Developing urban growth predictions from spatial indicators based on multi-temporal images

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Abstract

Landuse change in metropolitan areas is largely focused on the dynamic nature of urban landuse change. In this research, a spatial statistical model was used to support decision-making with regard to urban growth predictions in the urban fringe of Beijing, China. The model adopted in this study was based on the integration of remote sensing, geographical information systems, and multivariate mathematical models. The model emphasises the spatial distribution of the landuse/cover units and the spatio-temporal patterns, which were modelled by landuse/cover change trajectories over a series of observation years. The main trajectories for the landuse/cover change model were based on five sets of multitemporal landuse/cover data derived from remotely sensed images. Using the integrated GIS, several spatial variables were derived, including the proximity to major roads and built-up areas. A multivariate model was established to establish relationships between urban expansion and above spatial variables. The landuse/cover change trajectories and the multivariate model were then integrated to construct a multivariate spatial model that is capable of estimating the spatial probability of the urban expansion. © 2005 Elsevier Ltd. All rights reserved.
1. Introduction

Urban growth prediction is often based on the dynamic landuse/cover pattern and its relationship with selected socio-economic factors. Landuse change in metropolitan areas typically reflects economic development and population growth. Thus the analysis of spatial-temporal patterns for landuse/cover provides an objective basis for understanding the relationships between urban growth and related economic, population and environmental factors (Irwin & Geoghegan, 2001).

Civco, Hurd, Wilson, Song, and Zhang (2002) have reported on various aspects of landuse/cover change studies. Change detection for landuse/cover categories, through the integration of satellite imagery, environmental and socio-economic data, has been commonly used for the analysis of the dynamic pattern of urban growth (Amissah-Arthur, Mougnot, & Lioreau, 2000; Masek, Lindsay, & Goward, 2000; Roy & Tomer, 2001). Numerous research efforts were focused on the spatio-temporal aspects of shifting landuse patterns (Roy & Tomer, 2001; Weng, 2001), while other works employed Markov chains and change matrices as the tools for the dynamic pattern analysis (Boerner et al., 1996; Lo & Shipman, 1990). The use of land-cover change trajectories to analyse the temporal patterns, with more than two observation incidences, has also been reported (Mertens & Lambin, 2000; Petit, Scudder, & Lambin, 2001). However, previous research has largely been focused on the dynamic nature of the urban landuse change. Few examples have been reported for the integrated study of both spatial and temporal change patterns in urban area (Yeh & Li, 2001).

From the point of view of urban studies, the spatial context of landuse/cover change in the urban fringe is of particular importance since it comprises a critical consideration for decision-making in urban landuse (Reenberg & Fog, 1995). The spatial growth of urban areas often follows the pattern of proximity to spatial factors such as transportation lines and existing urban centres. Urban growth prediction based on objective spatio-temporal models is therefore a fundamental component for the management and planning of a metropolitan area. Many models for urban growth prediction, such as the cellular automata (CA) model and land conversion in the urban fringe area, have been developed (e.g. Li & Yeh, 2000; White & Engelen, 1993; Wu, 1998). Among these models, Geographical Information System (GIS) based urban models have been widely used (e.g. Sui, 1998; Wu & Webster, 2000; Yeh & Li, 1998). In practice, however, the use of these models has been limited in urban growth analysis because of the difficulty in obtaining all of the required factors or enough data for the model.

The rapid growth and development of cities in China has been a subject of active study in recent years. Studies of major cities, such as Beijing, Shanghai and Guangzhou, have focused on their landuse change, urban transformation and population densities (e.g. Gaubatz, 1999; Wang & Zhou, 1999; Wu & Yeh, 1997).

This study attempts to develop a multivariate spatial model for urban growth prediction, with a case study at the urban fringe of Beijing. This model was based on the integration of remote sensing, GIS and multivariate mathematical models. The emphasis of the model was on the spatial distribution of landuse/cover units and spatio-temporal patterns, which were modelled by landuse/cover change trajectories.
over a series of observation years. Remotely sensed images were used as the major data source to derive the input variables for the model.

This paper reports the methodology adopted for predicting spatial patterns of urban expansion, which involved analysing land use change trajectories and stimulating factors such as transportation lines (highways and roads). An urban expansion prediction model has been established based on the development of the multivariate spatial model that considers three categories of spatial variables, namely:

1. Land use/cover change trajectories derived from multitemporal remote sensing images,
2. the proximity to transportation lines, and,
3. the proximity to the existing (or established) urban centres.

Based on the multivariate spatial model, the areas with high probabilities of urban expansion are mapped so that their spatial distribution can be analysed.

2. Study area and data

This study was undertaken at Chaoyang District, one of the fastest growing parts of the Beijing metropolitan area. The district is located in eastern Beijing and covers an area of 455 km², with a population over 1.3 million—the most populous of all districts in Beijing. The majority of the district is characterised as an urban fringe with rapid urban expansion having occurred in the past two decades. Since 1978, the area of agricultural land has decreased sharply—by 18.8% from 1982 to 1989 and by 6.5% from 1989 to 1992. The residential and industrial land, on the other hand, increased by about 28.2% from 1982 to 1989 and by 14.9% from 1989 to 1992 (Cao & Cai, 1993).

Landsat Thematic Mapper (TM) images were acquired for 2 October 1984, 21 April 1988, 6 May 1991, 28 August 1994 and 16 May 1997. In addition, a land use map, compiled in 1991 at a field survey scale of 1:50,000, was used for the accuracy assessment. The master scene (the 1991 TM image) was geometrically corrected and registered to the land use map, using 36 Ground Control Points (GCP) and second-order polynomial transformation with the nearest neighbour resampling method. The other scenes were then registered to the master scene by image-to-image registration. Major urban transportation lines (roads and highways) were mapped using the 1991 land use map and updated with information from later remotely sensed images (1994 and 1997 TM images).

3. Methodology

The methodology for this study includes three components, namely:

- *Land use/cover change trajectory analysis*, which derives the probability of land use transformation from various non-urban land use categories to urban land use (i.e. built-up area),
• spatial proximity analysis, which derives the probability of urban growth in relation to the distance to transportation and the existing built-up areas, and,
• establishment of a multivariate spatial model to predict urban growth, which integrates the above derived variables in order to derive the overall probability of urban expansion for each given location in the study area.

3.1. Landuse/cover change trajectory analysis

A time series of remote sensing images (Landsat TM), spanning 17 years, were used to obtain landuse change information, using the post-classification comparison technique (Lillesand & Kiefer, 2000).

3.1.1. Landuse classification

Two classifiers were tested in this study, namely, the maximum likelihood (MLC) and artificial neural network (NNC) classifiers. One major difference between the two classifiers is the number and purity requirement of the training areas (Atkinson & Tatnall, 1997; Kanellopoulos & Wilkinson, 1997). The NNC needs fewer, and less pure, seeding data in comparison with that of MLC.

PCI 6.0 remote sensing image processing software was used for the classification. 4835 pixels were selected as the training data on the 1991 TM image. The BP (Backward Propaganda) model of NNC was applied in the classification, with a structure of 6, 32 and 7, which refers to input, number of nodes and output, respectively. After classification, the post processes were applied to both sets of results from MLC and NNC in order to aggregate classified categories and to match the classes of the landuse map. Five land-cover classes were mapped, namely, water, vegetable garden, forest, farmland, and built-up areas (including residential, industrial, and commercial areas), based on the capability of image interpretation of the TM.

The one-time classification error matrix was constructed for the land-cover classification on the 1991 image using the 1991 landuse map as the reference data. With an overall classification accuracy of 79.6% (3% higher than that of MLC) and a kappa coefficient of 0.696, NNC was chosen as the preferred classifier. The other four multitemporal images were then classified using NNC. Together with the 1991 image, the five multitemporal classified images were used to establish the land-cover change trajectory for each pixel from 1984 to 1997.

3.1.2. Landuse change analysis

Changes in landuse between successive dates were detected by post-classification comparison. The post-classification comparison leads to a categorical map that indicates the landuse classes at the two successive observation years for every pixel. The traditional post-classification cross-tabulation (Lunetta & Elvidge, 1999) was employed to establish “from” and “to” categories for the two dates of the images, which was essential for the definition of landuse change trajectories.
3.1.3. Trajectories of landuse change

Lambin (1997) suggested that generic paths of landuse change could be identified, noting examples of sequences of landuse changes found across tropical regions. From the point of view of change detection, the change trajectory was defined as trends over time among the relationships between the factors that shape the changing nature of human-environment relations and their effects within a particular region (Kasperson, Kasperson, & Turner, 1995). The trajectory of land-cover change refers to successions of land-cover types for a given sampling unit over more than two observations (Mertens & Lambin, 2000; Petit et al., 2001). Markov chain and the change matrix could be used to analyse the possibility of landuse shift and to define the trajectories when two-times change detection is applied. When the observation time series becomes long, the primarily two-time comparison methods are not applicable. To establish the trajectory of landuse change, we have selected numerous sample points over the study area and recorded for each sample point the landuse category at every image date using GIS functions.

In the urban fringe area, the primary landuse change concerns urban growth. Among all the possible landuse change trajectories, the study focus is on the non-urban landuse categories turning into built-up areas by the end of the monitoring period. The majority of the various landuse change trajectories determines the probabilities of transforming to built-up areas from other landuse categories. The spatial variable is defined as cover type conversion probability (C) and is used to describe the spatial pattern of urban expansion in the multivariate spatial model.

3.2. Spatial proximity analysis

Spatial proximity analysis derives the probability of urban growth in relation to the distance to transportation and existing urban centres. Using GIS overlay functions, urban expansion areas can be mapped by comparing the landuse classification maps of successive dates. We have utilized two variables for the proximity analysis, namely, the distance between urban expansion areas and transportation lines, and the distance to existing built-up areas.

3.2.1. The distance between urban expansion areas and transportation lines

In order to analyze the influence of the transportation lines (e.g. highways) on urban expansion, we set the variables $K_n$ and $K_s$, which specify the relationship between transportation and urban expansion area by number count and area, respectively. To compute $K$, we first created a series of buffer zones using GIS along the transportation lines ranging from 50m, with an increment of 50 m, to the maximum increment $m$ (in this study we set $m = 10$). The variable $K$ for $i$th buffer zone (e.g. $i = 1$ means the first 50 m buffer, and $i = 2$ means the second 100 m buffer) can then be derived as:

$$K_{ni} = \frac{n_i}{N} \times 100\% \quad i = 1, 2, \ldots, m$$

(1)

and

\[ K_{s_i} = \frac{s_i}{S} \times 100\% \]  \hspace{1cm} (2)

where \( n \) and \( s \) denote the number count and area for the urban expansion areas (i.e. “clumps” of pixels identified as shifted from other landuse types to “built-up area”) in \( i \)th buffer zone. \( N \) and \( S \) denote the total number count and area for the urban expansion areas in one observation period. \( K_n \) was sensitive when “clumps” of urban expansion areas were small and many, which indicates how the urban expansion is spread out. \( K_s \) was sensitive when “clumps” of urban expansion area were large and few, which shows that the urban expansion is concentrated and continuous. Both \( K_n \) and \( K_s \) were expressed in relation to the degree of proximity to transportation lines. The higher were the values of \( K_n \) and \( K_s \), the higher was the degree of urbanisation in the given buffer zone.

### 3.2.2. The distance between urban expansion areas to existing built-up areas

The variable \( K_a \) was defined as the proximity of the urban expansion areas to existing built-up areas that could be considered as the urban growth origins (e.g. old city). The existing built-up areas were mapped from image classification on the earlier observation date. By statistical testing, about 50\% of the urban expansion areas were located within 100 m of existing built-up areas, for each testing period (i.e. the dates of the two observations). Buffer zones were then created 100 m from the existing built-up areas, with incremental distances of 25 m. The variable \( K_a \) was then computed in a manner similar to Eqs. (1) and (2) above:

\[ K_{a_i} = \frac{a_i}{S} \times 100\% \quad i = 1, 2, \ldots, m \]  \hspace{1cm} (3)

where \( a_i \) denotes the expansion area within the \( i \)th buffer zone to the existing built-up areas.

The value \( K \) of different buffers denotes distance to transportation lines and existing urban centres. The incremental change within each buffer zone can be computed as:

\[ \Delta K_i = K_{i+1} - K_i, \quad i = 1, 2, \ldots, m - 1 \]  \hspace{1cm} (4)

where \( \Delta K_i \) denotes the change of \( K \) (\( K_n \), \( K_s \) or \( K_a \)) within the \( i \)th incremental buffer zone.

During a given monitoring period \( t \), there is \( D_t \), which is defined as the buffer zone with the maximum \( \Delta K_i \) value. The \( D_t \) identifies the zone where the urban growth is most likely to happen at the given period, while \( \Delta K_i \) defines the probability of urban growth for the \( i \)th buffer zone.

### 3.3. Establishment of a multivariate spatial model to predict urban growth

The multivariate spatial model integrates various spatial variables to derive the overall probability of urban expansion for each given location in the study area. It is based on four spatial variables: the above \( K_n \), \( K_s \) and \( K_a \), and the probability of
various landuse change trajectories. The model is implemented in a GIS with each spatial variable represented as a data layer. The weighting factor can then be determined by specifying the given scenario based on a pre-determined urban expansion pattern (e.g., a transport dominating pattern).

To predict the spatial pattern of urban growth, the multivariate model is applied to derive the landuse transformation index for a “built-up area” at a given location. The variables were weighted, based on their influence on urban growth, and they were then overlaid to derive the weighted sum at a given location. The results were then divided into classes to produce a map showing the likelihood of urban growth for the urban fringe region. The urban growth index \( P \) can be expressed as:

\[
P = \frac{\omega_C C + \omega_n K_n + \omega_s K_s + \omega_a K_a}{\sum \omega}
\]

Where \( \omega \) denotes the weighting factor applied to a given variable.

4. Results and discussion

4.1. Landuse change analysis

During the entire study period from 1984 to 1997, the built-up area expanded from 26.7% to 55.9% of the total district, doubling in 14 years. On the other hand, the proportion of farmland and vegetable gardens decreased from 51.1% and 15.5% to 26.3% and 6.7%, respectively. The forest area decreased slightly but the area of water bodies increased sharply—mainly due to an increase in commercial fish ponds in the district (Table 1). By integrating the multitemporal classified images, we derived the urban expansion map shown as Fig. 1.

4.2. The trajectories of landuse change

The trajectories of landuse change were analyzed using 3171 randomly selected samples with no stratification over the district (Liu & Zhou, 2004). Among the total samples, 939 samples indicate the change from non-urban categories to built-up areas, showing 17 trajectories of landuse change. Among those trajectories, 43.7% were from vegetation garden to built-up area, 52.6% from farmland, and 3.8% from water (Table 2).

Table 1
The percentage of landuse categories for each image acquisition date

<table>
<thead>
<tr>
<th>Image date</th>
<th>Built-up area</th>
<th>Farmland</th>
<th>Forest</th>
<th>Vegetable garden</th>
<th>Water</th>
</tr>
</thead>
<tbody>
<tr>
<td>1984</td>
<td>26.7</td>
<td>51.1</td>
<td>3.7</td>
<td>15.5</td>
<td>3.0</td>
</tr>
<tr>
<td>1988</td>
<td>39.8</td>
<td>39.9</td>
<td>2.7</td>
<td>10.7</td>
<td>6.8</td>
</tr>
<tr>
<td>1991</td>
<td>46.0</td>
<td>34.9</td>
<td>2.7</td>
<td>8.2</td>
<td>8.2</td>
</tr>
<tr>
<td>1994</td>
<td>49.9</td>
<td>32.0</td>
<td>3.0</td>
<td>6.9</td>
<td>8.3</td>
</tr>
<tr>
<td>1997</td>
<td>55.9</td>
<td>26.3</td>
<td>2.9</td>
<td>6.7</td>
<td>8.2</td>
</tr>
</tbody>
</table>
4.3. The proximity to the transportation lines

Tables 3 and 4 show the results of $\Delta K_i$ calculated, using the urban expansion number and area respectively. Regarding the number of newly converted built-up areas, $D_i$ shifted from the buffer zone of 150–200 m to that of 50–100 m in late 1980’s. In terms of the area, there were a continued shifting from a close range of 50–100 m to that of 250–300 m (the bold numbers in the tables are the maximum $\Delta K_i$ for each period). By observing the two tables, it appears that differences of $\Delta K_i$ by numbers
between buffer zones were great, but differences of $\Delta K_i$ by area (i.e. $K_i$) were not significant until the distance was greater than 350 m. This suggests a strong relationship between urban expansion and transportation lines. $D_t$ by urban expansion area shifted from 50–100 m to 250–300 m from 1984 to 1991 as space with closer proximity was gradually occupied in the late stage. To make $\Delta K_i$ comparable between buffer zones, the original $\Delta K_i$ values were normalised for input to Eq. 5.

### Table 2

The trajectories of landuse change

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Others</td>
<td>Others</td>
<td>Water</td>
<td>Water</td>
<td>$\rightarrow$ Built</td>
<td>0.5</td>
</tr>
<tr>
<td>2</td>
<td>Others</td>
<td>Others</td>
<td>Water</td>
<td>$\rightarrow$ Built</td>
<td>Built</td>
<td>1.3</td>
</tr>
<tr>
<td>3</td>
<td>Water</td>
<td>$\rightarrow$ Built</td>
<td>Built</td>
<td>Built</td>
<td>1.1</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Water</td>
<td>Water</td>
<td>$\rightarrow$ Built</td>
<td>Built</td>
<td>0.9</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Veg.</td>
<td>$\rightarrow$ Built</td>
<td>Built</td>
<td>Built</td>
<td>23.3</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Veg.</td>
<td>Veg.</td>
<td>$\rightarrow$ Built</td>
<td>Built</td>
<td>5.2</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Veg.</td>
<td>Veg.</td>
<td>Veg.</td>
<td>$\rightarrow$ Built</td>
<td>3.8</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Veg.</td>
<td>Veg.</td>
<td>Veg.</td>
<td>Veg.</td>
<td>$\rightarrow$ Built</td>
<td>3.4</td>
</tr>
<tr>
<td>9</td>
<td>Farm</td>
<td>Veg.</td>
<td>$\rightarrow$ Built</td>
<td>Built</td>
<td>2.0</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>Farm</td>
<td>Veg.</td>
<td>Veg.</td>
<td>$\rightarrow$ Built</td>
<td>Built</td>
<td>1.9</td>
</tr>
<tr>
<td>11</td>
<td>Farm</td>
<td>Veg.</td>
<td>Veg.</td>
<td>Veg.</td>
<td>$\rightarrow$ Built</td>
<td>1.1</td>
</tr>
<tr>
<td>12</td>
<td>Farm</td>
<td>Farm</td>
<td>Farm</td>
<td>Veg.</td>
<td>$\rightarrow$ Built</td>
<td>3.0</td>
</tr>
<tr>
<td>13</td>
<td>Veg.</td>
<td>Farm</td>
<td>$\rightarrow$ Built</td>
<td>Built</td>
<td>1.1</td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>Farm</td>
<td>$\rightarrow$ Built</td>
<td>Built</td>
<td>Built</td>
<td>27.7</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>Farm</td>
<td>Farm</td>
<td>$\rightarrow$ Built</td>
<td>Built</td>
<td>6.6</td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>Farm</td>
<td>Farm</td>
<td>Farm</td>
<td>$\rightarrow$ Built</td>
<td>Built</td>
<td>6.4</td>
</tr>
<tr>
<td>17</td>
<td>Farm</td>
<td>Farm</td>
<td>Farm</td>
<td>Farm</td>
<td>$\rightarrow$ Built</td>
<td>10.8</td>
</tr>
<tr>
<td>18</td>
<td>Farm</td>
<td>Farm</td>
<td>Farm</td>
<td>Farm</td>
<td>Build</td>
<td>10.80</td>
</tr>
</tbody>
</table>

The arrow (\(\rightarrow\)) symbols show when the landuse transformation has happened from other landuse types to built-up areas.

### Table 3

$\Delta K_i$ (by number count) values for different buffer zones to transportation lines

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta K_i$</td>
<td>Normalised</td>
<td>Normalised</td>
<td>Normalised</td>
<td>Normalised</td>
</tr>
<tr>
<td>50–100 50–100</td>
<td>8.5</td>
<td>15.0</td>
<td>7.8</td>
<td>13.7</td>
</tr>
<tr>
<td>100–150 50–100</td>
<td>8.3</td>
<td>14.7</td>
<td>7.2</td>
<td>12.6</td>
</tr>
<tr>
<td>150–200 50–100</td>
<td><strong>8.8</strong></td>
<td><strong>15.6</strong></td>
<td>6.5</td>
<td>11.4</td>
</tr>
<tr>
<td>200–250 50–100</td>
<td>5.7</td>
<td>10.1</td>
<td>7.5</td>
<td>13.2</td>
</tr>
<tr>
<td>250–300 50–100</td>
<td>6.4</td>
<td>11.3</td>
<td>6.5</td>
<td>11.4</td>
</tr>
<tr>
<td>300–350 50–100</td>
<td>5.8</td>
<td>10.3</td>
<td>5.8</td>
<td>10.2</td>
</tr>
<tr>
<td>350–400 50–100</td>
<td>5.6</td>
<td>9.9</td>
<td>4.4</td>
<td>7.7</td>
</tr>
<tr>
<td>400–450 50–100</td>
<td>4.7</td>
<td>8.3</td>
<td>6.5</td>
<td>11.4</td>
</tr>
<tr>
<td>450–500 50–100</td>
<td>2.7</td>
<td>4.8</td>
<td>4.8</td>
<td>8.4</td>
</tr>
</tbody>
</table>

(i.e. $K_n$) between buffer zones were great, but differences of $\Delta K_i$ by area (i.e. $K_i$) were not significant until the distance was greater than 350 m. This suggests a strong relationship between urban expansion and transportation lines. $D_t$ by urban expansion area shifted from 50–100 m to 250–300 m from 1984 to 1991 as space with closer proximity was gradually occupied in the late stage. To make $\Delta K_i$ comparable between buffer zones, the original $\Delta K_i$ values were normalised for input to Eq. 5.
4.4. The proximity to the existing built-up areas

$\Delta K_a$ for each buffer zone was computed in the same way as that for $\Delta K_i$. The $K_a$ value for each township was then computed using area weighted $\Delta K_a$ values within the township. The result shows that $D_t$ for $K_a$ occurred at the 125 m buffer zone (Fig. 2), in which all townships yielded $K_a$ greater than 60% with a majority being >80% (Table 5). This clearly shows the strong tendency that the areas next to the existing built-up areas have higher probability for urban expansion. The spatial distribution of $K_a$ also demonstrated the tendency that higher growth rates are associated with townships with closer proximity to the city centre (Fig. 3). In Fig. 3, the centre of

![Diagram showing $K_a$ values decrease with increasing distance to built-up areas.](image-url)
Beijing was located to the southwest, next to the townships, shown with a dark grey shade, where the $K_a$ value ranged between 98% and 100%.

4.5. Urban growth prediction

In this study, the urban growth index ($P$) has been computed with all weighting coefficients set to 1 (i.e. $\omega_c = \omega_n = \omega_s = \omega_a = 1$) by considering the four factors had equal effect on the spatial pattern of urban growth. It might be arguable that some factors may deserve higher weighting values, but assigning variable weighting values to different factors can be very subjective and is beyond the scope of this study. In order to assess the prediction results, we have tested the model on the 1984 landuse classification map in order to predict urban growth probability for 1988. The resulting $P$ values were then classified into three classes by selecting threshold values for a clear map presentation. On the 1988 landuse classification, the prediction results were tested showing that 100% Class I areas were transformed to built-up areas, and that most of the Class II areas were transformed as well, except for the south part of the region (e.g. Xiao Hong Men township), where a special protection policy for vegetation gardens was applied by the city government. For most of the Class III areas, the landuse categories were not transformed, except for some farmlands on the outskirt of the urban fringe region.

Based on the findings of the test, we have processed data using the 1997 image and have computed the $P$ value. The result has been classified using the threshold $P$ values of <50%, 50–60% and >60% corresponding to Classes III, II and I shown on the urban growth prediction map (Fig. 4). Fig. 4 shows the probability classes for
urban expansion, which also clearly shows the influence of existing built-up areas and major transportation lines. We predict that Class I areas would be most likely to be transformed into built-up areas prior to the other two classes and the unclassified areas. Class II areas might also present a high likelihood for such transformation. It should be noted that different threshold $P$ values may apply to different prediction scenarios (i.e. different cities or different periods of time), and that objective determination of the threshold values is certainly subject to further studies.

Fig. 3. Distribution of $K_a$ within 125 m buffer zone in Chaoyang District of Beijing (1997).
5. Conclusion

In this study, we have developed a multivariate spatial model, which integrates spatial variables including landuse trajectory, proximity to transportation lines, and existing built-up areas, to assess the probability of urban growth indicated by the land cover transformation to built-up areas. This allows prediction of future urban growth in the urban fringe region, which should assist decision making.
This study has demonstrated a promising approach to model urban growth based on multi-temporal remotely sensed imagery. The data for the model were acquired from remote sensing images that comprise a reliable and sustained data resource for urban growth monitoring. The model is a spatio-temporal model that is based on the historical landuse change pattern in space and time, which distinguishes it from other methods, such as multi-criteria, spatial regression methods, and so on. Although the accuracy of the model is yet to be proved, and requires more detailed analysis and data, and it is still questionable whether the selected spatial variables and parameters are suitable and adequate for predicting the urban growth, the study has nevertheless demonstrated a practical technical methodology which can be further fine-tuned to fit into different urban growth patterns.

Future studies will further investigate the impacts and interactions of spatial variables on urban growth patterns. Suitable methodology to quantify socio-economic factors that may also play important roles in urban growth should also be studied and adopted in the multivariate spatial model. Appropriate and practical methodologies for accuracy assessment for multi-temporal landuse change trajectory analysis should also be further studied.

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