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Urban dynamics analysis using spatial metrics: A case study of Yokohama city

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Abstract

Analyzing the dynamics of urban land-use pattern to abstract spatial process of urbanization is an important step towards the construction of spatial model in order to simulate urban land-use pattern of the past, more importantly, forecast the future condition. Spatial metrics provide good links between urban land-use pattern and process. This paper analyzes urban dynamics of Yokohama city at multi-category system and high spatial resolution scale in terms of spatial metrics under the support of the data set "Detailed Digital Information (10m Grid Land Use) of Metropolitan Area" of Tokyo. The results show that the dynamics are well presented using the spatial metrics at the micro-scale. Comparison of the results of the analysis between multi-category system and binary-category system is carried out to investigate the difference in presenting urban dynamics in terms of spatial metrics at different spatial scales. The results indicate that the difference in depicting the process of urban dynamics exists at different scales, and analyzing urban dynamics at multi-scale using spatial metrics contributes to the comprehensive interpretation of urban dynamics. The analyses also offer useful information for research on selecting metrics in interpreting urban dynamics.

Key words: urban dynamics, spatial metrics, land-use pattern, urban modeling

1. Introduction

The past century was such a period of rapid urbanization all over the world, in which most people quickly congregated in the urban areas. The urban population in the world was estimated at 2.4 billion in 1995 and is expected to double by 2025 (Antrop, 2000). While the urban areas taken by the huge population account for only 2% of the Earth's land surface (Grimm et al., 2000), land-use and land-cover changes caused by the rapid urbanization have greatly impacted the local (McKinney, 2006; Paul and Meyer, 2001; Lin and Ho, 2003) and global environmental changes (Grimm et al., 2000; Lambin et al., 2001). Therefore, to effectively understand the spatial processes of urbanization and explore the extent of future urban land-use changes, has attracted many scientists' attention coming from different disciplines (Alberti and Waddell, 2000; Batty, 1989, 1994).

Cities are among the most complex structures created by the human societies. Their complex system is characterized by the complex patterns of land-use. However, the phenomena are not easily experimented with on the ground. Realistic but synthetic computer simulations by modeling the complex land-use dynamics based on GIS can be built as a laboratory for exploring ideas and plans that we would not otherwise be able to effect on the ground (Clarke et al., 1997; White et al., 1997). This method represents the implementation of links between land-use pattern and land-use process. Spatial metrics, which come from landscape field and are used to characterize the spatial pattern and composition of landscapes, have been argued as one impactful tool to link urban land-use pattern and dynamic process when coupled with remote sensing (Parker et al., 2001; Herold et al., 2003; Herold et al., 2005). Herold et al. (2005) especially, have discussed the role of spatial metrics in the analysis and modeling urban growth. However, most of the literature, which emphasizes the importance of spatial metrics in linking between pattern and process, consider the urban area as one object, and generally classify the study area into binary categories of land-use – built-up area and non-built-up area. As urban area is the dynamic composition of a variety of land-use categories, such as industrial, residential, commercial and so on, it should be essential to analyze the dynamic patterns of urban land-use at high-resolution scale and multi-classification system. Only a few scientists have discussed this kind of issue. This paper focuses on this topic and tries to interpret the differences in the results of the analysis at different spatial scales.

In the next section, we briefly review the history of spatial metrics and the current status in urban dynamics analysis. Section 3 presents the study area and the data set. The limitation of remote sensing in high-resolution urban analysis is discussed. We emphasize the significance of the data set "Detailed Digital Information (10m Grid Land Use) of Metropolitan Area" (DDIMA10m) of Tokyo in empirical study for high-resolution urban analysis. The

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analysis and results are described in Section 4, and Section 5 presents some concluding remarks.

2. Spatial metrics

Spatial metrics come from the concept of landscape metrics which were developed in the late 1980s and incorporated measures from both information theory and fractal geometry (Mendelbrot, 1983; Shannon and Weaver, 1964) based on a categorical, patch-based representation of the landscape. Patches are defined as homogenous regions for a specific landscape property of interest, such as "industrial land", "park" or "high-density residential area". Landscape metrics are used to quantify the spatial heterogeneity of individual patches, all patches belonging to a common class, and the landscape as a collection of patches. When applied to multi-scale or multi-temporal datasets, the metrics can be used to analyze and describe the changes in the degree of spatial heterogeneity (Dunn et al., 1991; Wu et al., 2000). In the application to urban domain, Herold et al. (2003) pointed out that the approaches and assumptions might be more generally described as "spatial metrics".

The interest in using spatial metric concepts for the analysis of urban environments is starting to grow. In 1997, Geoghegan et al. firstly explored spatial metrics in modeling land and housing values (Geoghegan et al., 1997). Alberti and Waddell (2000) substantiated the importance of spatial metrics in urban modeling. They proposed specific spatial metrics to model the effects of the complex spatial pattern of urban land-use and land-cover on social and ecological processes. Parker et al. (2001) summarized the usefulness of spatial metrics with respect to a variety of urban models and argued for the contribution of spatial metrics in helping link economic processes and patterns of land-use. Herold et al. (2003) proposed the integration approach of remote sensing and spatial metrics in spatiotemporal analysis and modeling of urban growth. In 2005, Herold et al. systematically analyzed the role of spatial metrics in the analysis and modeling of urban growth and argued that spatial metrics definitely deserve a place in the urban dynamics research agenda.

While many literatures have discussed the usefulness of spatial metrics in urban research, most of them have focused on just two categories of landscape heterogeneity: built-up area and non-built-up area. We assume that it should also be very useful for high-resolution analysis of urban land-use changes. Considering the rapid urban growth and the availability of high-resolution land-use data set, Yokohama city is a data-rich area to study the dynamics of spatial and temporal urban land-use change.

FRAGSTATS, a public domain spatial metrics

Table 1 Spatial metrics used in this study, adopted from McGarigal *et al*. 2002

Metric	Description	Units	Range
CA-Class Area	CA equals the sum of the areas (m^2) of all patches, divided by 10,000 (to convert to hectares).	Hectares	CA>0, no limit
NP-Number of patches	NP equals the number of patches in the landscape.	None	NP>=1, no limit
ED-Edge density	ED equals the sum of the lengths (m) of all edge segments involving the patch type, divided by the total landscape area (m^2), multiplied by 10,000 (to convert to hectares).	Meters per hectare	ED>=0, no limit
LPI-Largest patch index	LPI equals the area (m^2) of the largest patch of the corresponding patch type divided by total area (m^2), multiplied by 100 (to convert to a percentage).	Percent	0<LIP<=100
ENNMN-Euclidian mean nearest neighbor distance	ENNMN equals mean value of the distance (m) over all patches to the nearest neighboring urban patch, based on shortest edge-to-edge distance from cell center to cell center.	Meters	ENNMN>0, No limit
FRACAM-Area weighted mean patch fractal dimension	Area weighted mean value of the fractal dimension values of all patches, the fractal dimension of a patch equals two times the logarithm of patch perimeter (m) divided by the logarithm of patch area (m^2); the perimeter is adjusted to correct for the raster bias in perimeter.	None	1<=FRACAM<=2
SPLIT-Splitting index	SPLIT equals the total landscape area (m^2) squared divided by the sum of patch area (m^2) squared, summed across all patches of the corresponding patch type.	None	1<=SPLIT<=number of cells in the landscape area squared
CONTAG-Contagion	CONTAG measures the overall probability that a cell of a patch type is adjacent to cells of the same type.	Percent	0<=CONTAG<=100
SHDI-Shannon's diversity index	SHDI equals minus the sum, across all patch types, of the proportional abundance of each patch type multiplied by that proportion.	Information	0<=SHDI

program, was developed in the mid-1990s and has been continuously improved (McGarigal et al., 2002). FRAGSTATS provides a large variety of metrics at class, patch and landscape levels. Table 1 describes the subset of available metrics used in this research. A more detailed description including the specific mathematical equations of all of the metrics can be found in McGarigal et al. (2002).

Class area (CA) is the measure of the area of all the categories of urban land-use. Change of CA across time can present the dynamic changes of urban land-use structure. The number of patches (NP) metric quantifies the number of individual areas for all the categories of urban land-use. The dynamics of NP coupled with CA can describe the fragmentation of one category of urban land-use. The edge density (ED) is a measure of the total length of the edge of land-use patches. In certain extent, it can present the spatial complexity of the urban land-use pattern. The largest patch index (LPI) describes the percentage of total landscape area comprised by the largest patch. As such, it is a simple measure of dominance and presents the extent of the aggregation of one category of urban land-use. The mean nearest neighbor distance (ENNMN) represents the average minimum distance between the individual urban land-use category blocks. Hence, it is a measure of the extent of disperses.

The fractal dimension describes the complexity and the fragmentation of a patch by a perimeter-area proportion. The value of the fractal dimension falls into the interval between 1 and 2. Low values are derived when a patch has a compact rectangular form with a relatively small perimeter relative to the area. If the patches are more complex and fragmented, the perimeter increases and yields a higher fractal dimension. The area weighted fractal dimension improves the measure of class patch fragmentation because the structure of smaller patches is more often determined by image pixel size than by characteristics of natural or manmade features found in the landscape (Milne, 1991).

The splitting index (SPLIT) is based on the cumulative patch area distribution and is interpreted as the effective mesh number or number of patches with a constant patch size when the corresponding patch type is subdivided into S patches, where S is the value of the splitting index. SPLIT increase as the focal patch type is increasingly reduced in area and subdivided into smaller patches.

All the metrics were calculated for each land-use category using the software of FRAGSTATS.

3. Study area and data set

The study area includes all the 18 administration wards of Yokohama city with about 434 km^2, shown in Fig. 1. We used the data set of DDIMA10m of Tokyo, which was released in 1998 by the Geographical Survey Institute.

Contrary to land cover defined by Barnsley et al. (2001) as “the physical materials on the surface of a given parcel of land (e.g. grass, concrete, tarmac, water)”, land-use refers to “the human activity that takes place on,

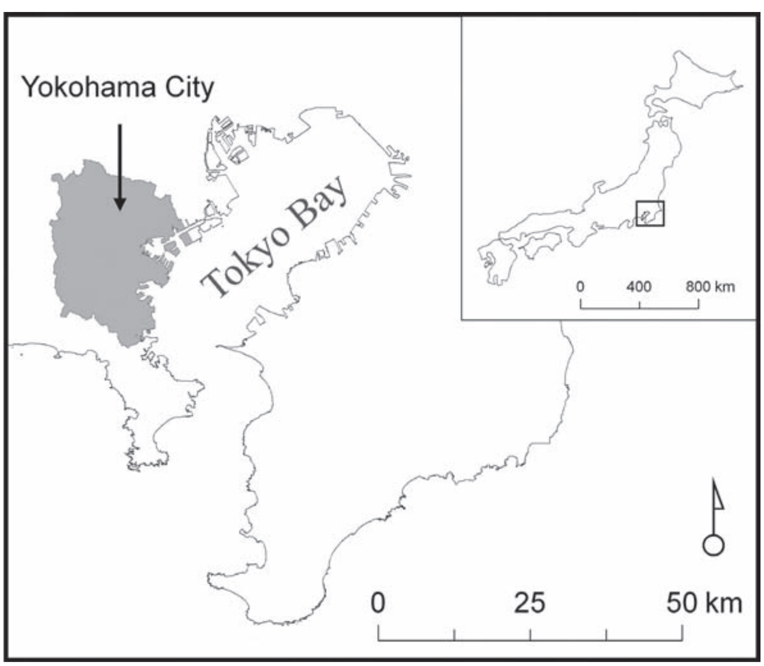

Fig. 1 Study area

Table 2 Land-use classification systems

Categories in the original data set	Categories in the multi-category system	Categories in the binary-category system
A. Woods	1.Non built-up	I.Non-built-up (nonurban)
B. Paddy field		
C. Dry fields		
D. Under construction	2.Under construction	II. Built-up (urban)
E. Vacant	3.Vacant	
F. Industrial	4.Industrial	
G. Low storey residential	5.Low storey residential	
H. Densely developed low storey residential	6.Densely developed low storey residential	
I. Medium and high storey residential	7.Medium and high storey residential	
J. Commercial & service industrial	8.Commercial	
K. Road	9.Road	
L. Park	10.Park	
M. Public	11.Public	
N. Special	12.Special	
O. River, lake & pond	13.Water	III.Water
P. Sea		

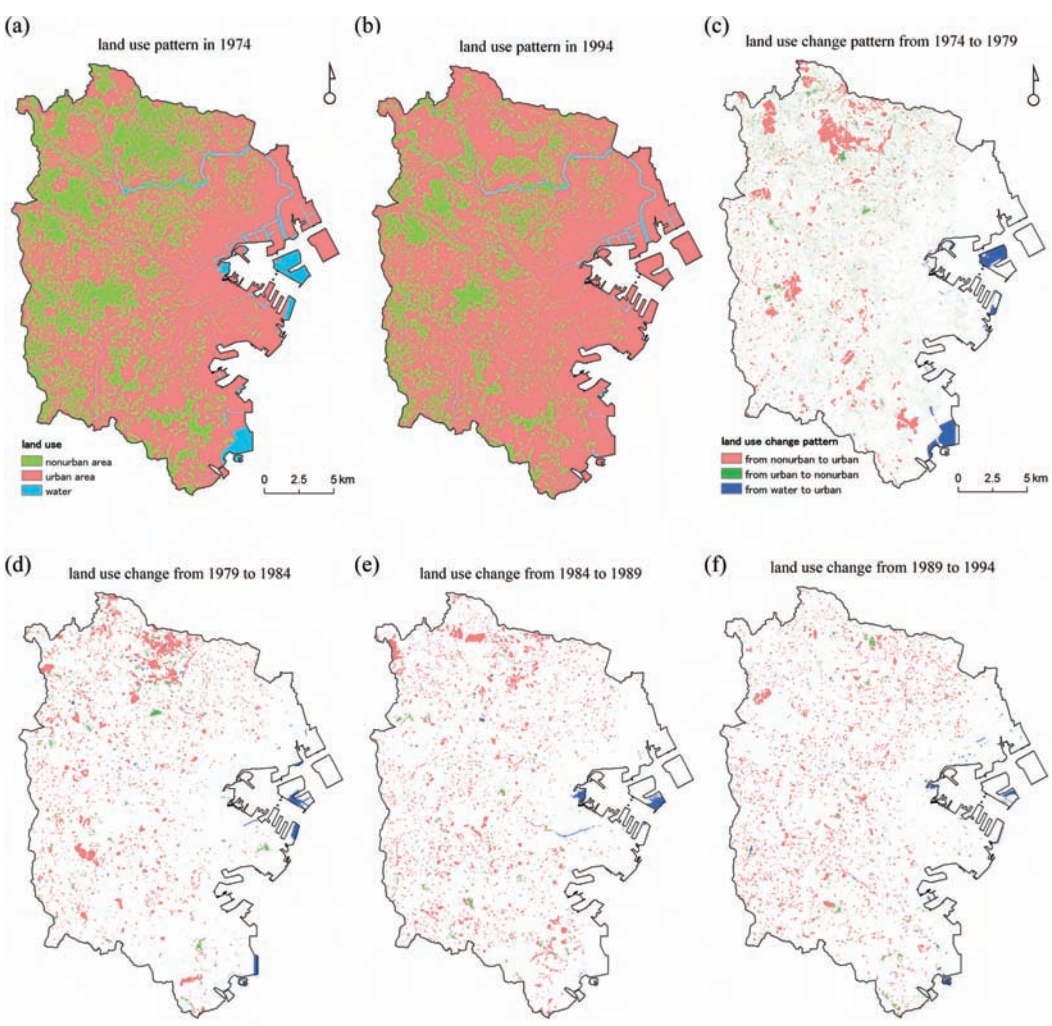

Fig. 2 Land-use of Yokohama city in 1974 (a) and 1994 (b), and land-use change pattern from 1974 to 1979 (c), 1979 to 1984 (d), 1984 to 1989 (e), and 1989 to 1994 (f) in the binary-category system

or makes use of that land (e.g. residential, commercial, industrial)". Remote sensing techniques have already showed their value in mapping urban areas, and as data sources for the analysis and modeling of urban growth and land-use change (Batty and Howes, 2001; Clarke et al., 2002; Treitz and Rogan, 2004). Remote sensing provides spatially consistent data sets that cover large areas with both high spatial detail and high temporal frequency. Batty and Howes (2001) have emphasized the importance of remote sensing as a "unique view" of the spatial and temporal dynamics of the processes of urban growth and land-use change. However, land-use is an abstract concept, constituting a mix of social, cultural, economic and policy factors, which has little physical importance with respect to reflectance properties, and hence has a limited relationship to remote sensing (Treitz and Rogan, 2004). That may be one of the reasons why the study area was always divided in many literatures into two types - built-up area and non-built-up area - only using remote sensing technique, as such detailed land-use information cannot be detected easily. The data set DDIMA10m of Tokyo provides an abundant and detailed urban land-use classifications including a variety of socio-economic information.

The study area was originally classified into 17 land-use categories. We did not alter the classification system for urban area, just grouped the non-built-up area into one category in a multi-category system. In order to compare the results of the analysis between macro-scale and micro-scale, we arranged a binary-category system for this area. All the classification systems are shown in Table 2. Fig. 2 presents the land-use pattern of Yokohama city in 1974 and 1994, and the land-use change patterns from 1974 to 1994 at 5 years increment in binary-category system.

4. Urban dynamics of Yokohama city

4. 1. Change in land-use structure

We calculated the transformation matrix of land-use from 1974 to 1994 for both the binary-category system and the multi-category system (see Tables 3 and 4). Table 3 shows that the general change of land-use in this period exhibits the transformation from non-built-up area to built-up area comprising of 5204.77 ha. or about 74.6% of the total changes. During this period, the land-use mainly took the characteristic of urban growth. More importantly, the change of land-use not only took the transformation from non-built-up area to built-up area, but also from built-up area to non-built-up area which constitutes 825.07 ha. or 12.8% of the total changes. It indicates the self-adjustment or somewhat decay of the city at certain places. Urban growth also occurred at former water areas, especially the sea, presenting one of the special characteristics of land-use change in this area. Moreover, some vacant areas and land under construction may have been reclaimed for agricultural use.

Table 3 Transformation matrix of land-use in the binary-category system from 1974 to 1994

Land-use in 1974	Land-use in 1994		
	Non built-up	Built-up	Water
	(ha.)	(ha.)	(ha.)
Non built-up	8928.74	5204.77	30.35
Built-up	825.07	26921.18	20.17
Water	5.77	894.48	733.09

The growth of built-up area came from the interaction and competition of sub-categories of urban area. The analysis above could not show the significance. Table 4 illustrates the dynamics among the sub-categories as well as the dynamics between the non-built-up area and sub-categories of the built-up area. We can find that most of transformation of land-use from non-built-up area to built-up area took place within vacant and low storey residential and very little in the industrial. This shows the demand for open space in the urban area to create a living charm in Yokohama as the suburb of the Tokyo metropolitan area.

4. 2. Analysis of spatial and temporal urban land-use pattern

We selected land-use categories of industrial, residential (low storey residential, densely developed low storey residential, and medium and high storey residential), and commercial in order to catch the main characteristics of the urban area. Fig. 3 to Fig. 6 present the urban dynamics in terms of the selected spatial metrics.

Fig. 3 shows the histogram of the dynamics of CA for each land-use category. It reflects the change in the urban land-use structure. Built-up area in the binary-category system kept increasing over the whole period, as discussed in the previous subsection. For the multi-category system, although the area of all land-use categories increased in this period, the increase rates were different.

The spatial diagrams of metrics of NP, LPI, ED, FRACAM, and ENNMN, for different land-use categories are shown in Fig. 4. Fig. 4a shows that although the area of all the land-use categories increased, the trends of the NP value were different. In the multi-category system, the value of NP for low storey residential and commercial categories decreased rapidly from 1974 to 1979, and then increased gradually till 1994. It means that these land-use categories grew dispersively from 1974 to 1979 and got compact gradually after 1979. The value of NP for other land-use categories did not obviously change in this period as the increases in the area were not so much. The value

Table 4 Transformation matrix of land-use in the multi-category system from 1974 to 1994

Land-use in 1974	Land-use in 1994												
	Non-built-up	Under construction	Vacant	Industrial	Low-resi[1)]	Densely-resi[2)]	Medium-resi[3)]	Commercial	Road	Park	Public	Special	Water
	(ha.)	(ha.)	(ha.)	(ha.)	(ha.)	(ha.)	(ha.)	(ha.)	(ha.)	(ha.)	(ha.)	(ha.)	(ha.)
Non-built-up	8928.74	426.82	1411.3	85.87	1060.37	19.59	367.92	276.25	811.77	254.36	489.71	0.81	30.35
Under construction	129.52	64.43	240.01	275.9	330.12	2.79	152.27	119.37	334.93	114.23	248.18	0.02	1.02
Vacant	212.23	36.64	1351.38	90.65	895.17	23.62	140.92	216.29	243.49	88.03	218.23	0.08	5.55
Industrial	11.36	34.16	58.25	1665.45	15.77	0.37	54.44	86.93	32.27	20.4	25.29	0.01	2.19
Low-resi[1)]	125.92	38.56	227.54	17.78	7107.19	4.38	96.67	70.49	131.97	16.77	25.38	0.09	2.75
Densely-resi[2)]	8.89	1.34	9.14	0.88	24.14	407.11	3.68	4.61	5.26	0.66	1.25	0.03	0.04
Medium-resi[3)]	10.43	6.18	11.03	0.46	10.4	0.87	831.75	4.22	7.77	2.22	1.88	0.00	0.02
Commercial	43.75	16.1	71.95	16.03	86.14	7.81	36.73	1673.25	54.3	7.9	29.54	0.09	1.44
Road	183.29	29.29	144.58	28.77	499.96	21.75	71.86	164.34	3621.92	20.29	38.67	0.31	5.33
Park	27.46	2.79	11.38	2.2	12.56	0.73	9.22	9.21	46.33	1069.45	20.19	0.02	0.7
Public	63.37	17.38	88.91	11.46	43	1.95	20.75	56.79	82.47	17.44	2146.55	0.11	1.13
Special	8.85	3.07	30.52	0.01	6.43	0.05	8.2	8.98	11.48	5.58	7.99	274.61	0.00
Water	5.77	105.11	51.41	121.72	17.65	0.47	10.03	158.77	154.08	89.23	189.73	0.28	733.09

Note:

1) Low-resi stands for low storey residential
2) Densely-resi stands for densely low storey residential
3) Medium-resi stands for medium and high storey residential

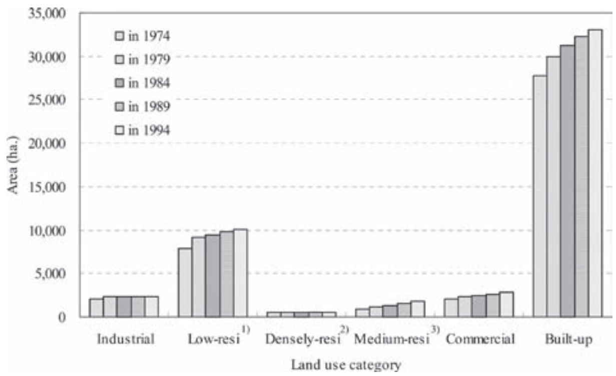

Fig. 3 CA by land-use category (1974-1994)
Note:
1) Low-resi stands for low storey residential
2) Densely-resi stands for densely low storey residential
3) Medium-resi stands for medium and high storey residential

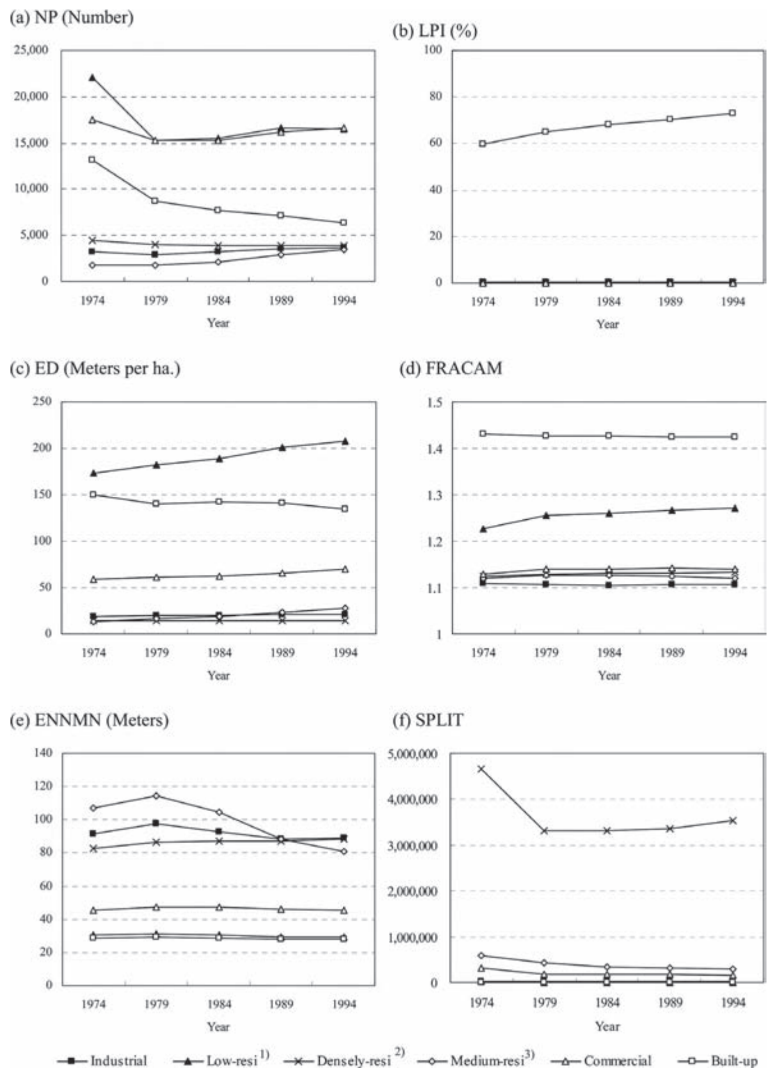

Fig. 4 Six spatial metrics of each land-use category in time series
Note:
1) Low-resi stands for low storey residential
2) Densely-resi stands for densely low storey residential
3) Medium-resi stands for medium and high storey residential

of NP for built-up area in binary-category system has decreased all along, indicating that urban growth mainly took place at the fringe of urban area and got close to the urbanized area.

The LPIs of all of the land-use categories in multi-category system have not changed in this period (Fig. 4b). This implies that the growth of these land-use categories did not show the characteristics of dominance. The LPI of built-up area in binary-category system increased gradually however, indicating the centralization of urban growth. The land-use categories in multi-category system did not show this kind of characteristics.

The dynamics of ED and FRACAM describe the complexity of urban landscapes (Figs. 4c and 4d). Low storey residential increased gradually in both the value of ED and FRACAM, indicating the increasing complexity. Values of ED and FRACAM metrics of other land-use categories did not change significantly.

Fig. 4d illustrates that the value of ENNMN for medium and high storey residential had increased a little from 1974 to 1979 then declined gradually while the value of other land-use categories only changed slightly. It indicates that from 1974 to 1979, medium and high storey residential was settled away from the existing place of these categories due to city planning or developers' decision. From 1979, new developed places of these categories turned close to the existing ones. This phenomenon shows the characteristics of aggregation of urban land-use changes in this period.

The value of SPLIT for densely low storey residential, which was smaller than the other land-use categories in area (Fig. 3), was much higher than that of other land-use categories. Coupled with Figs. 4a and 4b, we can see that the densely low storey residential grew mostly at neighborhood area from 1974 to 1979. This has caused the rapid decline of SPLIT metrics. The values of SPLIT for built-up area in binary-category system were nearly 2; this was quite small. It substantiates the characteristic of aggregation in the process of urban growth as shown using NP and LPI metrics.

CONTAG and SHDI can be used to investigate the general characteristics of the whole landscape. The values of CONTAG for binary-category system were bigger than that of multi-category system in time series as shown in Fig. 5. This validates the function of CONTAG in representing the heterogeneity of the landscape. In binary-category system, as the numbers of categories were not many and built-up area tended to aggregate, the area of most patches was large. In multi-category system, urban area was divided into more categories and became more heterogeneous. For binary-category system, from 1974 to 1989, the value of CONTAG had increased gradually,

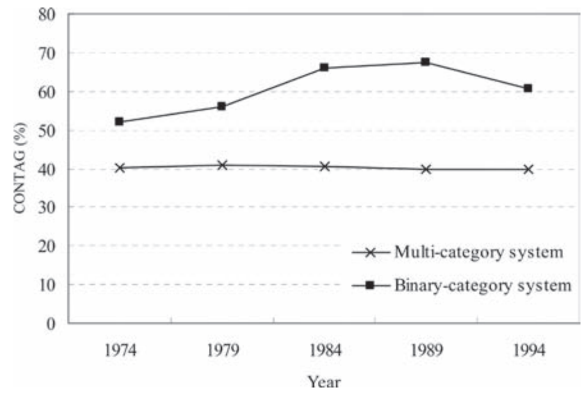

Fig. 5 CONTAG of two land-use classification systems in time series

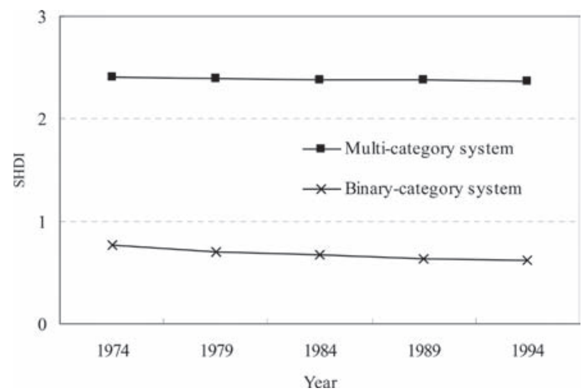

Fig. 6 SHDI of two land-use classification systems in time series

indicating that with urban growth the built-up area connected into bigger blocks and the landscape became homogeneous. From 1989 to 1994, the landscape of the city became more heterogeneous insofar as most of the urban growth did not connect with existing built-up area. For multi-category system, the value of CONTAG has declined a little across the time series. It indicates that the growth of the urban land-use categories has dispersively occurred in non-built-up area and the landscape gradually became more heterogeneous.

The SHDI metric is a popular measure of diversity of landscape. From Fig. 6 we can find that the values of SHDI for multi-category system across the time series were larger than that of the binary-category system as the information in multi-category system was abundant. Nevertheless, the values of the SHDI metric in both systems seldom changed across the time series. It means that the SHDI metric is not sensitive in representing urban dynamics within a short period.

5. Concluding remarks

This paper has presented a detailed analysis using spatial metrics to interpret urban dynamics at two scales of land-use classification in a case of Yokohama city. The results validated the effectiveness of spatial metrics in linking land-use pattern with land-use process in the detailed land-use classifications and the urban area as one category, as investigated in literatures (Herold et al., 2003; Parker et al., 2001). However, even for the same place, the characteristics of urban dynamics differ with land-use classification system reflecting the effect of spatial scale. This indicates that differences in understanding the process of urban dynamics exist at different scales and analyzing urban dynamics at multi-scale using spatial metrics would contribute to the comprehensive interpretation of urban dynamics, and improve the construction of spatial model for urban dynamics. More empirical case studies will be needed on this phenomenon.

Although spatial metrics have been applied in some cases of urban growth or sprawl analysis (Herold et al., 2003; Herold et al., 2005; Torrens, 2006), there are some fundamental problems which should be further discussed, such as selection of metrics described by Herold et al. (2005). This study analyzed urban dynamics at multi-categories system using multiple spatial metrics. The authors found that some metrics show similar characteristics in representing the process of urban land-use categories. For instance, both of ED and FRACAM, which are defined differently, can be applied to present the dynamics of the complexity of urban landscapes. Moreover, the value of SHDI is not sensitive in representing urban dynamics for a short period. These findings can offer some useful information for discussion of selecting metrics.

It is generally recognized that in the field of landscape ecology, spatial pattern and spatial scale are inseparable in theory and reality. Spatial pattern occurs on different spatial scales, and spatial scale affects spatial pattern to be observed (Qi and Wu, 1996; Turner et al., 1989). Spatial scale also affects the interpretation of urban land-use pattern as well as land-use process. Zhao and Murayama (2005, 2006) have systematically investigated the effect of spatial scale on the result of urban land-use pattern analysis using spatial autocorrelation indices. In this study, the results came from the original 10m×10m spatial resolution of land-use cells. To discuss how spatial scale affects the results of urban dynamic analysis in terms of spatial metrics would be a valuable extension to the current study.

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