EFFECT CHARACTERISTICS OF SPATIAL RESOLUTION ON THE ANALYSIS OF URBAN LAND USE PATTERN: A Case study of CBD in Tokyo Using Spatial Autocorrelation Index

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Abstract
The paper studies the effect characteristics of spatial scale on analysis of urban land use pattern using spatial autocorrelation index – Moran’s I – in the case of CBD in Tokyo, Japan. The concepts of single-state structure and multi-states structure are proposed for the representation of urban land use in terms of fuzzy mathematics. The results indicate that while the patterns of all the urban land use types show a positive spatial autocorrelation across a range of scales, Moran’s I decrease with the increasing grain size, and the pattern of different urban land use types show different effect characteristics of spatial scale.

Introduction
Land use and land cover changes, as one of the main driving forces of global environmental change (Fresco et al. 1997; Turner et al. 1997), significantly affect key aspects of Earth System functioning (Lambin et al. 2001). They directly impact biotic diversity worldwide (Sala et al. 2000); contribute to local and regional climate change (Chase et al. 1999) as well as to global climate warming (Houghton et al. 1999); are the primary source of soil degradation (Tolba et al. 1992); and, by altering ecosystem services, affect the ability of biological systems to support human needs (Vitousek et al. 1997). While it is recognized that biogeophysical as well as human drivers have to be taken into account to bear responsibility for the change of land use and land cover (Turner II et al. 1995; Bilsborrow and Okoth Ogendo 1992; Riebsame et al. 1994), urbanization, which brings on the most striking human-induced land transformation, becomes one of the most important driving forces of land use and land cover changes in the current era (Clarke et al. 1997; Pond and Yeates 1994; Weber and Puissant 2003). Urbanization from a global environmental context is the conversion of natural to artificial land cover characterized by human settlements and workplaces. This single transformation involves a wholesale modification of natural processes such as runoff and evapotranspiration, and the short-term and long-term impacts touch every member of the human race every day (Clarke et al. 1997).

In perspective of landscape, urbanization is characterized by urban area sprawl and the change of urban land use structure. This can be understood as a complex process with their intrinsic characteristics of emergence, self-organizing, self-similarity and non-linear behavior of land use dynamics. In order to understand the mechanism and spatial process of urban land use change so as to provide spatial decision-making systems and a basis for assessment of the ecological impacts of urban change to urban planners, various spatial dynamic models, especially based on cellular automata (CA), of urban change have been constructed and successfully applied to many cities in the world (Barredo et al. 2003; Batty 1970; Batty and Xie 1994; Clarke et al. 1997; White and Engelen 1993; White et al. 1997; Yeh and Xia 2001). According to O’Sullivan...
and Unwin (2002), as spatial pattern in any time is generated from corresponding spatial process, spatial model which aims at simulating the spatial process can be constructed through analyzing spatial patterns in series of time. Construction of spatial models of urban change also takes the same procedure. That is, spatial models underlying certain urban change theory need to be calibrated using urban land use patterns in series of time. Therefore, spatial models of urban change are influenced by the result of urban land use pattern analysis.

It has been recognized that spatial pattern and spatial scale are inseparable in theory and in reality (Qi and Wu 1996; Turner et al. 1989). Spatial pattern occurs on different spatial scales, and spatial scale affects spatial pattern to be observed. Consequently, the results of urban land use pattern analysis also show difference in different spatial scales, and it will influence the construction of spatial model of urban land use change. However, little systematic investigation has been done as to how changing spatial scale affects analysis of urban land use pattern.

Spatial scale encompasses both grain and extent (Turner et al. 1989). Grain refers to the resolution of the data, i.e., the area represented by each data unit. Extent refers to the overall size of the study area. Now, the problems with which we are being confronted are how to identify appropriate spatial resolution of urban land use map for modeling urban change of one city at local scale. Up to now, for example, various types of spatial resolution of urban land use map have been used in many literatures: 500m×500m (White and Engelen 1993), 300m×300m (Clarke et al. 1997), 250m×250m (White and Engelen 1997), 240m×240m (Yang and Lo 2003), 100m×100m (Barredo et al. 2003), 80m×80m (White et al. 1997), and so on. It seems that no theoretical justification can be given to adopting any specific spatial resolution. Accordingly, this study concentrates on the problem of grain, i.e., spatial resolution, of urban land use map, especially aims at exploring the effect characteristics of spatial resolution on the analysis of urban land use pattern.

Methodology

Study area and land use data

“Detailed Digital Information (10m Grid Land Use) Metropolitan Area” of Tokyo was released in 1998 (Geographical Survey Institute 1998). The data set was produced by the Geographical Survey Institute, the Ministry of Construction in Japan, and it has the data on the category of land use of each 10 meters square cell, which we call “base unit cell”, surveyed in 1979, 1984, 1989 and 1994. It provides the probability of changing spatial resolution of urban land use map from high resolution (10m) to low resolution (200m, even less than 200m) in analyzing urban land use pattern. In “Detailed Digital Information (10m Grid Land Use) Metropolitan Area”, the area is divided into regular grid map with 3km×4km, and land use information is stored in TDU format for every grid map. As the minimum spatial unit is 10m, there are 120,000 units for one grid map. Considering the speed of calculation in computer, we select one of grids map located in the central business district (CBD) as study area (Figure 1), and use the digital data in one time, 1994.

There are 15 categories of land use classification in original data sets (Table 1). We aggregate some categories which have the same functions and group land uses into 10 categories for the research (Table 1).

The study area lies between Shinjyuku station and Tokyo station. Shinjyuku station is located in the west of the area (Figure 2). Figure 2 shows the land use map of study area in 1994 according to the new categories. Land use structure is shown in Figure 3 (category, area in ha. and proportion to the study area).
Table 1: Categories in original data set and those in this study

<table>
<thead>
<tr>
<th>Categories in original data set</th>
<th>Categories in this study</th>
</tr>
</thead>
<tbody>
<tr>
<td>A. Woods</td>
<td>1. Park and woods</td>
</tr>
<tr>
<td>B. Paddy field</td>
<td>2. Agriculture</td>
</tr>
<tr>
<td>C. Dry fields</td>
<td>2. Agriculture</td>
</tr>
<tr>
<td>D. Under construction</td>
<td>3. Vacant</td>
</tr>
<tr>
<td>E. Vacant land</td>
<td>3. Vacant</td>
</tr>
<tr>
<td>F. Industry</td>
<td>4. Industry</td>
</tr>
<tr>
<td>G. Low storey residence</td>
<td>5. Low-storey residence</td>
</tr>
<tr>
<td>H. Densely developed low storey residence</td>
<td>5. Low-storey residence</td>
</tr>
<tr>
<td>I. Medium and high storey residence</td>
<td>6. High-storey residence</td>
</tr>
<tr>
<td>J. Commercial &amp; service industry</td>
<td>7. Commercial</td>
</tr>
<tr>
<td>K. Road</td>
<td>8. Road</td>
</tr>
<tr>
<td>L. Park</td>
<td>1. Park and woods</td>
</tr>
<tr>
<td>M. Public facilities</td>
<td>9. Public</td>
</tr>
<tr>
<td>N. River, lake &amp; pond</td>
<td>10. Water</td>
</tr>
<tr>
<td>O. The others</td>
<td>9. Public</td>
</tr>
</tbody>
</table>

Figure 2: Land use map of study area in 1994

In the study area, Commercial and residential take area of the main land use types, more than 46% of all the study area. Land use of public and park shows strong characteristics of spatial association. Other land use types display heterogeneous as be mixed together.
Data processing

In order to allow a systematic analysis of spatial resolution effects, the original grid cells (basic spatial unit, BSU, here 10m) were aggregated into larger grid cells in the following way. Each BSU was treated as one basic unit, and therefore the grain size at this scale was expressed as 1 by 1. A 2×2 areal unit, then, corresponded to the grain size that contained four BSUs (two on each side). This was accomplished by aggregating four adjacent basic areal units, assigning the arithmetic mean of the four to the newly formed areal unit. This procedure was repeated until the entire region of the data sets was covered. In total, 20 different grain sizes (spatial scales) were created, ranging from 1×1 through 20×20 BSUs (i.e., 1, 2^2, 3^2, ..., 20^2).

![Figure 3: Land use structure of study area in 1994](image)

(Category, area in ha. and proportion to the study area)

![Figure 4: Schematic process of aggregation of four BSUs into one cell](image)

Every cell at certain level of spatial resolution always is assigned just one main state of land use at stated period in traditional method, especially Cellular Automata (CA) approach (Batty and Xie 1994; Clarke et al. 1997; White and Engelen 1993; White et al. 1997). The state of the cell which is aggregated from some BSUs is identified using maximum proportion approach (Turner et al. 1989). Figure 4a and 4b indicate the schematic process of aggregation of four BSUs into one cell with 20m×20m. In Figure 4a, as the state of all the BSUs is park and woods, the aggregated
cell is assigned land use type of park and woods. In Figure 4b, the proportion of park
and woods, road, commercial to the area of four BSUs is 50%, 25% and 25%
respectively. As the proportion of park and woods is more than that of others, the
aggregated cell is assigned land use type of park and woods.

Here, every cell is considered as homogeneous rather than heterogeneous. We call
the result of simplification of land use as representation of single-state structure.
However, the process of simplification may generate area errors of land use (Moody
and Woodcock 1994). The errors inevitably influence the result of urban land use
pattern analysis. In order to identify how the influence is, the concept of grade of
fuzzy membership is introduced to represent the attribute information of the cell at
every level of grain size. In fact, because of the limitation of corresponding spatial
resolution, land use attribute of every cell in certain spatial scale takes characteristics
of fuzzy uncertainty (Zhang and Stuart 2001; Zhao et al. 1999). That is, as the land
use of the cell at the scale is heterogeneous, the cell is assigned different land use type
at corresponding grade of fuzzy membership. We call the representation as multi-state
structure as following:

\[
R_{ij} = \{\mu_{R_{ij}}(1), \mu_{R_{ij}}(2), \ldots, \mu_{R_{ij}}(k)\}
\]

Where, \(R_{ij}\) stands for one cell in \(i^{th}\) row and \(j^{th}\) column; \(k\) land use type; \(\mu_{R_{ij}}(k)\) the
extent to which the cell belongs to land use type \(k\), i.e. grade of fuzzy membership in
\([0, 1]\). \(\sum_k \mu_{R_{ij}}(k) = 1\) for one cell is required so as to ensure the integrality of attribute
information of cells. Figure 4c, for example, indicates the schematic process of
aggregation of four BSUs into one cell with 20m×20m using multi-state structure.

\[
R_{ij} = \{\mu_{ij}(public), \mu_{ij}(commercial), \mu_{ij}(park \& woods), \mu_{ij}(vacant), \mu_{ij}(low-s-resi),
\mu_{ij}(high-s-resi), \mu_{ij}(road), \mu_{ij}(water), \mu_{ij}(industry) \}
\]

Where:
\(\mu_{ij}(public) = 0.25, \mu_{ij}(commercial) = 0.25, \mu_{ij}(park \& woods) = 0.5, \mu_{ij}(others) = 0\).

As we aggregate BSUs (10m) into larger grid cells systematically in data
processing, at all the levels of scale we can identify attribute information of land use
for every cell in both single-state structure and multi-state structure. The results of
land use pattern analysis in both structures are used to compare so as to analyze the
effect of simplification of land use with changing spatial resolution in single-state
structure.

Spatial autocorrelation index
Spatial autocorrelation is general geographical phenomena in nature (O’Sullivan and
Unwin 2002), which indicates spatial association and spatial dependence of
geographic phenomenon. Measures of spatial autocorrelation work by examining how
objects at one location are similar to objects located nearby (Goodchild 1986). If
features situated close together have similar attribute information, then the pattern in
the data can be described as exhibiting positive autocorrelation. When features close
together are more dissimilar in attribute value than features further away, pattern in
the data is negatively auto correlated. Zero autocorrelation exists when attributes or
their values are independent of location (Goodchild 1986).

Moran’s I and Geary’s c are two common indices for the analysis of spatial
have used both the indices to analyze the effect of changing spatial resolution on the
results of topography and biomass pattern in 1972 of Peninsular Malaysia. They found no appreciable difference among them with regularly gridded data sets. Therefore, we select Moran’s I as analysis index in this research. Moran’s I is defined as follows:

\[ I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (X_i - \bar{X})(X_j - \bar{X})}{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} \left( \sum_{j=1}^{n} (X_j - \bar{X}) \right)^2} \]

Where, \( x_i \) and \( x_j \) stand for feature value of two cells nearby; \( \bar{X} \) average value of feature of all the study area; \( n \) total number of cells; \( W \) weight (connectivity) matrix. When cell i and cell j are neighboring, \( w_{ij}=1 \), otherwise \( w_{ij}=0 \). The value of Moran’s I generally varies between 1 and -1, although values lower than -1 or higher than +1 may occasionally be obtained. Positive autocorrelation in the data translates into positive values of I; negative autocorrelation produces negative values. No autocorrelation results in a value close to zero (Goodchild 1986).

Definition above shows that the value of Moran’s I is determined by two factors: the value of cell and weight matrix. Here, the value of cell adopts the grade of fuzzy membership to which the cell belongs to one or more types of land use. The weight matrix is constructed in queen case (similar to Moore neighborhood).

**Results and analysis**

The values of Moran’s I (VMI) of the land use types at all the levels of scale are calculated using Geoda software (https://geoda.uiuc.edu/default.php). Figure 5 illustrates the variogram of the value of Moran’s I of all the land use types in series of spatial resolution using single-state structure.

Figure 5 indicates that all the data sets show a positive spatial autocorrelation across a range of scales except land use type of vacant at the level of scale more than 100m×100m. That is, almost all the types of urban land use exhibit characteristics of spatial association across the range of scales. It also indicates that the spatial autocorrelation of all the land use types are scale-dependent as VMI of all the types of urban land use decrease with increasing grain size.

![Figure 5: Variogram of the value of Moran’s I of all the land use in the series of spatial resolution](image)

However, the effect of spatial scale shows different characteristics on different urban land use types. In order to analyze the differences of effect characteristics, we divide the variogram of VMI of all the types of urban land use into three groups.
according to the value of Moran’s I at original grid cells (Figure 6).

![Variogram of Value of Moran's I](image)

**Figure 6:** three groups of variogram of value of Moran’s I. (a) park and woods, water, public, industry; (b) high-storey residential, low-storey residential, commercial; (c) Vacant, road.

In Figure 6a, VMI of four types of urban land use are highest, more than 0.75, at level of original grid cell. VMI of industry and water decrease rapidly across the range of scale but that of public decrease not so rapidly. VMI of park and woods decreases rapidly till spatial resolution of 80m, then keep stable approximately. VMI of three types of urban land use in Figure 6b keep between 0.6 and 0.7 at level of original grid cell. VMI of low-storey residential till 20m, commercial till 30m and high-storey till 50m of spatial resolution decrease rapidly, but slowly after that. VMI of two types of urban land use in Figure 6c are low and decrease rapidly from 10m to 50m of spatial resolution then keep stable approximately. However, VMI of vacant disappears from 100m of spatial resolution.

If we consult Figure 3 we can find that effect characteristics of changing spatial resolution on urban land use pattern is determined by the proportion of urban land use type to the whole study area and spatial association of it in general. Spatial autocorrelation of urban land use with low proportion and dispersed association decreases rapidly with increasing grain size, even disappear. But for high clustered (e.g., park and woods), the spatial autocorrelation decreases slowly, even does not decrease any more (more than 80m spatial resolution). Spatial autocorrelation of urban land use with high proportion decrease rapidly in high resolution range (10m-50m), then show no much effect in low resolution range.

In order to identify how the simplification of urban land use in single-state structure influences the result of land use pattern analysis, we compare the variogram of VMI in both single-state structure and multi-state structure for all the types of urban land use, see Figure 7. As VMI of all types of urban land use in multi-state structure is more than that in single-state structure at any level of spatial resolution, multi-state structure takes less effect of changing spatial resolution on analysis of urban land use pattern than single-state structure.
Figure 7: Compare of variogram of VMI of different type of urban land use. (a) Park and woods; (b) Vacant; (c) Industry; (d) Low-storey residential; (e) High-storey residential; (f) Commercial; (g) Road; (h) Public; (i) Water.

Figure 8: Change histogram of area of different urban land use type in a range of spatial resolution (for each type of urban land use, the pillars from left to right stand for change of area of land use in 10×10m, 20×20m, ..., 200×200m respectively)

Figure 8 illustrates the change of area of urban land use across the range of scale in single-state structure. It is obvious that the area of all types of urban land use vary with changing spatial resolution in this structure. However, as heterogeneity is considered in multi-state structure, the area of all types of urban land use does not change across the range scale. Therefore, the change of area of urban land use across
the range of scale may be one of the reasons of generating effect of changing spatial resolution on urban land use pattern analysis.

**Conclusion**

Construction of spatial model of urban land use contributes to understand the mechanism of urban change and provides spatial making-decision system to urban land use planners. Because spatial patterns of urban land use, which are scale-dependent, always are used to calibrate spatial model of urban change, research of that how the scale influences the analysis of urban land use pattern is of importance in construction of spatial model of urban change. This paper studies the effect characteristics of spatial scale on analysis of urban land use pattern using spatial autocorrelation index – Moran’s I – in the case of CBD in Tokyo, Japan. The concepts of single-state structure and multi-states structure are proposed for the representation of urban land use in terms of fuzzy mathematics. The results show that while the patterns of all the urban land use types show a positive spatial autocorrelation across a range of scales, Moran’s I decrease with the increasing grain size, and the pattern of different urban land use types show different effect characteristics of spatial scale. The results may provide profitable idea of selection of appropriate spatial resolution for the construction of spatial model of urban change.

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