ecological process of the landscape. In this study, landscape shape index (LSI), interspersion juxtaposition index (IJI), Shannon's diversity index (SHDI), and aggregation index (AI) are selected to analyze the landscape pattern of the PRD.

4. Results and Discussion

4.1. Trends of LUCC

Land use is mainly occupied by forestland, cropland and built-up land in the PRD. The main types of land use are different in different cities; the forestland is located primarily on Zhaoqing, Huizhou and Guangzhou. Built-up land is mainly located in Guangzhou, Foshan and Shenzhen. From 1995 to 2015, the land use structure in the PRD changed significantly (Figure 2). The main characteristics are the continuous growth of built-up land and the occupation of cropland and forestland. In detail, the expansion of built-up land spread from the Pearl River to the surroundings. Foshan, Guangzhou, Shenzhen and Dongguan have the most significant areas of urban-land expansion (Table 3). For example, the percentage of built-up land in Dongguan has increased from 28.6% in 2000 to 41.4% in 2005; it has a high-speed urban expansion.

Table 1. Class Distribution Statistics

Index	Formula	Parameter
Total Area (CA)	$CA_i = \sum_{j=1}^{n} A_{ij}$	A_{ij} is the area of patch *ij*.
Percentage of landscape (PLAND)	$PLAND_i = \sum_{j=1}^{n} A_{ij} / A$	*A* equals total landscape area.
Number of patches (NP)	$NP_i = N_i$	N_i equals number of patches in the landscape of patch type (class) *i*.
Patch density (PD)	$PD_i = N_i / A \times 10,000 \times 100$	
Edge density (ED)	$ED = \sum_{k=1}^{m} E_{ik} / A \times 10,000$	E_{ik} equals the total length of edge in landscape involving patch type (class) *i*.
Patch cohesion index (COHESION)	$COHESION = \left[1 - \frac{\sum_{i=1}^{m}\sum_{j=1}^{n} P_{ij}^*}{\sum_{i=1}^{m}\sum_{j=1}^{n} P_{ij}^* \cdot \sqrt{A_{ij}^*}}\right] \times \left[1 - \frac{1}{\sqrt{Z}}\right]^{-1} \times 100$	P_{ij}^* is the perimeter of patch *ij* in terms of number of cell surfaces; A_{ij}^* equals area of patch *ij* in terms of number of cells; *Z* equals total number of cells in the landscape.
Splitting index (SPLIT)	$SPLIT = A^2 / \sum_{j=1}^{n} A_{ij}^2$	
Fractal dimension index (FRAC)	$FD_i = 2\ln\left(P_{ij}/4\right) / \ln\left(A_{ij}\right)$	P_{ij} equals perimeter of patch *ij*.

Table 2. Landscape Distribution Statistics

Index	Formula	Parameter
Landscape shape index (LSI)	$LSI = 0.25E^* / \sqrt{A}$	E^* equals total length of edge in landscape.
Interspersion juxtaposition index (IJI)	$IJI = -\sum_{i=1}^{m}\sum_{k=i+1}^{m}\left[\left(\frac{e_{ik}}{E}\right) \cdot \ln\left(\frac{e_{ik}}{E}\right)\right] \times 100 / \ln\left(0.5\left[m(m-1)\right]\right)$	E_{ik} equals the total length of edge in landscape between patch types *i* and *k*; *E* equals total length of edge in landscape, excluding background; *m* equals number of patch types present in the landscape.
Shannon's diversity index (SHDI)	$SHDI = -\sum_{i=1}^{m}\left(P_i \times \ln P_i\right)$	P_i equals proportion of the landscape occupied by patch type *i*.
Aggregation index (AI)	$AI = \left[\sum_{i=1}^{m}\left(\frac{g_{ii}}{\max \to g_{ii}}\right) P_i\right](100)$	g_{ii} equals number of like adjacencies between pixels of patch type *i* based on the single-count method; $\max \to g_{ii}$ equals a maximum number of like adjacencies between pixels of patch type *i* based on the single-count method.

From 1995 to 2015, the area of built-up land increased by 6.43% (3,466.09 km^2), the LUCC of the PRD mainly manifested in the conversion of other land types to built-up land (Table 4). The population (permanent population at the year-end) increased from 32.90 million in 1995 to 58.27 million in 2015. The increase in population is closely related to the increase in built-up land. Specifically, the area of cropland and forestland decreased by 4.34% (2,339.47 km^2) and 1.97% (1,061.93 km^2), respectively. It shows that the industrial transfer of the PRD has reduced the proportion of the primary industry. The percentage of the primary sector in GDP dropped from 5.4% to 1.8% during 1995 ~ 2015. The interference of land use by human activities has increased, which is related to the transformation of industrial structure.

Furthermore, analyzing LUCC in different cities from 1995 to 2015 (Figure 3). The LUCC in all cities has shown the expansion of built-up land and the rapid decrease in cropland and forestland. Among them, the increase in built-up land in Shenzhen and Dongguan accounted for the highest proportion of the total administrative area. The percentage of built-up land in Shenzhen has doubled from 22.03% in 1995 to 44.06% in 2015. Similarly, the growing portion of built-up land in Dongguan accounts for 16.55%. The area of built-up land in Foshan and Guangzhou increased the most considerable (659.7 km^2 and 659.6 km^2, respectively). The expansion of built-up land is obtained by occupying cropland and forest land.

For the land use structure in 2015, the proportion of forestland in Zhaoqing, Huizhou, and Guangzhou is more than 50%; the forestland is the dominant landscape occupied in the PRD. The Zhaoqing's economic development is the lowest in the PRD; however, as approximately 70.1% forest coverage and contains a national nature reserve in there (Hu et al., 2019). Guangzhou presents the highest GDP and has a significantly high forest cover. It indicates that Guangzhou employed adequate environmental protection. There is also the similarity in Shenzhen; it has 46.44% forest coverage and the fastest economic growth rate in the PRD. Dongguan's water area accounts for 25.47% (with most complicated river network in the PRD), and forestland occupied 20.24%, the land use mainly for built-up land (35.35%). Consequently, the land use structure of

Dongguan is relatively unreasonable. The government should pay more attention to ensuring that the ecological area is not over-occupied, while economic development is in progress.

Based on the transition matrix of land use types between 1995 and 2015, Figure 4 shows the land use transformation networks. Land use transfer in Shenzhen, Foshan, and Dongguan is more complicated, mainly other types of land transferred to construction land. Taking Shenzhen as an example, the cropland decreased by 10.65%, the forestland decreased by 10.88%, and the built-up land increased by 22.03%. From the perspective of the reduction of forest land, Shenzhen has the most considerable decline, but forestland is still the primary land-use type in Shenzhen. The cropland in Dongguan decreased by 10.49%; the forestland decreased by 5.12%, and the built-up land increased by 16.55%. The urban-land expansion primarily driven by population growth and economic development. The direction and complexity of land-use change can be more clearly represented by using a transfer matrix diagram.

4.2. Variance of Landscape Pattern

The landscape index of patch size, scale, structure and combination in the PRD is calculated though Fragstats software (Figure 5). From 1990 to 2015, the area of built-up land continued to increase, and human activities continued to increase. The area of water area changed relatively gently, but show a

Table 3. The Change Trend of Land Use/Cover in the PRD from 1995 to 2015 (%)

	1995	2000	2005	2010	2015		1995	2000	2005	2010	2015
			Guangzhou (GZ)						Shenzhen (SZ)		
Cropland	38.8	37.5	35.5	32.9	32.1	Cropland	18.6	17.1	11.6	9.5	6.7
Forestland	44.0	44.1	43.2	42.4	42.2	Forestland	53.2	48.2	46.6	42.4	41.5
Grassland	1.4	1.4	1.5	1.3	1.3	Grassland	1.6	1.6	1.3	1.1	1.0
Water	4.4	4.4	4.3	4.6	4.4	Water	2.2	2.2	2.3	2.1	2.2
Built-up land	11.3	12.5	15.5	18.9	20.0	Built-up land	24.4	30.9	38.2	44.9	48.6
Unused land	0.1	0.1	0.0	0.0	0.0	Unused land	0.0	0.0	0.0	0.0	0.0
			Foshan (FS)						Dongguan (DG)		
Cropland	54.7	52.2	47.3	42.6	40.2	Cropland	31.7	31.2	22.9	18.3	16.4
Forestland	23.7	23.5	22.9	22.4	22.1	Forestland	30.2	29.5	25.4	24.9	23.3
Grassland	0.5	0.5	0.5	0.2	0.2	Grassland	3.7	3.5	3.1	2.7	2.5
Water	6.1	6.0	5.9	6.1	6.0	Water	7.3	7.2	7.2	8.6	7.1
Built-up land	15.0	17.8	23.3	28.7	31.5	Built-up land	27.2	28.6	41.4	45.5	50.7
Unused land	0.0	0.0	0.0	0.0	0.0	Unused land	0.0	0.0	0.0	0.0	0.0
			Huizhou (HZ)						Zhongshan (ZS)		
Cropland	24.4	22.9	25.2	24.5	22.9	Cropland	58.3	57.4	48.9	44.7	42.0
Forestland	65.8	67.0	65.3	64.9	64.6	Forestland	23.7	23.2	21.0	20.9	20.5
Grassland	2.5	2.4	2.5	2.5	2.4	Grassland	0.2	0.2	0.2	0.2	0.2
Water	2.1	2.2	2.2	1.6	2.2	Water	5.3	5.3	5.3	5.3	5.2
Built-up land	5.2	5.5	4.9	6.5	7.9	Built-up land	12.4	14.0	24.6	29.0	32.1
Unused land	0.0	0.0	0.0	0.0	0.0	Unused land	0.0	0.0	0.0	0.0	0.0
			Zhuhai (ZH)						Jiangmen (JM)		
Cropland	46.0	44.9	42.5	40.7	38.3	Cropland	34.8	34.4	34.8	34.0	33.4
Forestland	37.2	35.8	35.2	34.2	33.9	Forestland	52.0	52.2	52.0	51.2	50.9
Grassland	0.6	0.5	0.4	0.5	0.5	Grassland	3.4	3.4	3.4	3.5	3.5
Water	5.9	5.3	4.8	4.8	4.8	Water	4.0	3.9	4.0	4.0	3.9
Built-up land	10.2	13.5	17.0	19.7	22.5	Built-up land	5.7	6.1	5.8	7.2	8.3
Unused land	0.1	0.0	0.1	0.0	0.0	Unused land	0.0	0.0	0.0	0.0	0.0
			Zhaoqing (ZQ)						Pearl River Delta (PRD)		
Cropland	18.1	18.2	18.0	17.9	17.8	Cropland	30.2	29.4	28.4	26.9	25.9
Forestland	76.3	75.9	75.9	75.5	75.3	Forestland	56.4	56.3	55.4	54.7	54.4
Grassland	1.6	1.6	1.6	1.8	1.8	Grassland	2.0	2.0	2.0	2.0	2.0
Water	2.1	2.1	2.2	2.2	2.2	Water	3.5	3.4	3.4	3.4	3.4
Built-up land	1.9	2.1	2.3	2.6	2.9	Built-up land	7.9	8.9	10.8	12.9	14.4
Unused land	0.0	0.0	0.0	0.0	0.0	Unused land	0.0	0.0	0.0	0.0	0.0

Table 4. Land Use Transfer Matrix (%)

					1995			
		Cropland	Forestland	Grassland	Water	Built-up land	Unused land	Total
2015	Cropland	24.74	0.35	0.09	0.13	0.63	0	25.95
	Forestland	0.34	53.70	0.13	0.02	0.14	0	54.34
	Grassland	0.01	0.30	1.64	0.01	0.01	0	1.96
	Water	0.11	0.05	0.02	3.20	0.02	0	3.40
	Built-up land	5.08	1.91	0.15	0.09	7.10	0.01	14.34
	Unused land	0	0	0	0	0	0	0
	Total	30.29	56.31	2.03	3.45	7.91	0.02	100.00

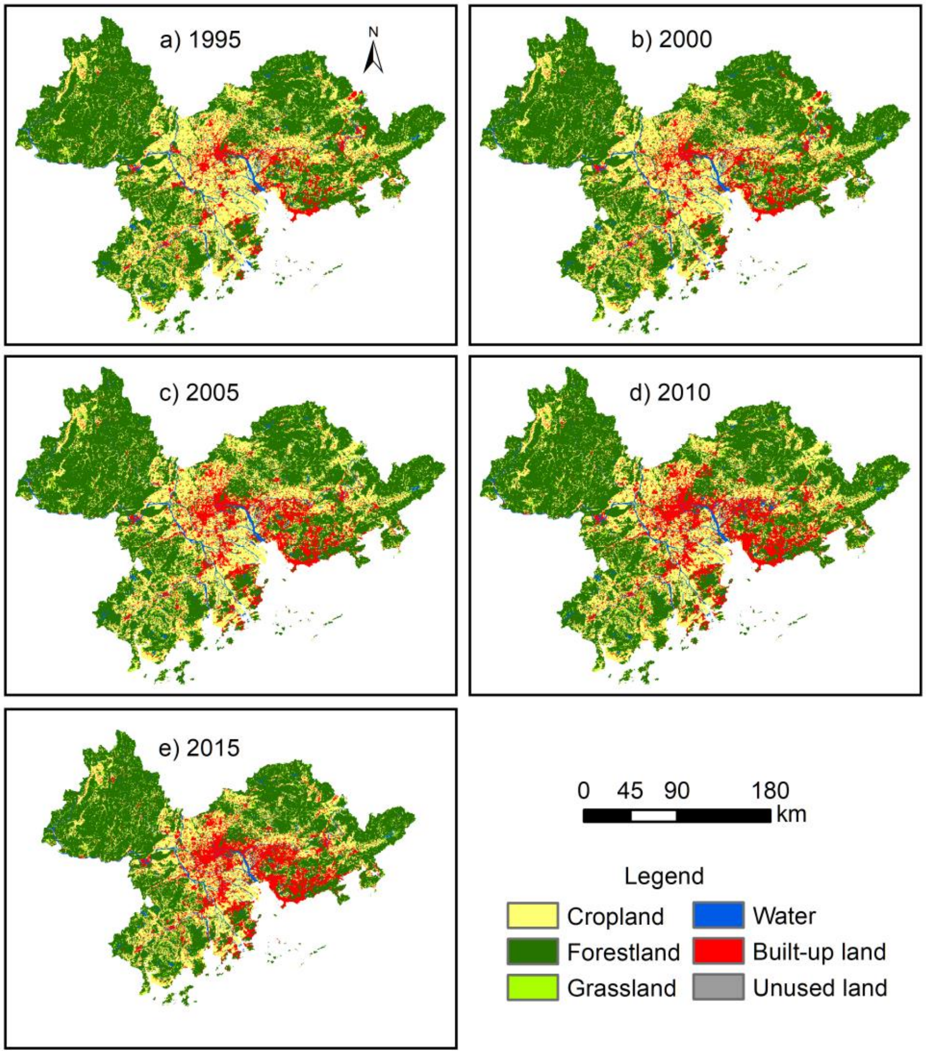

Figure 2. The LUCC in the PRD from 1995 to 2015.

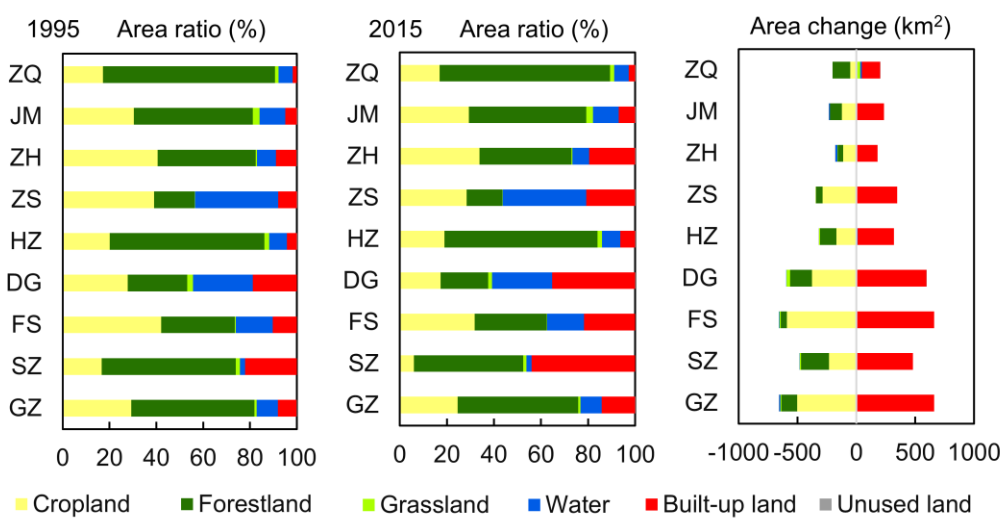

Figure 3. LUCC in different cities.

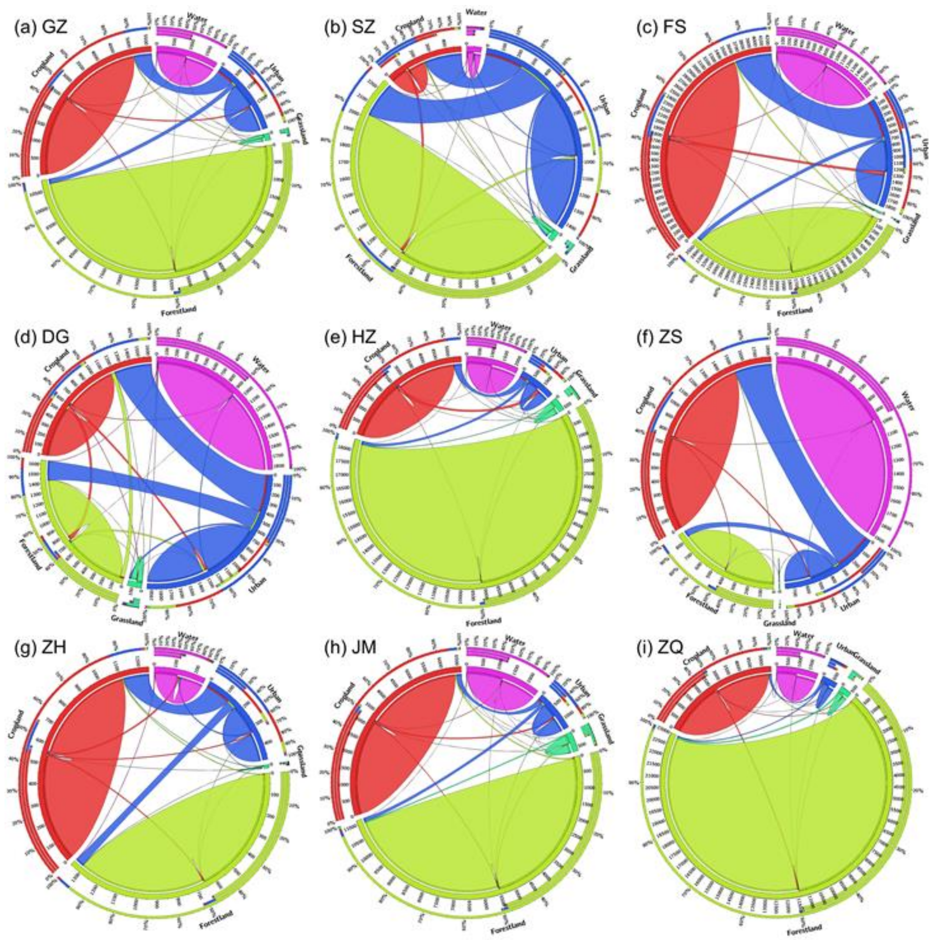

Figure 4. Land-use type transformation network in different cities.

downward trend, from 1859.7 km^2 in 1995 to 1832.8 km^2 in 2015. The area of cropland shows a significant downward trend; it means that the industrial structure has changed, and the proportion of primary industry has decreased significantly. The land use pattern is forestland > cropland > built-up land > water area > grassland > unused land.

Affected by human activities, the edge density (ED) of cropland is the largest in all landscapes, showing a declining trend. There is a significant increase in ED of built-up land; the landscape heterogeneity is correspondingly improved. The dynamic characteristics of forestland are similar to the built-up land. From 1995 to 2000, the number of patches (NP) of built-up land is the largest, and it of cropland ranks second. However, from 2000 to 2015, the NP of cropland is the largest, and it of built-up land ranks second. It showed that the fragmentation of cropland increased and the scale of farming decreased. Built-up land presents the opposite trend, and the phenomenon of clustering is more noticeable. Mainly due to the acceleration of the urbanization process, the region witnesses a vigorous expansion of built-up land. Moreover, large areas of forestland are more conducive to the protection of biodiversity and the environment.

The value of fractal dimension is cropland > forestland > grassland > built-up land > water area > unused land > 1. The fractal dimension index of cropland and forestland is the largest with the most complicated shape. However, the fractal dimension of the forestland has decreased, which indicates that human disturbance is increasing. In contrast, the fractal dimension index of built-up land is closer to 1. It means that the built-up land with strong self-similarity, regular and simple shape. Furthermore, the cohesion index of built-up land has increased from 89.27 in 1995 to 98.07 in 2015. It shows that the built-up land presents agglomerated expansion mode, alleviates the negative effects of habitat fragmentation, and has a corresponding promotion effect on regional diversity protection. The cohesion index of unused land is fluctuating, showing a downward trend; It indicates that the transformation of unused land by human beings has increased, and unused land tends to be scattered.

There is a notable difference in patch density (PD) of different landscapes, among which the increase in grassland patch density is the most obvious. The PD of built-up land shows a downward trend. Urban expansion on the basis of original spatial distribution, which leads to the decreasing number of patches and the clustering pattern of land use. The split index of cropland has increased from 0.978 in 1995 to 0.997 in 2015. With

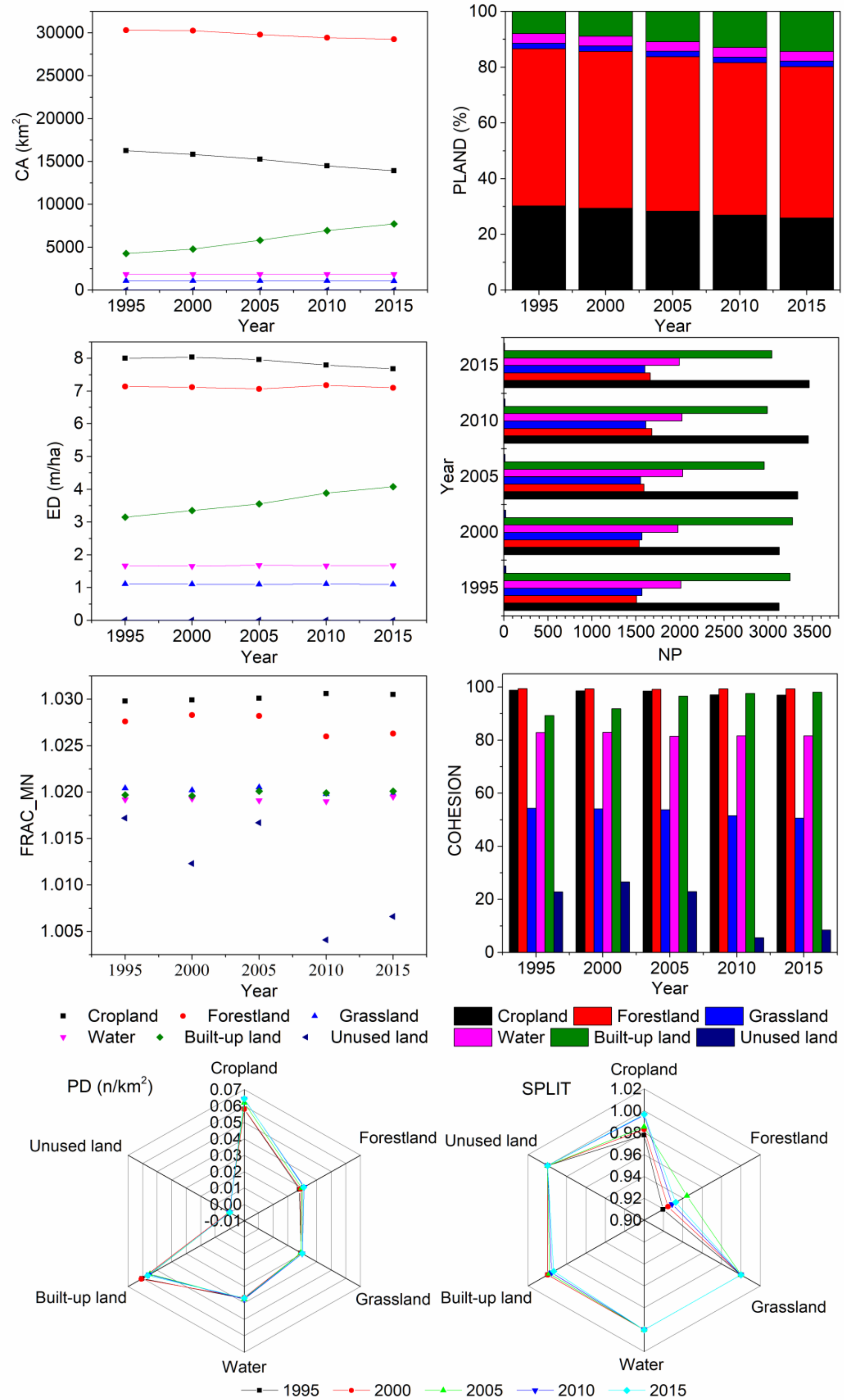

Figure 5. Patch characteristics of land use in the PRD from 1990 to 2015.

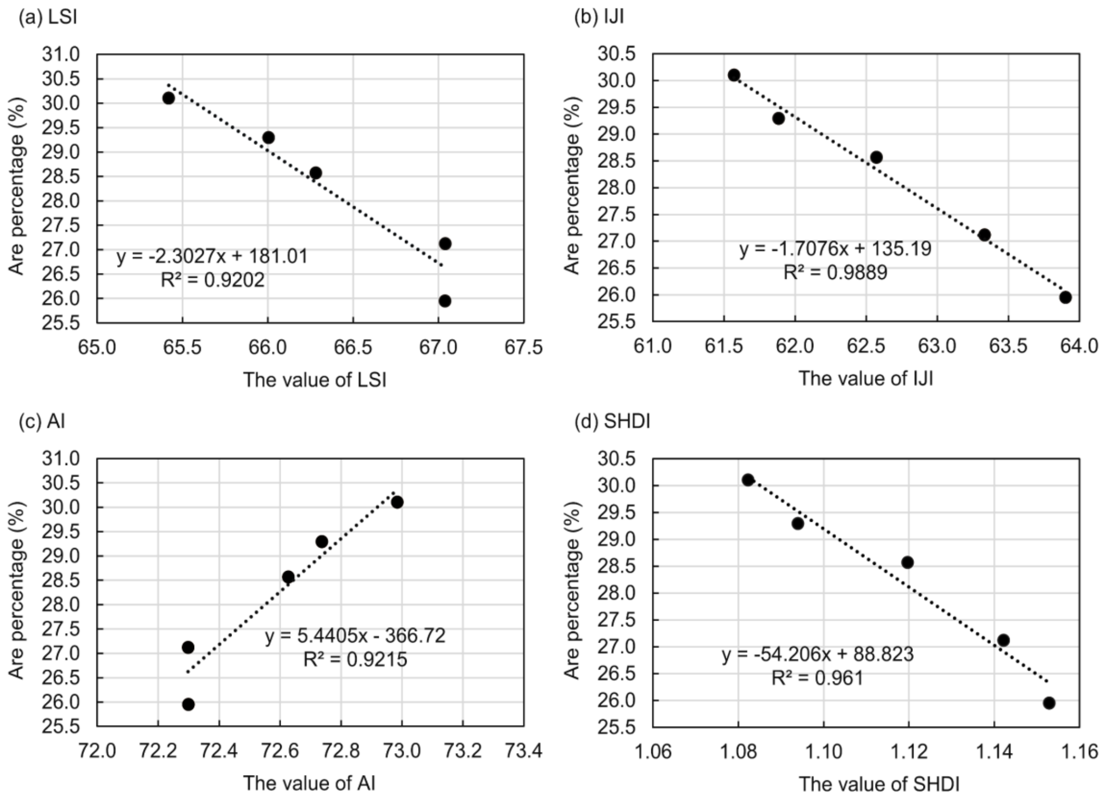

Figure 6. Relationship between cropland and landscape metrics: (a) LSI; (b) IJI; (c) AI; and (d) SHDI.

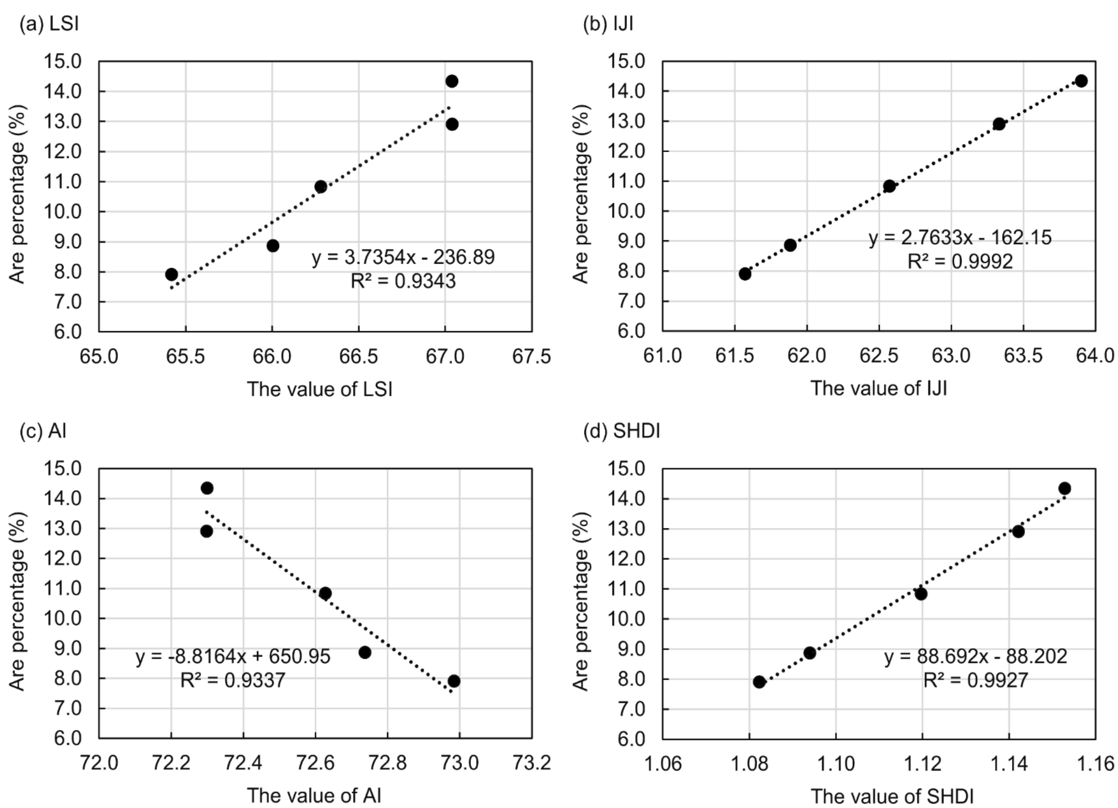

Figure 7. Relationship between built-up land and landscape metrics: (a) LSI, (b) IJI, (c) AI, and (d) SHDI.

the development of urbanization, a large amount of the cropland has requested by urban industrialization, and the extensive management of farmland in rural areas has become a serious phenomenon. The small-scale of self-cultivated land and decentralized collective agricultural has become an obstacle to the development of agricultural modernization (Ye, 2015). Meanwhile, the split index of forestland has increased due to the influence of human activities.

From 1995 to 2015, the LSI increases by 1.618, indicating that the landscape shape of the PRD has become more irregular, and the perimeter has gradually increased (Table 5). The increase in IJI means that one patch type is adjacent to more other classes, and the complexity of the landscape has grown. The most popular diversity index is Shannon's diversity index (SHDI). For details, SHDI is risen from 1.082 in 1995 to 1.153 in 2015, indicating an increase in landscape diversity. A decrease in AI means a reduction in the degree of patch type aggregation. Overall, the landscape shape tends to become more complex and the pattern of different patch types appearing alternately more apparent. The landscape index indicates that the interference from human activities is increasing in the PRD.

Table 5. Landscape Metrics for the PRD from 1995 to 2015

	LSI	IJI	SHDI	AI
1995	65.419	61.570	1.082	72.984
2000	66.004	61.883	1.094	72.737
2005	66.280	62.572	1.120	72.627
2010	67.040	63.332	1.142	72.298
2015	67.037	63.901	1.153	72.300

4.3. LUCC impact on landscape pattern

The results show that LUCC has changed significantly, with imbalanced and a one-way transition. Landscapes tend to be more fragmented and diversified. The relationship between LUCC and landscape pattern shows that changes in cropland and built-up land may be the main driving factors of observed landscape pattern changes. LUCC is caused by both natural and human activities (Liu et al., 2017; Guo et al., 2019), with the latter being the major driving forces in the rapid urbanization process (Huang et al., 2014).

With the economic development and population growth, the area of the built-up area has nearly doubled, and with the imbalance of the one-way transition (the change of cropland and forestland to construction land), some positive changes in landscape phenomena have occurred. LUCC has a direct impact on landscape patterns. Analyzing the interaction between land use and landscape patterns can help improve the effectiveness of land use management (Nagendra et al., 2004; Abdullah and Nakagoshi, 2006). From the PRD, different types of patches tend to be more complicated, the diversity is increased, and the agglomeration is reduced. It is the concrete manifestation of landscape heterogeneity and the result of various ecological processes.

Figure 6 shows the relationship between the area percentage of cropland and landscape indexes, indicating that changes in cropland directly affect the landscape pattern. The area percentage of cropland showing a downward trend, from 30.29% in 1995 to 25.95% in 2015. The landscape tends to be more complex, the higher diversity and lower aggregation. The impact of built-up land on the landscape pattern of the study area is significant, and the correlation coefficient is higher (Figure 7). When the area percentage of built-up land is increased, the LSI, IJI and SHDI will increase, and AI will decrease.

5. Conclusion

This study reveals the spatial-temporal changes in land-use coverage and landscape pattern changes in the PRD from 1995 to 2015. Twelve landscape indexes are selected from the perspectives of class and landscape distribution statistics. Finally, we comprehensively analyze the impact of LUCC on landscape pattern.

Overall, the area percentage of built-up land increase from 7.91% in 1995 to 14.34% in 2015, and the urban expansion nearly doubled. The prominent built-up land expansions find in Foshan, Guangzhou, Shenzhen and Dongguan; mainly though the occupation of large amounts of forest and cropland. Forestland has the largest area in all landscape types, occupying more than 50%, and has the largest cohesion index. It shows that the forest coverage rate of the PRD is relatively high, and with the form of spatial cluster distribution. Urban expansion on the basis of original spatial distribution, which leads to the decreasing number of patches and the clustering pattern of land use. More patches in cropland mean weak connectivity; thus, the landscape is more fragmented. With the development of urbanization, a large amount of the cropland has occupied by urban industrialization, and the extensive management of farmland in rural areas has become a serious phenomenon. Human activities, as the main driving force, need to avoid the acceleration of urbanization process to occupy a large amount of ecological land in future development. This study could provide more targeted information that may support to improve environment-friendly policies and land use planning strategies.

Acknowledgments. This research was supported by the International Program for Ph.D. Candidates Sun Yat-Sen University.

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