

# Relationship Between the Landscape Structure of Urban Green Spaces and Residents' Satisfaction: The Case of a Central District in Hanoi (Vietnam)

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## Abstract

In urban planning, it is crucial to develop our understanding of human preferences for green spaces in order to maintain and develop them more efficiently and effectively. However, the research available on this issue is limited to developing and tropical countries. In this study, we investigated the relationships between residents' satisfaction with green spaces in their neighbourhoods and the landscape structure of green spaces in Hanoi, where intensive transformations in built environment are threatening the existence of green spaces and hence the quality of life. Data on the satisfaction level of residents were obtained from a governmental survey. Vegetation classes were identified from a QuickBird image by applying object-oriented classification. We then computed landscape metrics for *street-side trees* and *all trees*. The results confirmed that people were more satisfied in areas where 1) *all trees* were more abundant, well-connected and of variable sizes; and 2) *street-side trees* were of considerable size and complex canopy shape. These findings are consistent with similar studies in Western countries, at an even higher degree, and underscore the urgent need to plant more trees along the streets of the Old Quarter in Hanoi and along the Red River banks.

**Key words:** Urban green space, human preferences, landscape metrics, vegetation mapping, very high resolution image

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## 1. Introduction

Growing concern and commitment to urban sustainability and resilience are making urban green spaces a central issue, especially in the context of climate change. Numerous studies have demonstrated the role of green spaces in improving various biophysical qualities of urban environments, namely by providing cooling effect, reducing air pollution and noise levels, and fixing carbon (Ridder *et al.* 2004). These outcomes, in turn, can lead to significant economic gains (McPherson *et al.* 2005). This is especially true for tropical countries where urban green spaces provide

much needed shade, as well as refreshing views (Thaiutsa *et al.* 2008). In terms of social benefits, studies in cities worldwide have shown that green spaces help to reduce stress levels (Cackowski and Nasar 2003) and promote the social integration of older adults and children, especially in a multi-ethnic context (Castonguay and Jutras 2008, Seeland *et al.* 2009). Other authors have also claimed that the presence of vegetation increases property values (Anderson and Cordell 1988, Kong *et al.* 2007).

Land managers are thus facing the challenge of maintaining and creating green spaces, particularly in densely built cities

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(Bjerke *et al.* 2006). Consequently, it is imperative that decision makers understand which types of green space (parks or tree-lined streets) and which shapes and distributions of trees and lawn people prefer. Since the 1970s, environmental perception and preference studies have been addressing these key questions (Kaplan 1985). Presently, several approaches are used to examine the relationship between people's perceptions and various characteristics of urban vegetation, like their dimension, texture, color and distribution. Architecture and urban design studies use pictures of different types of green spaces and ask people to evaluate them (Serpa and Muhar 1996, Muderrisoglu *et al.* 2006, Lange *et al.* 2008). As the evaluation is based on simulated pictures of urban vegetation and the interviewees do not usually live in the urban environment under investigation, the preferences that are assessed may not reflect how urban vegetation would actually influence their daily activities and perceptions.

In another approach, preferences are determined by studying the satisfaction felt towards green spaces by the people who actually live or spend time in these areas (Ahmed and Hassan 2003). For example, Lee *et al.* (2008) investigated the relationship between residents' satisfaction with their neighbourhood and landscape metrics of green space structure measured at the neighbourhood scale. While this approach provides more quantitative information about landscapes than the first one, the choice of metrics was not based on a statistical analysis and the chosen metrics may be highly correlated, thus leading to misinterpretations. Therefore, we need to refine this approach if we want to gain a better understanding of residents' preferences for green spaces in their neighbourhoods.

To our knowledge, there are very few studies for tropical cities or developing countries on human preferences or perceptions of green spaces. While one study investigated people's perception of the value of urban green spaces in Bangladesh, it did not evaluate their level of satisfaction (Ahmed and Hassan 2003). Nevertheless, developing countries, in Asia in particular, are facing rapid urbanization with an annual rate of 1.24% comparatively to 0.30% in Europe and North America (UN 2008: 5). In Vietnam, for example, in the next 25 years, estimated annual urban growth is estimated to a 6%, which should boost the urbanization rate of the country from 30% to 50% (MoC 2009). Since the beginning of economic reforms in 1986, rapid urbanization and inefficient urban planning, especially in Hanoi, have resulted in a lack of public places, densification and demolition of heritage buildings (Drakakis-Smith and Kilgour 2001, Quang and Detlef Kammeier 2002). These problems, which are typical of big cities in developing Asian countries (Ahmed and Hassan 2003), have a major impact on people's quality of life. Understanding how these transformations in urban structure influence people's satisfaction may allow decision makers to find alternatives in urban designs and call for more political investments in

improving the quality of life of city inhabitants.

In this study, our main objective is to understand how residents' satisfaction varies as a function of the spatial distribution of vegetation in their neighbourhood, and more specifically its relationship to the size, shape and connections between groups of trees, taking Hanoi as the study area. Our three goals are to: 1) map urban green spaces, especially parks and tree-lined streets, with very high resolution optical images; 2) select relevant metrics; and 3) examine the association between the chosen metrics and citizens' satisfaction. In the next sections, we provide more details on these three issues.

## 2. Literature Review

### 2.1. Green Space Mapping

Remote sensing is an important tool for urban vegetation mapping; in particular, very high resolution imagery and aerial photography provide synoptic and easily updated views of extremely heterogeneous urban areas (Herold *et al.* 2003). These types of spatial data are even more handy in developing countries, where conventional data is often imprecise and hard to update and access to traditional sources of information may be limited because of organizational or budgetary reasons (Miller and Small 2003).

Very high resolution images have recently been used for identifying different types of urban vegetation, especially in combination with object-based methods (Damm *et al.* 2005, Lang *et al.* 2006, Puissant *et al.* 2006, Mathieu *et al.* 2007). The object-based approach was first applied in remote sensing by Kettig and Landgrebe in the 1970s (Kettig and Landgrebe 1976). Since the arrival of very high resolution and commercial software such as eCognition or Envi Feature Extraction, it gained more attention from the remote sensing community and became a new discipline called GEOBIA (Hay and Castilla 2008). This approach is based on the creation of image objects (the segmentation) and their classification. Segmentation consists in subdividing the image into separate regions of spatially grouped pixels that should represent meaningful objects in the real world (Benz *et al.* 2004, Bock *et al.* 2005). As to the classification, it is based, in particular in eCognition, on fuzzy membership functions or a fuzzy realization of the nearest neighbour algorithm. The software offers a wide choice of object features, such as spectral statistics, texture, shape and topological features (neighbor objects, super-level objects, etc), that can be integrated in the classification. These are main advantages of GEOBIA to deal with low spectral resolution of images and high intra-spectral variability of urban features (Herold *et al.* 2003). Burgeoning studies provide evidence that GEOBIA outperforms pixel-based methods in obtaining detailed vegetation mapping in Californian forests, in land cover and impervious surface mapping (Yu 1995, Thomas *et al.* 2003, Yuan and Bauer 2003, Bhaskaran *et al.* 2010). Last but not least, this approach

allows for the production of meaningful objects (i.e. similar to real word objects) and vectors which are easily integrated into GIS for further analysis (Benz *et al.* 2004). Therefore, we were interested in using this paradigm for the detection of urban vegetation from very high resolution images.

In most of the studies in urban vegetation mapping, two or three types of objects are classified, namely trees and/or shrubs and grasses (Table 1). Trees and grasses can be extracted with an accuracy varying from 65% to 100% depending on studies. However, the accuracy of the shrub class was usually poor (about 50%) because shrubs have a spectral response similar to that of the other two classes. The confusion is especially problematic in areas where the three classes are mixed up, for example in vacant lots, railways or gardens (Damm *et al.* 2005, Mathieu *et al.* 2007).

Other authors have attempted to improve the accuracy of urban vegetation mapping by integrating GPS measures or height information extracted from airborne laser scans during the process of segmentation and classification (for example Zhou and Troy (2008)). Nonetheless, LiDAR or height data are not always affordable or available, especially to researchers in developing countries.

Table 1. Summary of previous studies on urban vegetation mapping

| Land-use                                                       | Image     | Vegetation types                                   | Producer; user accuracy                                                    |
|----------------------------------------------------------------|-----------|----------------------------------------------------|----------------------------------------------------------------------------|
| Arid and semi-arid prairie<br>(Laliberte <i>et al.</i> , 2004) | QuickBird | Shrubs<br>Meadow                                   | Not documented                                                             |
| Urban<br>(Lang <i>et al.</i> , 2006)                           | QuickBird | Tree groups<br>Grass<br>Meadow<br>Forest           | 65%; 75%<br>57%; 36%<br>67%; 77%<br>96%; 100%                              |
| Urban<br>(Puissant <i>et al.</i> , 2006)                       | QuickBird | Trees<br>Grass                                     | 88%; 89%<br>86%; 100%                                                      |
| Urban<br>(Mathieu <i>et al.</i> 2007)                          | IKONOS    | Trees<br>Shrubs<br>Grass                           | 63%; 70%<br>49%; 59%<br>66%; 90%                                           |
| Urban (railway)<br>(Damm <i>et al.</i> 2005)                   | QuickBird | Trees and shrubs<br>Grass<br>Vegetation on railway | 64% (overall accuracy)<br>84% (overall accuracy)<br>73% (overall accuracy) |

Consequently, we expect the classification of several classes to reach an accuracy rate of 70-80% or more. Although this is not as precise as photo-interpretation, it is easy to achieve, especially with eCognition, is less labour-intensive and can be adapted and then applied to other study areas (Yu *et al.* 2006). In this study, we attempted to map two types of vegetation: tree groups located in parks and along streets,

which are the two most common types of green space in the central districts of Hanoi.

## 2.2. People's Preferences and Spatial Characteristics of Green Spaces in Urban Areas

As mentioned above, there are two main approaches used to study people's preferences for green spaces (Table 2 resuming these studies). The first approach, in architecture and urban design studies, uses real photographs or simulated pictures of different types of green spaces and people are asked about their preferences toward such photographs or pictures.

Table 2. Preference and perception studies on urban green spaces

| Authors                                       | Study site                                        | Method                                 | Urban land use        | Preferred pattern                                            |
|-----------------------------------------------|---------------------------------------------------|----------------------------------------|-----------------------|--------------------------------------------------------------|
| Tree density and placement                    |                                                   |                                        |                       |                                                              |
| Kuo <i>et al.</i> (1998)                      | Chicago (USA)                                     | Simulated pictures                     | Residential areas     | High tree density, well-maintained grass                     |
| Schroeder and Anderson (1984)                 | Chicago and Atlanta (USA)                         | Real photographs <sup>2</sup>          | Parks                 | Density varying from open lawn to closely spaced tree groups |
| Jorgensen <i>et al.</i> (2002)                | Sheffield (UK)                                    | Simulated pictures                     | Parks, streets, roads | Open woodland                                                |
| Anderson and Stokes (1989)                    | Athens and Atlanta (USA)                          | Real photographs                       | Parking lots          | Well-maintained vegetation                                   |
| Lange <i>et al.</i> (2008)                    | Zurich (Swiss)                                    | Simulated pictures                     | Urban-rural fringe    | Meadows with orchards, single trees, shrubs and forest       |
| Bjerke (2006)                                 | Trondheim (Norway)                                | Real photographs                       | Parks                 | Moderate tree density                                        |
| Tree geometry                                 |                                                   |                                        |                       |                                                              |
| Serpa (1996)                                  | Vienna (Austria); Salvador and Sao Paolo (Brazil) | Real photographs                       | Parks                 | Smaller trees and light texture                              |
| Muderrisoglu (2006)                           | Adapazari, Duzce, and Bolu (Turkey)               | Pictures drawn by hand                 | Not mentioned         | Pyramid-, conical- and round-formed trees                    |
| Both aspects (density/placement and geometry) |                                                   |                                        |                       |                                                              |
| Lee (2008)                                    | College Stations (USA)                            | Remote sensing data, landscape metrics | Not mentioned         | Abundant vegetation<br>Small and varying-sized vegetation    |

<sup>2</sup> Photographs of existing environments

Serpa and Muhar (1996) used photographic simulations to assess the influence of plant size, texture and color on people's perceptions of spatial dimensions (in two cities in Austria and Brazil). Their results showed that smaller trees and lighter textures enlarged an open space according to the perception of the study's participants. In three regions of Turkey, Muderrisoglu *et al.* (2006) found that pyramidal, conical and round-shaped trees were the most appreciated by the participants in their study. However, the evaluation of

visual attributes was also affected by other factors, such as places where the participants lived, education level, employment, gender, and income level. In Zurich (Switzerland), Lange *et al.* (2008) used five simulated landscapes to study people's preferences for landscapes at the urban-rural fringe. The best-rated scenes included vegetation elements like meadows with orchards, single trees, shrubs and forest. All of these findings demonstrated that people prefer vegetation having particular shapes and planted in particular patterns. However, people may also tend to prefer types of landscapes with which they are more familiar as opposed to others (Kaplan and Herbert 1987). In addition, several factors may have an impact on people's preferences for natural settings, such as familiarity, culture and education (Kaplan and Herbert 1987, Yu 1995, Muderrisoglu *et al.* 2006). In other words, the responses that are given by interviewees who do not live in urban environments might not accurately reflect what urban dwellers would feel.

In a second type of approach, Lee *et al.* (2008) conducted a survey on the level of residents' satisfaction towards groups of trees in their neighbourhood. The level of satisfaction was then compared to 14 landscape metrics measuring five characteristics of the vegetation patches: 1) fragmentation (measured by patch size), 2) proximity (distance between tree patches), 3) shape complexity, 4) variance of patch size (measured by the standard deviation of the patch size), and 5) connectivity<sup>1</sup>. They found that people were not only sensitive to the amount of vegetation, but also to its pattern, i.e. they prefer small and varying-sized vegetation, which is consistent with the results of previous studies (Serpa and Muhar 1996, Muderrisoglu *et al.* 2006, Lange *et al.* 2008). However, this study did not consider vegetation as a function of its usage (parks, streets or vacant lots) which may influence people's preferences differently (Bjerke *et al.* 2006). Another issue is that Lee *et al.* (2008) relied on theoretical landscape ecology to select their 14 metrics. Since different aspects of the landscape could be correlated, these metrics could be empirically redundant thus leading to misinterpretation of the results (for example Cushman *et al.* (2008)). In the next section, we discuss landscape metrics and propose ways to avoid redundancy.

### 2.3. Landscape Metrics

Landscape metrics are algorithms that measure the geometric shape and spatial configuration of landscape structures. They are widely used in landscape ecology (Turner *et al.* 2001). Many metrics are computed for entire landscapes or for specific land-cover or land-use types. Five common groups of metrics are used to characterize landscapes: 1) patch size

and density, 2) shape, 3) isolation and proximity, 4) contagion, and 5) connectivity. Because, each group contains a number of metrics which may be highly correlated, it is recommended to carefully select metrics that are not redundant (Riitters *et al.* 1995, Turner *et al.* 2001, Cushman *et al.* 2008).

Three criteria for selecting a useful set of metrics in landscape ecology have been suggested by Turner *et al.* (2001): 1) the metrics should answer a particular question or objective, 2) the measured values of the metrics should be distributed over the full range of potential values, and 3) the indexes should be relatively independent of each other. Several studies have attempted to reduce the number of landscape metrics by using statistical tools such as 3D plot (cited by Turner *et al.*, 2001), pairwise comparison (Lausch and Herzog 2002, Schindler *et al.* 2008), factor analysis, and clustering (Riitters *et al.* 1995, Cushman *et al.* 2008). In all of these methods, the metrics are selected if they are independent and if they subsume most of the variance. Despite their advantages, all of these studies were either carried out in natural forest areas or in the cases where urban vegetation was all lumped into a single class. It is therefore necessary to determine relevant landscape metrics for measuring different characteristics of urban vegetation and to uncover the relationships between the satisfaction of the population and different types of urban vegetation.

### 3. Research Hypothesis

The literature review revealed that existing studies on environmental preferences were usually conducted in developed countries, but rarely in developing countries. Thus, the main goal of this paper is to understand the preferences for urban green spaces of people living in a developing country, taking the city of Hanoi as an illustrative case. We put forward the three following hypotheses:

First, in a tropical city, like Hanoi, vegetation is crucial for reducing heat islands and creating shade (Thaiutsa *et al.* 2008). These benefits are more obvious when trees are abundant and when their canopies are large. We hypothesize that in Hanoi, people will express a higher level of satisfaction with their neighbourhoods if they have patches of trees that are abundant and large.

Second, it is shown that connected and complex shapes of tree canopy are usually perceived as natural landscapes (Lee *et al.* 2008). These structures are often favoured because they provide the feeling of being close to nature and away from the built environment, and thus bring a restorative experience. In a noisy and dense city as Hanoi, we expect that inhabitants would favour vegetation forms reminiscent of natural landscape.

Last, as trees are scarce in the study area, trees should be seen as important both in parks and along street sides. We postulate that there is no difference in preference for trees in general versus street-side trees.

<sup>1</sup>“Connectivity” is the name of a group of three metrics in FRAGSTAT: connectance index, patch cohesion index, traversability index. Other authors also use “connectedness” instead of connectance index. All the metrics' names in this paper are referred to according to their names in FRAGSTAT.

## 4. Methodology

### 4.1. Study Area

This study was conducted in Hoàn Kiếm district, one of the central districts of the city of Hanoi (Figure 1). It is composed of 18 wards covering 5.3km<sup>2</sup>. The district is densely populated with an average density of nearly 33 000 inhabitants/km<sup>2</sup> in 2001, 33 650 in 2004 and 27 800 in 2009 (Dang and Le 2004, GSO 2011). The central business district of the city is also located here, composed of governmental offices, banks, hospitals and private firms.

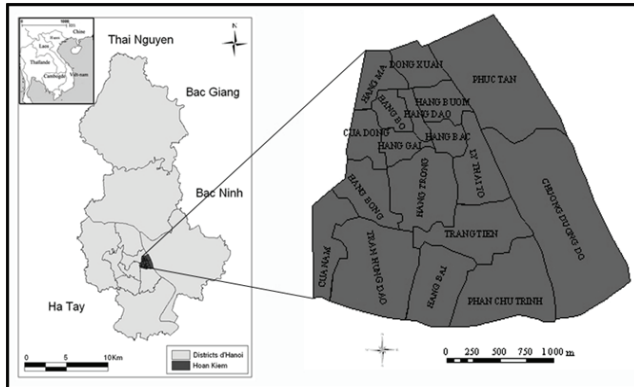


Figure 1. Location of Hanoi city and the study zone

Three quarters were distinguished according to their urban forms and street organization. In the north are Chinese-style compartments that are the small and narrow shop-houses constructed in the 19th century. The streets are narrow and meandering and trees are scarce (Procacci and Luong 2007, Tô 2008). In the south of the zone, there is a quarter constructed during the French colonization (1888-1954). The streets follow a regular checkerboard grid and are well-vegetated (Procacci and Luong 2007). Small houses and spontaneous settlements with sparsely scattered trees are located in the eastern quarter, in which a few agricultural fields are found along the Red River. A recent study demonstrated that between 1996 and 2003, urban green spaces in Hanoi became smaller and more fragmented (Pham and Nakagoshi 2008). Other studies have also outlined a number of environmental problems in the city, such as flooding, traffic jams, and air and noise pollution, caused by inefficient urban planning and management (Drakakis-Smith and Kilgour 2001, O'Rourke 2005). More research on people's perception and preferences is needed to understand the impact of these problems on quality of life in Hanoi.

### 4.2. Data

The satellite data used is a QuickBird image acquired on November 5, 2002. The image has four spectral bands varying from blue (0.45-0.52  $\mu\text{m}$ ), green (0.52-0.60  $\mu\text{m}$ ), red (0.63-0.69  $\mu\text{m}$ ) to near-infrared bands (0.76-0.90  $\mu\text{m}$ ). These bands were fused with the panchromatic band (0.450-0.900  $\mu\text{m}$ ) to obtain a finer spatial resolution of 0.7m for all of the

four spectral bands.

The satisfaction map was built based on face-to-face interviews with household members conducted between January and March of 2005 as part of the Comprehensive Urban Development Programme in Hanoi Capital City (HAIDEP), a collaborative project between Vietnam and Japan. Residents were asked about their level of satisfaction towards urban green spaces located in their neighbourhoods. Their satisfaction was assessed on a four-level scale: "not satisfied" (coded as 1), "so so" (2), "satisfied" (3) and "very satisfied" (4). The zoning of the survey area was based on wards (*phường*), which is the smallest administrative unit in Vietnam (HAIDEP 2005).

### 4.3. Vegetation Mapping Method

Firstly, we identified three classes of urban vegetation to be extracted from the study area: 1) tree groups in parks, 2) tree groups along street-sides, and 3) individual trees, which are sparse and isolated. In the image, the three classes are distinguished by their color, texture, size and shape. Parks are composed of large tree groups, while tree groups along the streets look like long and narrow polygons. Individual trees are identified by the size of their canopy. These characteristics of the three classes were transformed into rules and integrated into the classification that we describe below. These characteristics are important information to be integrated into the image classification. We carried out the classification with the help of the Definiens 5.0 software.

Image analysis using object-oriented approach follows three steps: segmentation (or creation of the objects), classification of the objects, and validation.

In the **segmentation** step, we created homogenous objects with a Definiens algorithm which minimizes the overall heterogeneity of objects. The algorithm is a function of several parameters which are defined by the users during the segmentation step, including scale factor, bands, color and shape weights, and compactness and smoothness weights (Baatz *et al.* 2004). The scale factor is related to the size of the objects that one would like to obtain. As the three classes of interest were of different sizes, we segmented the image with three different values for the scale factor (Figure 2).

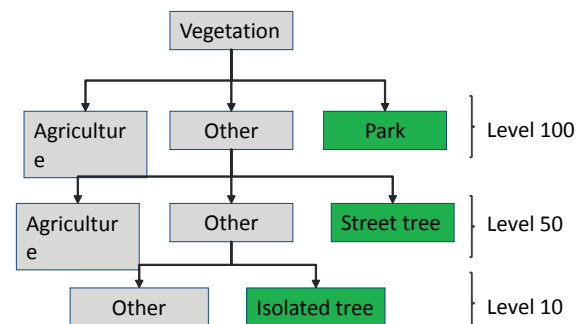


Figure 2. Scheme of segmentation and classification

We tested the segmentations on a new band of the NDVI (*Normalized Difference Vegetation Index*) and combinations of the NDVI with the four original bands. The NDVI band is calculated by the following equation:

$$NDVI = \frac{NIR - R}{NIR + R}$$

Where NIR and R are the spectral values in the near-infrared and red bands, respectively.

The best accuracy was found with the segmentation on the NDVI band.

The third parameter of the segmentation algorithm, the color and shape ratio, was weighted from 0 to 1; this parameter determined the contribution of spectral and shape values to the overall heterogeneity of the objects. As the color of the vegetation was quite different from the other categories of land use, we favoured the color parameter when segmenting the image in order to identify the vegetation. The weight for the color was set to 1 while the shape parameter was tested with values varying from 0 to 1. The last parameter determining the shape of the objects, the compactness and smoothness ratio, was weighted from 0 to 1. A high compactness index produced objects with meandering edges which can lead to over-segmentation. We conducted several empirical tests on color/shape and compactness/smoothness parameters in order to find the best parameters for the segmentation. The best combination was color/shape = 1/0, compactness/smoothness = 0/1.

Concerning the **classification**, the objects were classified by different types of features (Table 3). Values and feature choice were chosen according to our knowledge of the study area and to empirical tests. For further detail on features, see the Definiens guide (Definiens 2009). Taking the *park tree* class as an example, objects, obtained at the level of 100, could be classified as *park trees* if they satisfied five rules. One of the rules states that the average NDVI value of each object should be higher than 0.35 (meaning that the object contains essentially vegetation). We also set other rules indicating a weak homogeneity and an important areal surface for this class. Finally, we had chosen a rule wanting that at finer scales (level 50 and 10); all objects segmented from the *park trees* objects (earlier classified at level 100) had to be assigned to the class *park trees*.

**A validation** of the classification was conducted on objects representing groups of pixels, rather than on points representing individual pixels, as suggested by Platt and Rapoza (2008) and Mathieu *et al.* (2007). We chose test zones for each of the four classes of green space and digitized the classes with reference to our knowledge of the study zone. Finally, we compared the classification to the digitized polygons of each class (Figure 3) to assess the accuracy of the classification.

Table 3. Features used to classify the three classes of urban green spaces

| <i>Park</i>                           | <i>Street-side trees</i>     | <i>Isolated trees</i>                     |
|---------------------------------------|------------------------------|-------------------------------------------|
| NDVI > 0.35                           | NDVI > 0.31                  | NDVI > 0.31                               |
| Homogeneity < 0.155                   | Perimeter > 36m              | Perimeter < 70m                           |
| (band 4, dir 0)                       | Length/Width < 23m           | Length/Width < 3m                         |
| Area > 1 500 m <sup>2</sup>           | Distance to <i>park</i> > 1m | Existence of <i>street-side trees</i> = 0 |
| Width > 6m                            |                              |                                           |
| Relation to object of super scale = 1 |                              |                                           |

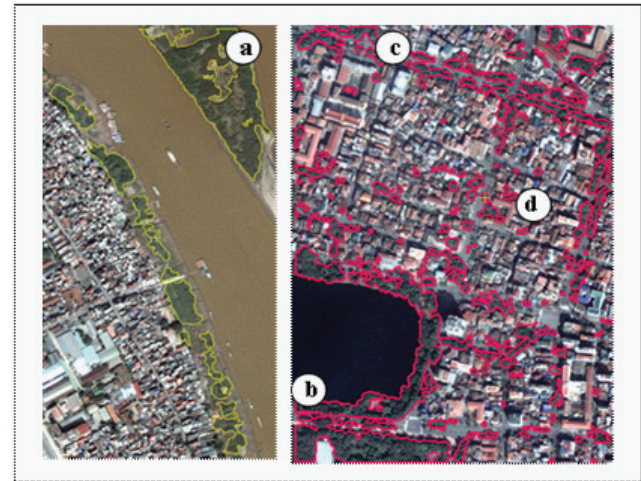


Figure 3. a) Agricultural zones, b) Park trees, c) Street-side trees, d) Isolated trees

#### 4.4. Metrics

The calculation and analysis of the metrics were only applied to the classes referred to as *all trees* and *street-side trees* because the accuracy of the class *isolated trees* was not satisfactory; in addition, *park trees* were only present in eight wards of the study area. For each of the two classes (*all trees* and *street-side trees*), we used FRAGSTAT 3.3 to compute 36 metrics that belonged to five groups: 1) size and density, 2) shape complexity, 3) isolation and proximity, 4) fragmentation, and 5) connectivity. Further descriptions of the metrics can be found in McGarigal *et al.* (2002). Correlations computed on these metrics showed that they are intercorrelated (Table 4).

In order to reduce the redundancy of the metrics, we used the pairwise comparison method (adapted from Lausch and Hergoz (2002) and Schindler *et al.* (2008)). For each pair of metrics, we looked at the correlation between them. If the correlation between two metrics was strong enough (at  $p\text{-value} \leq 0.05$ ,  $R = \pm 0.39$ ), we kept the one that showed lower correlations with the rest of the metrics. Moreover, if a

Table 4. Metrics and their correlations

| Group                   | Metrics   |                                                              | Number of correlations (of 35 metrics) |                  |
|-------------------------|-----------|--------------------------------------------------------------|----------------------------------------|------------------|
|                         | Acronym   | Name                                                         | All trees                              | Street-side tree |
| Patch size, density     | CA        | Class area                                                   | 28                                     | 32               |
|                         | PD        | Patch density                                                | 14                                     | 32               |
|                         | LSI       | Landscape shape index                                        | 11                                     | 31               |
|                         | AREA_MN   | Mean patch size                                              | 30                                     | 32               |
|                         | AREA_AM   | Area-weighted mean patch size                                | 29                                     | 33               |
|                         | AREA_CV   | Patch size coefficient of variation                          | 30                                     | 33               |
|                         | GYRATE_MN | Mean radius of gyration                                      | 29                                     | 34               |
|                         | GYRATE_AM | Area-weighted mean radius of gyration                        | 29                                     | 32               |
|                         | GYRATE_CV | Coefficient of variation of radius of gyration               | 28                                     | 33               |
| Shape                   | SHAPE_MN  | Mean shape index                                             | 13                                     | 31               |
|                         | SHAPE_AM  | Area-weighted mean shape index                               | 26                                     | 31               |
|                         | SHAPE_CV  | Shape index coefficient of variation                         | 29                                     | 30               |
|                         | FRAC_MN   | Mean fractal dimension index                                 | 28                                     | 11               |
|                         | FRAC_AM   | Area-weighted mean fractal dimension index                   | 18                                     | 30               |
|                         | FRAC_CV   | Fractal dimension index coefficient of variation             | 31                                     | 25               |
|                         | PARA_MN   | Mean perimeter: area ratio                                   | 29                                     | 11               |
|                         | PARA_AM   | Area-weighted mean perimeter-area ratio                      | 13                                     | 33               |
|                         | PARA_CV   | Perimeter-area ratio coefficient of variation                | 27                                     | 34               |
|                         | CONTIG_MN | Mean contiguity                                              | 27                                     | 11               |
|                         | CONTIG_AM | Area-weighted mean contiguity                                | 30                                     | 33               |
|                         | CONTIG_CV | Contiguity coefficient of variation                          | 9                                      | 18               |
|                         | PAFRAC    | Perimeter-area fractal dimension                             | 31                                     | 29               |
| Isolation/Proximity     | PROX_MN   | Mean proximity                                               | 30                                     | 32               |
|                         | PROX_AM   | Area-weighted mean proximity                                 | 30                                     | 33               |
|                         | PROX_CV   | Proximity coefficient of variation                           | 31                                     | 15               |
|                         | ENN_MN    | Mean Euclidean nearest-neighbor distance                     | 21                                     | 35               |
|                         | ENN_AM    | Area-weighted mean Euclidean nearest-neighbor distance       | 19                                     | 34               |
|                         | ENN_CV    | Euclidean nearest-neighbor distance coefficient of variation | 16                                     | 5                |
| Contagion Interspersion | CLUMPY*   | Clumpiness index                                             | 12                                     | 24               |
|                         | PLADJ     | Percentage of like adjacencies                               | 23                                     | 33               |
|                         | DIVISION  | Division (redundant with MESH)                               | 31                                     | 30               |
|                         | MESH      | Effective mesh size                                          | 27                                     | 32               |
|                         | SPLIT     | Split                                                        | 31                                     | 31               |
|                         | AI        | Aggregation index                                            | 26                                     | 32               |
| Connectivity            | CONNECT   | Connectance                                                  | 27                                     | 31               |
|                         | COHESION  | Patch cohesion                                               | 27                                     | 32               |

\*) For all trees, we computed the CONTAG metric (Contagion index)

given group of metrics were all intercorrelated, we chose the one that was most easily interpreted to represent the group. For example, for the group of connectivity of *all trees*, CONNECT was selected to represent the group. Following this approach, we obtained six metrics PD, SHAPE\_MN, CONTIG\_MN, ENN\_CV, CONTAG and CONNECT for *all trees*. Six other metrics were also chosen for *street-side trees*: AREA\_MN, FRAC\_MN, PARA\_MN, PROX\_CV, ENN\_CV and CONNECT (see Table 4 for the full names of the metrics).

## 4.5. Correlation with Satisfaction Levels

We correlated each of the retained landscape metrics with the level of the residents' satisfaction towards urban green spaces. As satisfaction was evaluated on a rank scale, we conducted the comparison with a Spearman correlation designed for ordinal data.

## 5. Results and Discussion

### 5.1. Image Processing

The final classification is shown in Figure 4. The confusion matrix shows that the vegetation classes were obtained with a reasonable accuracy (Table 5). The average accuracy of *park trees* and *street-side trees* was 87% and 73%, which is slightly higher than what is reported in the studies of Lang *et al.* (2006), Damm *et al.* (2005), and Mathieu *et al.* (2007). This level of accuracy may be due to the fact that there was no lawn in our study area, and consequently no confusion between lawn and trees. The accuracy of the *isolated trees* class was low because the resolution of the image was not fine enough to detect small-sized trees, as already noted by Laliberte *et al.* (2004) and Damm *et al.* (2005).

### 5.2. Metric Selection and Satisfaction Comparison

The correlation coefficients for *all trees* showed that the satisfaction levels were not correlated to metrics of patch size, proximity nor connectivity (Table 6). Satisfaction levels were significantly correlated to the patch density of vegetation, which is the number of patches per hectare. In the study site, the patch density varied from 51 to 563 patches/ha (Figure 5). The highest density was found in the areas around and to the south of Hoàn Kiếm Lake (in the French Quarter) and some wards to the west. These areas had more trees in parks and along the streets. The lowest density of patches was found in the north (in the Old Quarter) and in the east, where trees are scarce or even absent. Not surprisingly, people seemed to be more satisfied in areas where there were abundant patches of vegetation, whether or not they were park trees or street-lined trees.

Table 5. Confusion matrix

|                   | Interpretation   |                 |                 |                |           |           |
|-------------------|------------------|-----------------|-----------------|----------------|-----------|-----------|
|                   | No               | Park            | Street-side     | Isolated       | Total     | User acc. |
|                   | vegetation       |                 | trees           | trees          |           |           |
| No vegetation     | <b>284085.83</b> | 5050.43         | 10856.44        | 6710.06        | 306702.76 | 0.93      |
| Park              | 1046.64          | <b>26043.50</b> | 0.00            | 0.00           | 27090.14  | 0.96      |
| Street-side trees | 4511.92          | 1886.99         | <b>25716.67</b> | 532.14         | 32647.72  | 0.79      |
| Isolated trees    | 866.81           | 365.54          | 1465.59         | <b>2212.84</b> | 4910.78   | 0.45      |
| Total             | 290511.20        | 33346.46        | 38038.70        | 9455.04        | 371351.40 |           |
| Producer acc.     | 0.98             | 0.78            | 0.68            | 0.23           |           |           |



Figure 4. Classification of four urban green spaces in the study area

Table 6. Correlations between metrics and satisfaction levels (retained after filtering)

|                          | Correlation | p-value |
|--------------------------|-------------|---------|
| <i>All trees</i>         |             |         |
| PD                       | 0.42**      | 0.04    |
| SHAPE_MN                 | 0.20        | 0.21    |
| CONTIG_MN                | 0.12        | 0.32    |
| ENN_CV                   | 0.23        | 0.18    |
| CONTAG                   | 0.17        | 0.25    |
| CONNECT                  | -0.28       | 0.13    |
| <i>Street-side trees</i> |             |         |
| AREA_MN                  | 0.56**      | 0.01    |
| FRAC_MN                  | 0.44**      | 0.04    |
| PARA_MN                  | -0.34*      | 0.08    |
| PROX_CV                  | -0.23       | 0.18    |
| ENN_CV                   | 0.10        | 0.35    |
| CONNECT                  | -0.08       | 0.37    |

\*: significant at  $p \leq 0.05$ , \*\*: significant at  $p \leq 0.1$

We observed more significant correlations for the street-side trees. For example, the correlation between satisfaction and patch area was very high ( $R=0.56$ , significant at  $p\text{-value}=0.01$ ). The largest patches of street-side trees were observed in the French Quarter and in some wards to the west (mean patch size of 0.04 ha), whereas the smallest patches were located in the Old Quarter (mean patch size of 0.01ha). Also, a strong correlation between satisfaction levels with the Mean Fractal Dimension (FRAC\_MN) ( $R=0.44$ ) revealed that people tended to prefer tree groups with complex shapes compared to those with simple shapes. The third correlation, between the Mean Perimeter-Area Ratio (PARA\_MN) and satisfaction, was negative and less important ( $R=0.34$ ). It may reflect low satisfaction in wards where the tree groups had a complex shape (high value of PARA\_MN). This correlation is contrary to the one that we observed above with the Mean Fractal Dimension. However, it was suggested by the authors of FRAGSTAT that when the patch size is small, the PARA\_MN may not be able to adequately describe the patch complexity due to the formulation of this metric (McGarigal *et al.* 2002). Therefore, we believe this correlation is not reliable. The last two metrics, connectance and proximity, were not correlated with satisfaction levels.

In order to compare our results with those of previous studies, we also looked at other metrics used in the work of Lee *et al.* (2008) (Table 7). These metrics were highly correlated with the metrics that we presented in Table 4, especially with the Patch Density and Mean Area in the case of *street-side trees*.

Table 7. Correlations between metrics and satisfaction levels (suggested by Lee *et al.* (2008))

|          | <i>All trees</i> |         | <i>Street-side trees</i> |         |
|----------|------------------|---------|--------------------------|---------|
|          | Correlation      | p-value | Correlation              | p-value |
| SHAPE_MN | 0.20             | 0.21    | 0.51**                   | 0.02    |
| SHAPE_AM | 0.37*            | 0.07    | 0.71**                   | 0.00    |
| SHAPE_CV | 0.36*            | 0.07    | 0.66**                   | 0.00    |
| ENN_MN   | -0.46**          | 0.03    | -0.44*                   | 0.03    |
| ENN_AM   | -0.43**          | 0.04    | -0.53**                  | 0.01    |
| ENN_CV   | 0.23             | 0.18    | 0.10                     | 0.35    |
| COHESION | 0.11             | 0.33    | 0.67**                   | 0.00    |

\*: significant at  $p \leq 0.05$ , \*\*: significant at  $p \leq 0.1$

Table 7 reports four common correlations between satisfaction levels and the metrics measuring *all vegetation* and *street-side trees* (SHAPE\_AM, SHAPE\_CV, ENN\_MN and ENN\_AM). The correlations with the metrics measuring *street-side trees* are the strongest. The relationship between these metrics and residents' satisfaction levels was quite similar to the findings of Lee *et al.* (2008). The SHAPE

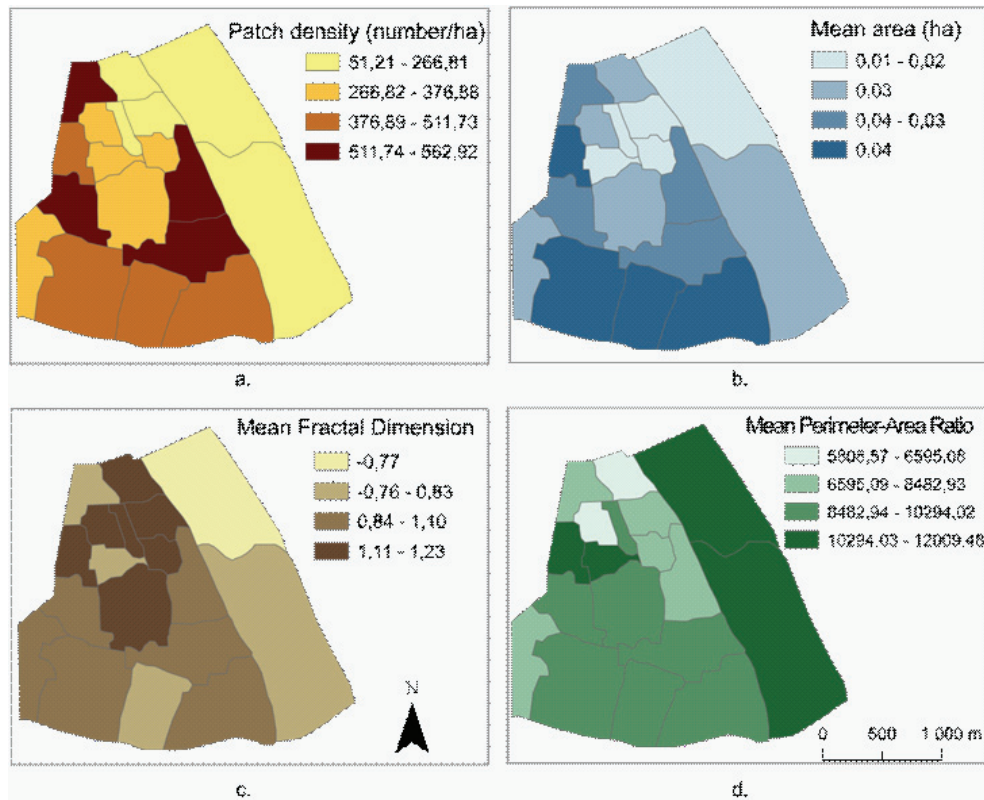


Figure 5. Four metrics having significant correlations with satisfaction (a: Patch density of *all trees*, b: Mean Patch Area, c: Fractal Dimension, d: Perimeter-Area of *street-side trees*)<sup>4</sup>

metrics showed positive correlations with satisfaction, meaning that people were more satisfied in areas where tree groupshad varied and complex shapes, especially along streets. The Euclidian distance metrics showed negative correlations with the satisfaction levels, meaning that satisfaction tended to increase in areas where tree patches were close to each other.

Two other metrics applied on *street-side trees* found correlated with residents' satisfaction are SHAPE\_MN (the Mean Shape Index) and COHE (patch cohesion). The former correlation confirms again that satisfaction tended to increase when trees along streets were of complex shape. The latter can be interpreted as a higher satisfaction when there are more aggregated tree patches, which is consistent with Lee *et al.* (2008). Nonetheless, bearing in mind that COHE may not be sensitive to patch configuration (McGarigal *et al.* 2002) and that it is the only connectivity metric that correlates with satisfaction, we think that this association needs to be investigated with more data.

$$^4PD = \frac{n_i}{A} * 10\,000 * 100; AREA = \frac{a_{ij}}{10\,000}; FRAC = \frac{2 * \ln(0.25 * n_{ij})}{\ln a_{ij}}; PARA = \frac{p_{ij}}{a_{ij}}$$

where  $n_i$  is the number of patches in the landscape of patch class  $i$ ,  $A$  ( $m^2$ ) is the total area,  $a_{ij}$  is the area ( $m_2$ ) of patch  $ij$ ,  $p_{ij}$  is the perimeter ( $m$ ) of patch  $ij$ .

## 6. Concluding Remarks

By investigating the link between residents' satisfaction and the greenscapestructure of their neighbourhoods, we attempted to gain insight into the configuration of trees in urban environments that satisfies people the most. In this research, we have used interdisciplinary tools and data such as remote sensing images, household surveys, and landscape ecology metrics.

Our results confirmed that very high resolution remote sensing is an effective means for measuring urbanvegetation. We also demonstrated that object-oriented method is useful for identifying different types of urban vegetation with good accuracy. Such an approach could open up a wide range of applications in urban environment studies,including environmental inventories, monitoring and intervention, ensuring equity in the distribution of greenery across cities.

Correlations computed on the metrics showed that a careful selection of landscape metrics is needed, as they are strongly inter-correlated. We recommend filtering the metrics in each group (patch size and density; shape; isolation and proximity; contagion; connectivity) before integrating them in further statistical analysis.

As hypothesized, satisfaction increasedin areas where tree groups were more prevalent, aggregated, and of variable

sizes, whether or not they were in parks or along street-sides. The impact of the distribution of *street-side trees* on residents' satisfaction was higher than that for *all trees*. Furthermore, large street-side trees with complex shapes were preferred. These findings resonate with the preferences for tree configurations documented in Western literature, but the preferences seem to be even more strongly expressed in Hanoi probably due to the need for shade in the hot and sunny summer. Particularly in areas lacking green spaces, it is important to preserve existing trees and plant more, notably in the northern parts (the Old quarter) and eastern parts (along the Red river) of Hoàn Kiếm district. As *street-side trees* were highly preferred among local residents, we recommend prioritizing the planting of trees along sidewalks in areas like the Old Quarter where there is almost no land available for new parks.

The fact that this study was restricted to 18 wards limits both its statistical significance and its potential for examining the relationships between residents' satisfaction and landscape structure. A more in-depth survey would allow a deeper understanding of residents' perception of urban green spaces, for example, by examining differences amongst social classes. Lastly, while the associations between satisfaction and spatial configuration of tree groups are statistically significant, we can only infer to what people might prefer. More qualitative research would enable us to validate the interpretations of these associations.

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## References

- Ahmed, M. R. and Hassan, R. (2003). People's perception toward value of urban greenspace in environmental development. In *XII World Forestry Congress*, September 23-30, 2003, Québec city.
- Anderson, L. M. and Cordell, H. K. (1988). Influence of trees on residential property values in Athens, Georgia (U.S.A.): a survey based on actual sales prices. *Landscape and Urban Planning*, 15, 153-164.
- Anderson, L. M. and Stokes, G. S. (1989). Planting in parking lots to improve perceived attractiveness and security. *Journal of Arboriculture*, 15 (1), 7-11.
- Baatz, M., Benz, U. C., Dehshani, S., Heynen, M., Höltje, A., Hofmann, P., Lingenfelder, I., Mimler, M., Sohlbach, M., Weber, M., Willhauck, G. and GmbH, D. I. (2004) *eCognition Professional, Userguide version 4.0*. pp. München:
- Benz, U. C., Hofmann, P., Willhauck, G., Lingenfelder, I. and Heynen, M. (2004). Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry & Remote Sensing*, 58, 239-258.
- Bhaskaran, S., Paramananda, S. and Ramnarayan, M. (2010). Per-pixel and object-oriented classification methods for mapping urban features using Ikonos satellite data. *Applied Geography*, 30, 650-665.
- Bjerke, T., Østdahl, T., Thrane, C. and Strumse, e. (2006). Vegetation density of urban parks and perceived appropriateness for recreation. *Urban Forestry and Urban Greening*, 5, 35-44.
- Bock, M., Xofis, P., Mitchley, J., Rossner, G. and Wissen, M. (2005). Object-oriented methods for habitat mapping at multiple scales – Case studies from Northern Germany and Wye Downs, UK. *Journal for Nature Conservation*, 13, 75-89.
- Cackowski, J. M. and Nasar, J. L. (2003). The restorative effects of roadside vegetation: implications for automobile driver anger and frustration. *Environment and Behavior*, 35 (6), 736-751.
- Castonguay, G. and Jutras, S. (2008). Children's appreciation of outdoor places in a poor neighborhood. *Journal of Environmental Psychology*, 29 (1), 101-109.
- Cushman, S. A., McGarigal, K. and Neel, M. C. (2008). Parsimony in landscape metrics: Strength, universality, and consistency. *Ecological Indicators*, 8, 691-703.
- Damm, A., Hoster, P. and Schiefer, S. (2005). Investigating urban railway corridors with geometric high resolution satellite data. In *ISPRS, Remote Sensing and Spatial Information Sciences*, 14-16 March, Tempe.
- Dang, X. D. and Le, H. K. (2004). La population de Hanoi. In P. Gubry (Eds.), *Population et développement au Viêt-nam*, pp. 243-262. Hanoi: La maison d'édition du monde.
- Definiens (2009) *eCognition Developer 8 - User Guide*. München, Germany: Definiens.
- Drakakis-Smith, D. and Kilgour, A. (2001). Sustainable urbanisation and environmental issues in Vietnam. In N. W. Adger, M. P. Nelly and H. N. Nguyen (Eds.), *Living with environmental change: Social vulnerability, adaption and resilience in Vietnam*, pp. 213-233. London and New York: Taylor and Francis Group.

- GSO (2011) *Population Survey*. Ha Noi: General Statistics Office of Viet Nam.
- HAIDEP (2005) *Hanoi environment fact book: Opinions of 20 000 households*. Hanoi: Hanoi People Commity, Japan International Cooperation Agency.
- Hay, G. J. and Castilla, G. (2008). Geographic object-based image analysis (GEOBIA): A new name for a new discipline. In T. Blaschke, S. Lang and G. J. Hay (Eds.), *Object-based image analysis: Spatial concepts for knowledge-driven remote sensing applications*, pp. 75-90. Berlin Heidenberg: Springer-Verlag.
- Herold, M., Gardner, M. E. and Roberts, D. A. (2003). Spectral resolution requirements for mapping urban areas. *IEEE transactions on geoscience and remote sensing*, 41 (9), 1907-1919.
- Jorgensen, A., Hitchmough, J. and Calvert, T. (2002). Woodland spaces and edges: their impac on perception of safety and preference. *Landscape and Urban Planning*, 60, 135-150.
- Kaplan, R. (1985). The analysis of perception via preference: A strategy for studying how the environment is experienced *Landscape Planning*, 12 (2), 161-176.
- Kaplan, R. and Herbert, E. J. (1987). Cultural and sub-cultural comparision in preferences for natural settings. *Landscape and Urban Planning*, 14, 281-293.
- Kettig, R. L. and Landgrebe, D. A. (1976). Classification of multispectral image data by extraction and classification of homogeneous objects. *IEEE Transactions on Geoscience Electronics*, GE-14 (1), 19-26.
- Kong, F., Yin, H. and Nakagoshi, N. (2007). Using GIS and landscape metrics in the hedonic price modeling of the amenity value of urban green space: A case study in Jinan City, China. *Landscape and Urban Planning*, 79, 240-252.
- Kuo, F. E., Bacaicoa, M. and Sullivan, W. S. (1998). Transforming inner-city landscape: Trees, senses of safety, and preference. *Environment and behavior*, 30 (1), 28-39.
- Lang, S., Jekel, T., Hölbling, D., Schöpfer, E., Prinz, T., Kloyber, E. and Blaschke, T. (2006). Where the grass is greener - mapping of urban green structures according to relative importance in the eyes of the citizens. In *First Workshop of the EARSeL - Special Interest Group on Urban Remote Sensing*, 2-3 March, Berlin.
- Lange, E., Hehl-Lange, S. and Brewer, M. (2008). Scenario-visualization for the assessment of perceived green space qualities at the urban-rural fringe. *Journal of environmental management*, 89 (3), 245-256.
- Lausch, A. and Herzog, F. (2002). Applicability of landscape metrics for the monitoring of landscape change: issues of scale, resolution and interpretability. *Ecological Indicators*, 2, 3-15.
- Lee, S.-W., Ellis, C. D., Kweonb, B.-S. and Hong, S.-K. (2008). Relationship between landscape structure and neighborhood satisfaction in urbanized areas. *Landscape and Urban Planning*, 85, 60-70.
- Mathieu, R., Aryal, J. and Chong, A. K. (2007). Object-based classification of Ikonos imagery for mapping large-scale vegetation communities in urban areas. *Sensors*, 7, 2860-2880.
- McGarigal, K., Cushman, S. A., Neel, M. C. and Ene, E. (2002) *FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps*. pp. Amherst: Computer software program produced by the authors at the University of Massachusetts.
- McPherson, G., Simpson, J. R., Peper, P. J., Maco, S. E. and Xiao, Q. (2005). Municipal forest benefits and costs in five U.S. cities. *Journal of Forestry*, 103 (8), 411-416.
- Miller, R. B. and Small, C. (2003). Cities from space: potential applications of remote sensing in urban environmental research and policy. *Environmental Science & Policy*, 6, 129-137.
- MoC (2009) *Directions of urban development planning in Viet Nam by 2025 and perspectives for 2050 (Định hướng quy hoạch tổng thể phát triển đô thị Việt Nam đến năm 2025 và tầm nhìn đến năm 2050)*. Ha Noi: Ministry of Construction.
- Muderrisoglu, H., Eroglu, E., Ozkan, S. and Ak, K. (2006). Visual perception of tree forms. *Building and Environment*, 41, 796-806.
- O'Rourke, D. (2005) *Community-driven regulation: balancing development and the environement in Vietnam*. pp. Cambridge: The MIT Press.
- Pham, D. U. and Nakagoshi, N. (2008). Application of land suitability analysis and landscape ecology to urban greenspace planning in Hanoi, Vietnam. *Urban Forestry & Urban Greening*, 7, 25-40.
- Platt, R. V. and Rapoza, L. (2008). An evaluation of an object-oriented paradigm for land use/land cover classification. *Professional Geographer*, 60, 87-100.
- Procacci, F. and Luong, T. T. (2007). Learning from KTT: Analysis of the collective residential quarters of Hanoi. In *International Conference on Sustainable Architectural Design and Urban Planning*, Hanoi. Hanoi Architectural University.

- Puissant, A., Weber, C., Sheeren, D., Wemmert, C. and Gañçarski, P. F. (2006). Amélioration des connaissances sur l'environnement urbain : intérêt de l'intégration de règles dans les procédures de classifications. In *Interactions Nature-Société, analyse et modèles*, 3-6 mai, La Baule.
- Quang, N. and Detlef Kammeier, H. (2002). Changes in the political economy of Vietnam and their impacts on the built environment of Hanoi. *Cities*, 19 (6), 373-388.
- Ridder, K. D., Adame, V., Banuelos, A., Brused, M., Burgend, M., Damsgaarde, O., Dufek, J., Hirsch, J., Lefebvre, F., Pérez-Lacorzana, J. M., Thierry, A. and Weber, C. (2004). An integrated methodology to assess the benefits of urban green space. *Science of the Total Environment*, 334-335, 489-497.
- Riitters, K. H., O'Neill, R. V., Hunsaker, C. T., Wickham, J. D., Yankee, D. H., Timmins, S. P., Jones, K. B. and Jackson, B. L. (1995). A factor analysis of landscape pattern and structure metrics. *Landscape Ecology*, 10 (1), 23-39.
- Schindler, S., Poirazidis, K. and Wrbka, T. (2008). Towards a core set of landscape metrics for biodiversity assessments: A case study from Dadia National Park, Greece. *Ecological Indicators*, 8, 502-514.
- Schroeder, H. W. and Anderson, L. M. (1984). Perception of personal safety in urban recreation sites. *Journal of Leisure Research*, 16 (2), 178-194.
- Seeland, K., Dübendorfer, S. and Hansmann, R. (2009). Making friends in Zurich's urban forests and parks: The role of public green space for social inclusion of youths from different cultures. *Forest Policy and Economics*, 11, 10-17.
- Serpa, A. and Muhar, A. (1996). Effects of plant size, texture and colour on spatial perception in public green areas- a cross-cultural study. *Landscape and Urban Planning*, 36, 19-25.
- Thaiutsa, B., Puangchit, L., Kjelgren, R. and Arunpraparut, W. (2008). Urban green space, street tree and heritage large tree assessment in Bangkok, Thailand. *Urban Forestry & Urban Greening*, 7, 219-229.
- Thomas, N., Hendrix, C. and Congalton, R. G. (2003). A comparison of urban mapping methods using high-resolution digital imagery. *Photogrammetric Engineering & Remote Sensing*, 69 (9), 963-972.
- Tô, K. (2008). Conservation pressing task and new documentation of old tube houses in Hanoi old quarter through the case of no. 47 Hang Bac street house. *Journal of Architecture and Planning*, 73 (624), 457-462.
- Turner, G., M., Gardner, R. H. and O'Neill, R. V. (2001). Quantifying Landscape Pattern. In (Eds.), *Landscape ecology in theory and practice*, pp. 93-134. New York: Springer-Verlag.
- UN (2008). World Urbanization Prospects: The 2007 Revision Highlights. Available online at: [http://www.un.org/esa/population/publications/wup2007/2007WUP\\_Highlights\\_web.pdf](http://www.un.org/esa/population/publications/wup2007/2007WUP_Highlights_web.pdf) (accessed March 1st 2011)
- Yu, K. (1995). Cultural variations in landscape preference: comparisons among Chinese sub-groups and Western design experts. *Landscape and Urban Planning*, 32, 107-126.
- Yu, Q., Gong, P., Clinton, N., Biging, G., Kelly, M. and Schirokauer, D. (2006). Object-based detailed vegetation classification with airborne high spatial resolution remote sensing imagery. *Photogrammetric Engineering & Remote Sensing*, 72 (7), 799-811.
- Zhou, W. and Troy, A. (2008). An object-oriented approach for analysing and characterizing urban landscape at the parcel level. *International Journal of Remote Sensing*, 11 (10), 3119-3135.