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Determining appropriate neighborhood shapes and sizes for modeling landscape satisfaction

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Landscape is a key factor in neighborhood satisfaction. Our aim here is to derive indicators of landscape satisfaction from land cover data; consequently the definition of the neighborhood around residential locations is of prime importance. Three shapes of neighborhood are compared in the paper, depending on individuals' relationships with their day-to-day environment: (1) a circular neighborhood representing an isotropic space; (2) a network neighborhood taking into account the potential spatial practices around the residential location; and (3) a visible neighborhood based on whether or not landscape features are in view. These neighborhoods are determined in a suburban area located near Besançon (France), where an indicator of landscape satisfaction was generated from a survey. Each neighborhood shape was used to define a series of landscape variables from a land cover map, by varying the neighborhood size to identify the most relevant spatial scales. Statistical models using correlation and regression were run to evaluate the connections between satisfaction and landscape variables. Comparisons between the models built with each neighborhood shape shows that the circular neighborhood is globally the most efficient. The results also emphasize the combination of several scales in the perception of residential environment.

1. Introduction

Neighborhood satisfaction is an important component of both residential satisfaction and global well-being (Barresi, Ferraro, & Hobey, 1984). It is based on residents' evaluation of the physical, social, and economic features of their neighborhood (Sirgy & Cornwell, 2002). The level of neighborhood satisfaction may also be determined from several types of analysis organized around two main approaches: (1) stated preferences using either satisfaction surveys (e.g. Hur, Nasar, and Chun (2010) and Ellis, Lee, and Kweon (2006)) or the contingent valuation method (Tyrväinen & Väänänen, 1998); (2) revealed preferences using the hedonic

pricing method applied to the housing market to evaluate the amenity value of environmental attributes (Cheshire & Sheppard, 1995; Cho, Poudyal, & Roberts, 2008; Lake, Lovett, Bateman, & Langford, 1998; Tyrväinen, 1997).

Many studies deal with neighborhood satisfaction in fields like sociology, psychology (Amérigo & Aragonés, 1997; Bonaiuto, Fornara, & Bonnes, 2003; Hur & Morrow-Jones, 2008), or urban planning (Ellis et al., 2006; Lovejoy, Handy, & Mokhtarian, 2010). Some of those papers focus on socio-demographic factors such as age, race, gender, or economic resources (Harris, 2001; Lu, 1999; Parkes, Kearns, & Atkinson, 2002), while others deal with the physical characteristics of the neighborhood that influence residential satisfaction (Kearney, 2006; Kim & Kaplan, 2004; Sirgy & Cornwell, 2002). Among those physical characteristics, landscape is an important feature and is related to visible amenities and to esthetic preferences.

Landscape may be thought of as a component of the physical neighborhood observed through individuals' perceptual filters.

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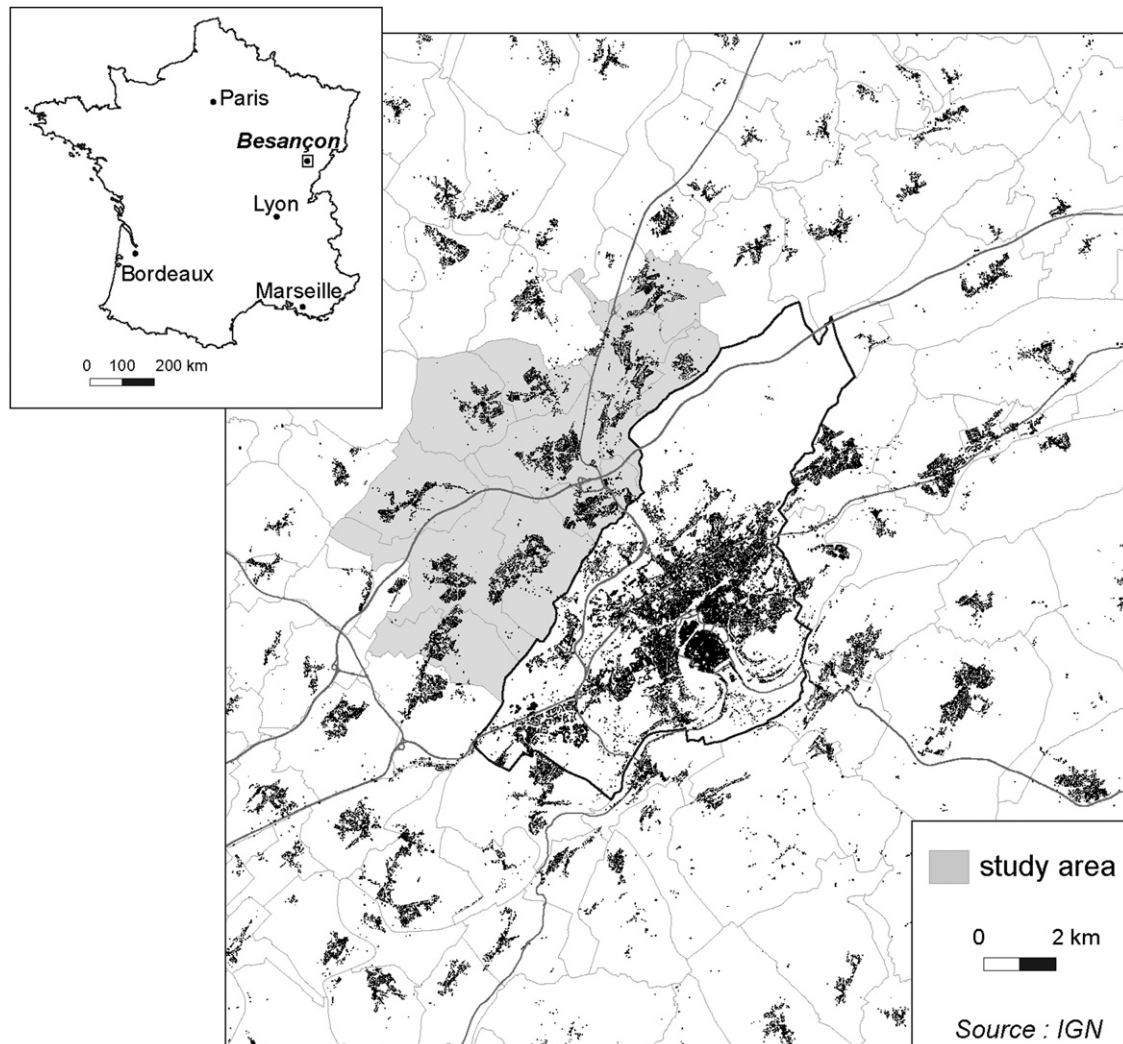


Fig. 1. The study area.

Using this approach, many researchers have measured the influence of landscape on neighborhood satisfaction, reporting the positive influence of natural features on the level of satisfaction (Ellis et al., 2006; Kaplan, 1985; Kearney, 2006; Kweon, Ellis, Leiva, & Rogers, 2010) and the negative influence of built environments (Kaplan, 2001). Many studies are based on the effect of landscape composition, measured by the presence or the frequency of different landscape features. For instance, earlier investigations have emphasized individuals' preferences for wooded lots in their neighborhood. Other studies try to assess the impact of landscape configuration on neighborhood satisfaction; however, those works fail to yield consistent results: for example, Lee, Ellis, Kweon, and Hong (2008) show that inhabitants prefer unfragmented and interconnected forest landscapes rather than small patches in their neighborhood, while Cho, Kim, Roberts, and Jung (2009) show that residents prefer neighborhoods containing relatively small patches of forest.

The analysis of the links between landscapes and neighborhood satisfaction requires relevant data with which to describe landscape features. Two main approaches can be defined, which differ according to the observer's position. The first approach is based on an in situ view and amounts to considering the landscape as it would actually be seen. This approach often relies on the analysis of landscape photos (see for example Dramstad, Tveit, Fjellstad, & Fry, 2006; Kaplan, 1987), which provide a wealth of information but

at the same time restrict the analysis to a limited set of areas. The second approach is based on a cartographic view, using geographic databases and Geographic Information Systems (GIS). Although this approach involves modeling the actual landscape by means of land cover maps and digital elevation models, it does offer the advantage of extending the landscape analysis to the entire study area. This approach seems preferable as a support for land-use planning.

Cartographically, the landscape visible from a given site can be represented by the set of features located within a given neighborhood of that site. This approach to landscape modeling involves two key points: (1) the categories used to define the features that are potentially visible; (2) the neighborhood type. The first point refers to the definition of the land cover categories and to the spatial resolution; it is highly dependent on the data sources. The second point, neighborhood type, which is defined by its shape and its size (Tomlin, 1990), depends both on the meaning given to the notion of neighborhood and on the available technical resources. The neighborhood may be circular (Kestens, Thériault, & Des Rosiers, 2004; Kong, Yin, & Nakagoshi, 2007; Kweon et al., 2010; Lee et al., 2008). This circular shape can be considered as a cognitive space in which individuals are more or less aware of the characteristics of their surroundings. However, there might be relations between the evaluation of a neighborhood and the activities carried out by the individuals in this neighborhood (Bonaiuto, Bonnes, & Continisio, 2004). Since such a circular shape may be irrelevant

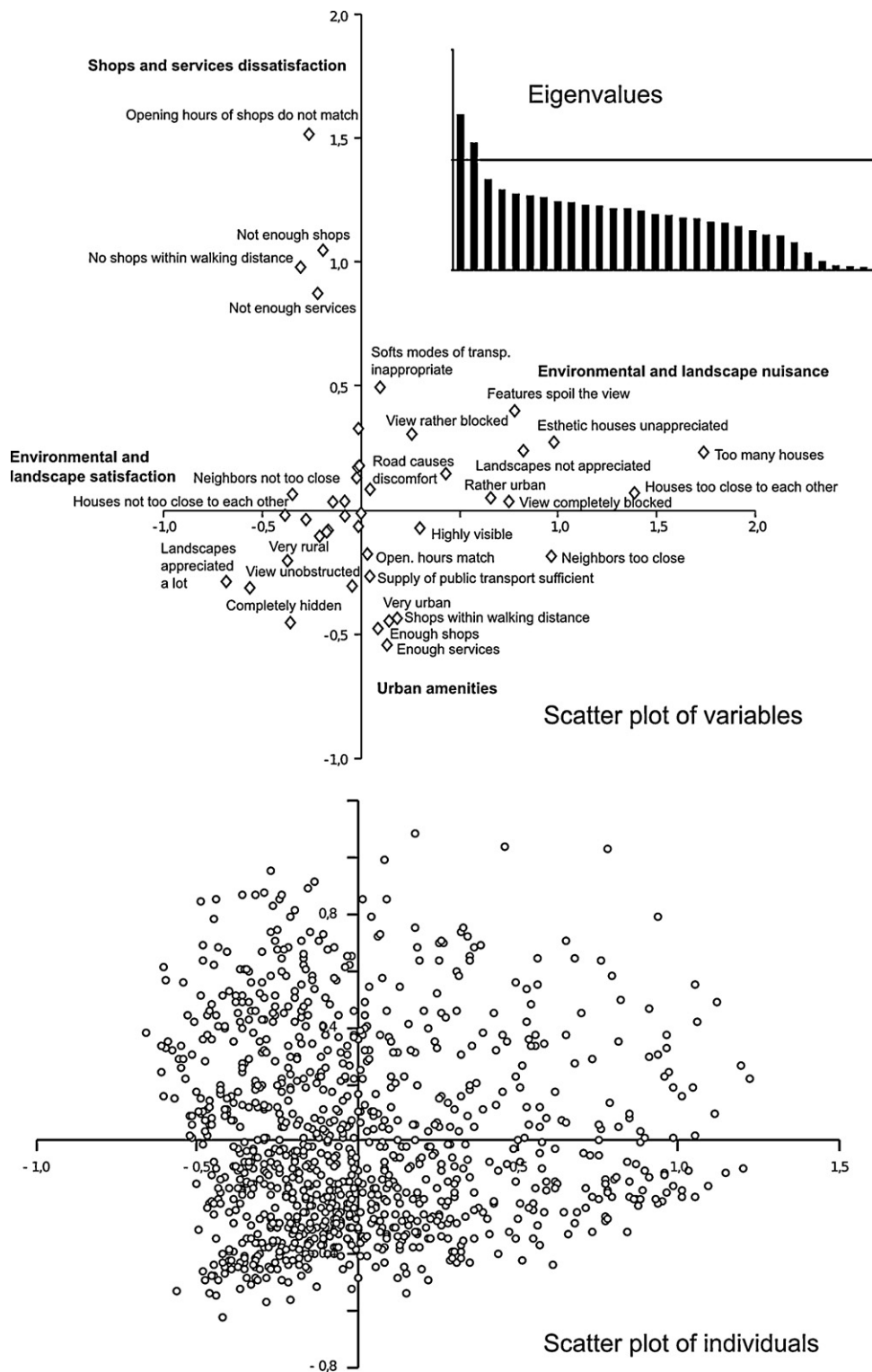


Fig. 2. The results of the MCA.

in the case of perceived or actual barriers, some authors use a network neighborhood determined by following the transportation network accessible from a given site (Hur et al., 2010). This neighborhood type assumes that the spatial practices associated with the daily mobility of individuals strongly determine the way they perceive their environment. Circular and network neighborhoods can be used to define the environment of residents as an area located in the vicinity of a site, but they omit the notion of visibility. As

visibility is a basic aspect of landscape, many previous works using GIS methods were based on a visible neighborhood to represent individuals' visual perception of the space (Cavailhès et al., 2009; Lake et al., 1998; Paterson & Boyle, 2002; Van der Horst, 2006).

Whatever its shape, the size of the neighborhood refers to the spatial scale, which, it is assumed, affects the way the environment is perceived. This issue of size also arises in the definition of socio-demographic neighborhood (Hipp, 2010; Hipp & Perrin,

Table 1

Demographic statistics of the surveyed population. All values are percentages with the exception of mean ages.

Age (years)	
Mean	50.2
15–19	2.1
20–29	6.4
30–39	15.0
40–49	25.1
50–59	23.4
60–69	16.5
Over 70	11.5
Gender	
Female	69.7
Male	30.3
Type of household	
Single person	8.5
Couple without children	12.6
Couple with children	72.5
Single-parent family	6.4
Education	
No diploma	3.1
Middle school	31.1
High school	16.8
Community college	19.0
College and graduate school	28.5
Others	1.5
Housing tenure	
Owner	84.0
Tenant	16.0

2009). Kong et al. (2007) find that a neighborhood with a 500-m radius is suitable for capturing the amenity effect of a series of landscape metrics on house prices. Lee et al. (2008) show that natural features influence the price of housing when present within a 1500 ft (457 m) circular neighborhood, while the macro-scale neighborhood of 3000 ft (914 m) is more appropriate when measuring the relationship between satisfaction and landscape structures. By using a network neighborhood, Hur et al. (2010) apply “a quarter-mile network buffer” in order to model the environment of residents within a 5-minute walk on the streets. A maximum distance must be chosen to limit computation of the visible neighborhood to the closer part of viewsheds; this distance is 500 m in Lake et al. (1998), 2000 m in Van der Horst (2006), and 280 m in Cavailhès et al. (2009).

Modeling landscapes by using cartographic data makes for more efficient analysis of the effect of landscape on neighborhood satisfaction. However, as neighborhood may be defined in many different ways, the choice of the appropriate shape and size remains difficult. The purpose of this paper is to compare the relevance of several neighborhood shapes and sizes used to compute spatial indicators of satisfaction. This comparison is based on modeling the neighborhood satisfaction of households in a suburban area, by combining a survey of satisfaction level regarding their day-to-day landscapes and spatial metrics based on land cover data. As the analysis focuses on the comparison of several shapes and sizes of neighborhood to provide significant indicators of neighborhood satisfaction, only landscape composition metrics (Gustafson, 1998; Li & Wu, 2004) are considered. The hypothesis of this study is that the more “realistic” neighborhood models (i.e. those seeking to best represent the perceived space, for example, through daily mobility) yield the more relevant indicators.

2. Materials and methods

The study area is a suburb of the city of Besançon (eastern France) (Fig. 1). Besançon is a medium-sized city where suburbanization has been on the increase since the 1970s. Currently, a suburban area of about 60,000 inhabitants surrounds the central

Table 2

The assertions used to evaluate landscape satisfaction. F1 and F2 correspond to the coordinates of the assertions in the MCA factorial space.

Assertions	MCA factors	
	F1	F2
Assessment of daily landscape		
In your neighborhood, you feel that your home is		
Completely hidden	−0.36	−0.45
A little hidden	−0.14	0.03
Rather visible	−0.02	0.13
Highly visible	0.30	−0.07
You think that the environment around your home is		
Very rural	−0.37	−0.20
Rather rural	−0.01	0.33
Rather urban	0.66	0.05
Very urban	0.18	−0.44
Around your home, you feel that the view is		
Completely blocked	0.75	0.04
Rather blocked	0.26	0.31
Rather unobstructed	−0.17	−0.09
Completely unobstructed	−0.56	−0.31
Around your home		
You do not appreciate the landscape	0.82	0.24
You rather appreciate the landscape	−0.08	0.04
You appreciate the landscape a lot	−0.68	−0.29
Accessibility to shops and services		
There are enough shops in your neighborhood		
Yes	0.09	−0.48
No	−0.19	1.05
Retail shops are within walking distance		
Yes	0.14	−0.45
No	−0.31	0.98
The opening hours of shops match your needs		
Yes	0.03	−0.18
No	−0.26	1.52
There are enough standard services in your neighborhood		
Yes	0.13	−0.54
No	−0.22	0.87
Perception of esthetics and density of built surroundings		
You feel that your neighbors are too close		
Yes	0.96	−0.18
No	−0.35	0.06
In your home, the proximity of the roads causes discomfort		
Yes	0.43	0.15
No	−0.08	−0.02
You enjoy the esthetics of the houses in your neighborhood		
Yes	−0.17	−0.08
No	0.98	0.27
In your neighborhood, you feel that the houses are too close to each other		
Yes	1.39	0.07
No	−0.38	−0.02
From your home, some features spoil the view		
Yes	0.78	0.40
No	−0.21	−0.10
You think that there are too many houses in your neighborhood		
Yes	1.74	0.23
No	−0.28	−0.04
Conditions of transportation and daily mobility		
For your daily movements, the bus takes more time than the car		
Yes	0.05	0.08
No	−0.04	−0.30
The supply of public transport is sufficient		
Yes	0.04	−0.27
No	−0.01	0.18
It is easy to move in the neighborhood by using soft modes (walking, cycling)		
Yes	−0.01	−0.06
No	0.10	0.50

city of 120,000 inhabitants. In order to consider suburban municipalities which share the same suburbanization profile, a statistical analysis was conducted by using data describing both demographic and housing dynamics between 1962 and 2007. This two-step analysis consisted in (1) applying a PCA on these population and

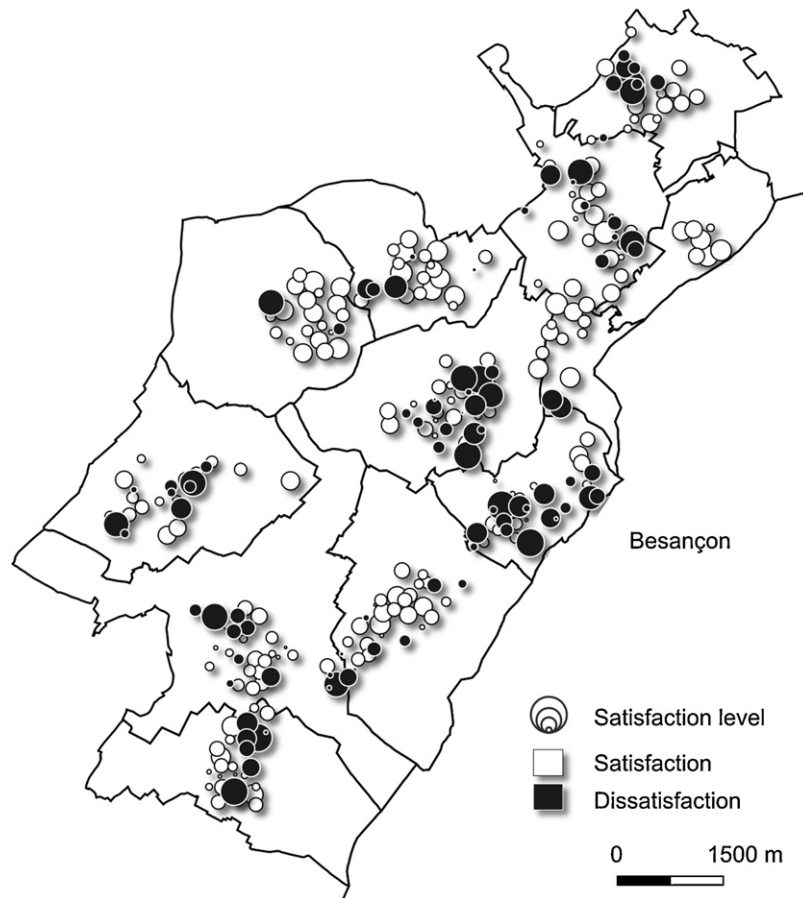


Fig. 3. The environmental and landscape neighborhood satisfaction level.

housing data so that the municipalities could be positioned in a factorial space according to their own characteristics; (2) using a hierarchical ascending classification (HAC) so as to group the municipalities according to their relative statistical distance as measured in the factorial space of the PCA. Five suburbanization profiles were identified from the analysis according to the intensity of the phenomenon and the time period over which the suburbanization process takes place. More specifically, the chosen study area is a set of 11 suburban municipalities belonging to the suburbanization class characterized by the strongest and longest demographic and housing dynamics.

2.1. Measurement of landscape satisfaction

In order to obtain individual opinions about the living environment, a survey of satisfaction was conducted in June 2009. Of a total of 4982 individuals called by telephone, 2389 (48%) could not be reached, 1518 (30%) declined to participate, and 1057 (21%) agreed to respond to the survey. The sample was checked throughout the survey so that the distribution of respondents was proportional to the demographic weight of the municipalities. This resulted in a sample of about 16% of households in each municipality being surveyed. The main descriptive statistics of the surveyed population are presented in Table 1. Each individual was located and geo-referenced using a GIS based on their postal address. Four main topics were investigated with the aim of characterizing several components of the residential environment: (1) assessment of daily landscape; (2) accessibility to shops and services; (3) perception of esthetics and density of

built surroundings; and (4) conditions of transportation and daily mobility.

The questionnaire used both closed and open questions, the open questions being omitted from this work. The closed questions consisted of a series of assertions to which the respondents had to choose those with which they agreed (Table 2). To provide an overview of these answers, a multiple correspondence analysis (MCA) was performed on the survey data. This analysis defined a series of orthogonal factors and positioned the initial variables and individuals in a new factorial space (Greenacre, 1984; Tenenhaus & Young, 1985). Given the decrease in the eigenvalues, only two factors were found to be significant (Fig. 2). Interpretation of the scatter plot of variables suggests the first factor was the level of satisfaction with the environmental and landscape neighborhood; it will be called "satisfaction" in the remainder of this paper. An individual's satisfaction is thus determined by the value on the x-axis. The second factor represents the level of satisfaction for accessibility to urban amenities. It was consequently omitted from this paper.

Several tests based on a correlogram describing the values of the Moran index for the landscape satisfaction variable showed a strong positive autocorrelation concerning the entire sample of respondents. In order to limit its effects on the statistical analysis, it was decided to sample 300 individuals among the 1057 respondents. This method was chosen because the usual way to avoid spatial autocorrelation, i.e. autoregressive models, precludes generalizing the model and mapping the distribution of satisfaction as it is presented in the final part of the results. Fig. 3 shows the spatial distribution of the satisfaction level for this sample of 300 individuals.

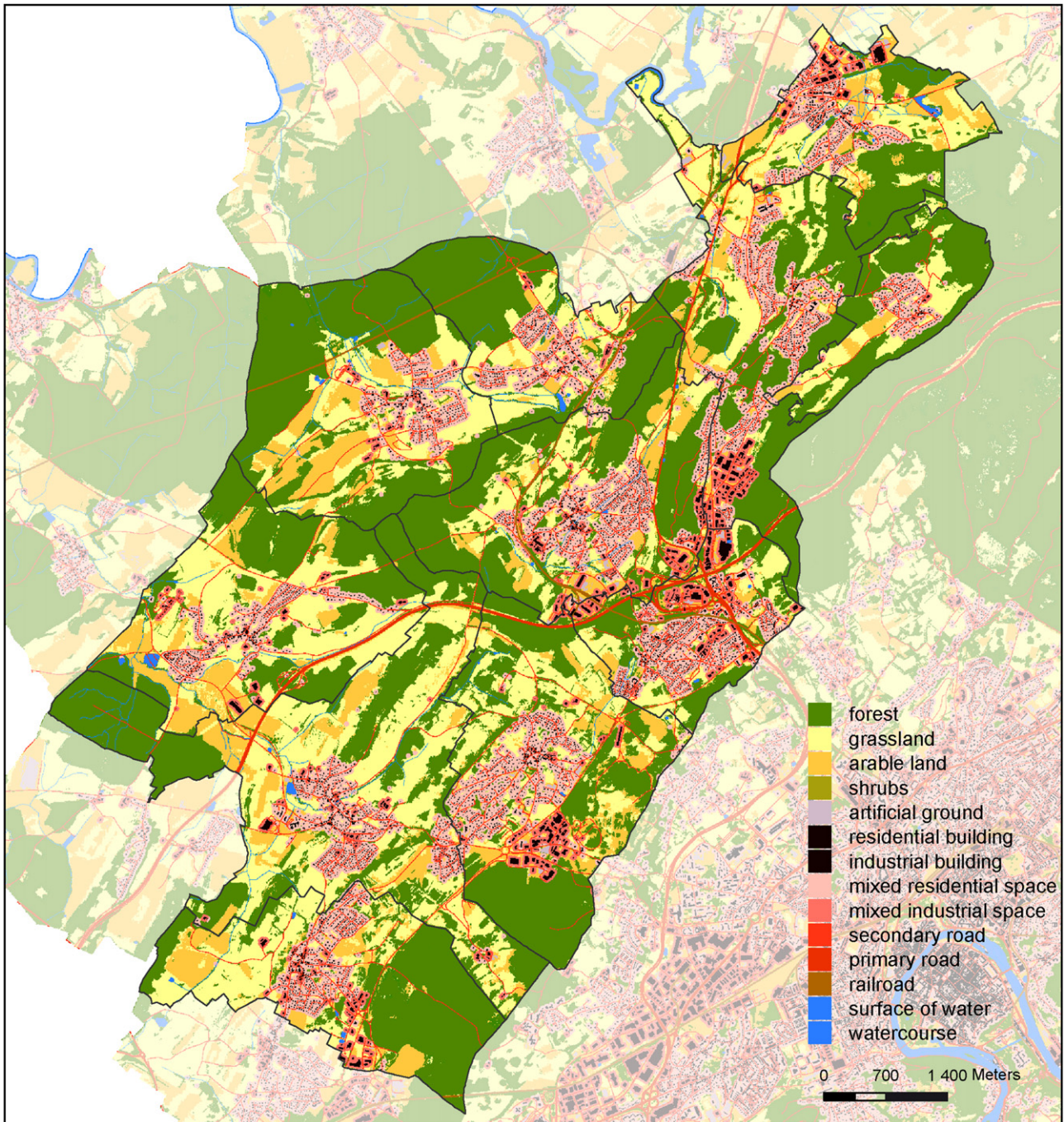


Fig. 4. The land cover database.

2.2. Landscape data

The landscape data were obtained by combining a vectorial land cover database (BD Topo IGN) and a satellite image (IRS-Liss1c+P) acquired in September 1999. The vectorial database was used to characterize residential, commercial, and industrial buildings, roads, water courses, and forests. The remotely sensed data were used to identify grassland, arable land, shrubs and parking lots by means of an unsupervised classification. The two sources were merged to obtain a 14-category raster land cover map with a spatial resolution of 7 m (Fig. 4). Among the categories present in the study area, the analysis focused on those identified in the literature as the key elements affecting the level of satisfaction: arable land, grassland, forest, and residential built.

2.3. Neighborhood shape and size

This study was based on the comparison of three different shapes of neighborhood:

- a circular neighborhood (CN) defined by a circular-shaped window around the residential location;
- a network neighborhood (NN) corresponding to the areas close to the roads accessible from a residential location and assumed to be the medium for the most frequent spatial practices;
- a visible neighborhood (VN) corresponding to the space that can be seen by individuals. VN was determined by the set of elements visible from the roads up to a given distance from the residential location in question. The implementation of this neighborhood

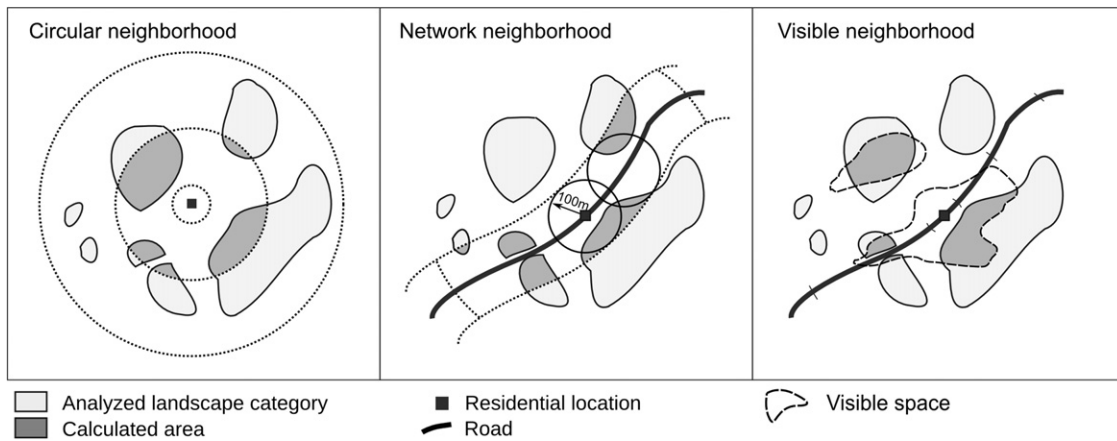


Fig. 5. The shapes and sizes of the neighborhoods.

required elevation data to model the masking effects which play a major role in visibility relationships. A sight-line method (Fisher, 1996; Garré, Meeus, & Gulinck, 2009), based on the combination of a digital elevation model (DEM) and a digital surface model (DSM), was used to evaluate the quantity of visible space for each category. The sight-line method was used to evaluate the visibility potential by means of visibility radii of 3500 m, separated by angles of 3° .

To compare the relevance of the neighborhood shapes, the analysis focused on the area of the landscape categories. Other landscape metrics based on the spatial configuration could be investigated, but could at the same time introduce difficulties in the comparison because of the difference between the surface areas of computations induced by the neighborhood shapes.

In order to identify the spatial scales of the more relevant indicators of satisfaction, each neighborhood shape was applied iteratively by varying its size (Fig. 5). For CN, this consisted in developing a series of circular buffers around the residential locations from a radius of 35 m up to a maximum of 3500 m. For a given radius, the percentage of area occupied by each landscape category was computed.

A similar approach was applied to NN: for a given network-distance from home, it consisted in implementing a circular buffer of 100-m radius around each pixel of a road defined in a raster format. For each network pixel tested, the area of the analyzed landscape category within the buffer was calculated and accumulated until the algorithm reached a maximum network-distance from home. It was applied from a minimum network-distance of 35 m to a maximum of 3500 m. In this model, the neighborhood size was assumed to correspond to the range of the most frequent spatial practices. In this way, the computation of the aggregate areas of each landscape category, measured in square meters, reflected the duration for which it was assumed that residents could see the landscape elements. However, such a model reflects a standard trip based on the network-distance but does not consider many modes of transport. A similar method was applied to VN, by summing the areas of the landscape categories visible from each cell of road, itself labeled by its network distance from the residential location. NN and VN were thus based on the same principle but differed in the way the areas of the landscape categories were computed: VN was based exclusively on the space visible from the roads while NN included all the areas within the 100-m radius buffer. It should be noted that VN, when calculated with a minimum size, corresponded to the space potentially visible from the residential location.

2.4. Statistical analysis

As a first step, a series of statistical tests was performed to assess the effect of distance independently of neighborhood shape. For each landscape category and for each neighborhood shape, these tests consisted in calculating the Pearson correlation coefficient between satisfaction and the area of the landscape categories according to the neighborhood size.

As a second step, as landscape perception pertains to the combination of several landscape features depending on several spatial scales, it was assumed that particular combinations of landscape variables may help to explain an individual's level of satisfaction. In order to integrate the set of variables within a multivariate predictive model, regression modeling was conducted by using satisfaction as the target variable for each shape of neighborhood. A multiple ordinary least squares (OLS) regression was used to model satisfaction from the landscape variables. As the computation of areas of landscape categories using similar neighborhood sizes tends to yield collinear variables, only the neighborhood sizes most closely correlated with satisfaction were implemented in the regression modeling. These regressions were first applied to each neighborhood shape separately, and then to combinations of these shapes. The stepwise procedure used to select the explanatory variables was based on the minimization of the Akaike Information Criterion (AIC).

3. Results

The results are presented in two steps: (1) focusing on the spatial scale effect using correlation analysis; (2) comparing the relevance of each neighborhood shape using multiple OLS regression.

3.1. Correlation analysis

The correlation analysis computed according to neighborhood size was used to draw curves where the x-axis represents the spatial scale (Fig. 6). Globally, CN appears as the most significant neighborhood while NN and VN prove to be less significant at the 5% level. Considering all the neighborhood shapes, forest and built areas yield more significant results than arable land and grassland. Given the global shapes of the curves, small spatial scales tend to be more significant than medium or large scales.

Closer examination of the curves reveals that forest is positively related to satisfaction for all distances using CN ($r_{1715\text{ m}} = 0.27, p < 0.00001$) and for distances less than 700 m using NN ($r_{315\text{ m}} = 0.17, p < 0.01$). Conversely, built elements are negatively related for all distances using CN ($r_{105\text{ m}} = -0.28, p < 0.00001$)

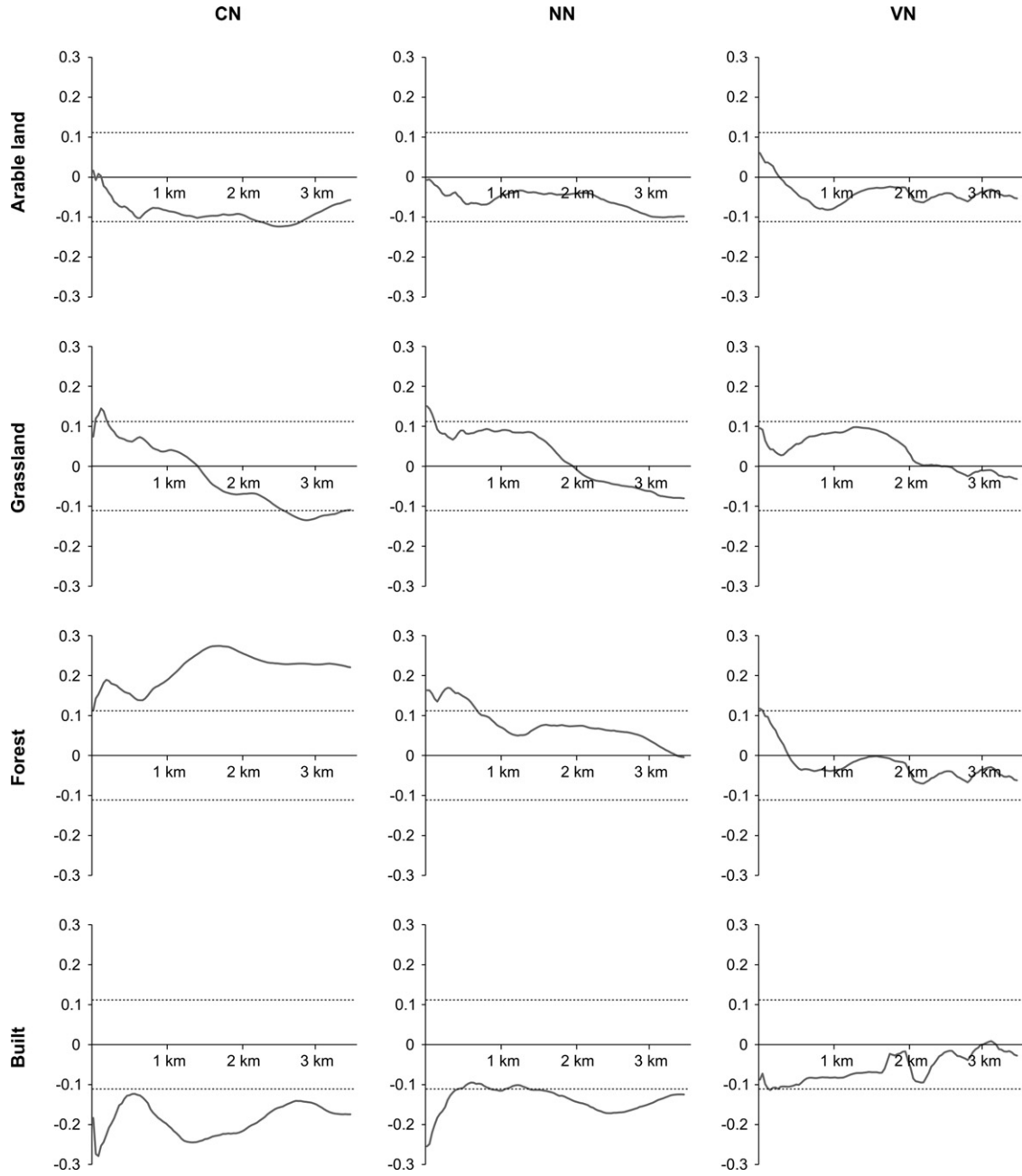


Fig. 6. Pearson correlation coefficients between satisfaction and landscape categories according to the neighborhood shape. The dotted lines correspond to a 5% significance level.

and for distances less than 450 m and greater than 1400 m using NN ($r_{35\text{m}} = -0.25, p < 0.00001$). While arable land is not significant, grassland is positively related for close distances using CN and NN, but negatively for large distances ($r_{2900\text{m}} = -0.13, p < 0.01$ using CN).

The landscape variables involving significant peaks in these curves of correlation (Fig. 6) were selected to carry out multivariate models. This selection is presented in Table 3 which describes the selected variables and their Pearson correlation coefficient with the level of satisfaction. Table 4 shows the inter-correlations among the selected landscape variables.

3.2. Results of the multiple OLS regression

The application of multiple OLS regression to the selected variables of each neighborhood shape yielded the results in Table 5.

Globally, the rates of variance explained by the models are quite low and the maximum value ($r^2 = 0.14, p < 0.0001$) is reached with CN. For this neighborhood shape, three variables were selected in the regression. Selecting also three variables, the analysis using NN showed a lower value ($r^2 = 0.09, p < 0.0001$) while VN appears as the least appropriate neighborhood for explaining the level of satisfaction ($r^2 = 0.01, p < 0.05$).

Following the interpretation of the selected variables, the ranking of the landscape categories varies with respect to satisfaction. However, several similarities can be noted between neighborhood shapes. First, the main finding relates to the contrast between forest landscapes that are appreciated, as can be noted in the model using NN and VN, and built landscapes that are disliked as in CN and NN. Second, the results show dissatisfaction for arable land while grassland is not significant in any of the models. With regard to spatial scales, all neighborhood sizes are present in the

Table 3
Landscape variables most correlated with satisfaction.

Code	Landscape category	Neighborhood shape	Neighborhood size	Pearson correlation coefficient
AraCN2555	Arable land	Circular	2555 m	-0.12 [*]
GrassCN140	Grassland	Circular	140 m	0.14 [*]
GrassCN2905	Grassland	Circular	2905 m	-0.13 [*]
ForCN210	Forest	Circular	210 m	0.19 ^{***}
ForCN1715	Forest	Circular	1715 m	0.27 ^{***}
BuiCN105	Build	Circular	105 m	-0.28 ^{***}
BuiCN1365	Build	Circular	1365 m	-0.24 ^{***}
GrassNN35	Grassland	Network	35 m	0.15 ^{**}
ForNN315	Forest	Network	315 m	0.17 ^{**}
BuiNN35	Build	Network	35 m	-0.25 ^{***}
BuiNN2485	Build	Network	2485 m	-0.17 ^{**}
ForVN35	Forest	Visible	35 m	0.12 [*]

^{*} $p < 0.05$.

^{**} $p < 0.01$.

^{***} $p < 0.001$.

models using CN and NN while VN is composed by only one variable.

Other tests were conducted in order to verify whether these types of neighborhood combine to influence satisfaction. Since CN provides the greatest explanatory power, the regression model based on this neighborhood shape was considered as the reference for assessing the contribution of the other shapes. This initial model (M) is based on the three significant explicative variables used in the OLS regression (AraCN2555, BuiCN105 and BuiCN1365). All the selected variables computed using NN and VN were then added to the set of variables based on CN. They were considered as providing a specific contribution when their addition gives a best model, i.e. a smaller value of AIC. The results of these tests are shown in Table 6.

Given these results, only two variables provided a decrease of AIC: the forest area in the network neighborhood up to a distance of 315 m, and the built surfaces in the network neighborhood up to a distance of 2485 m. Finally, adding both variables to the variables computed with CN led to an improvement by attaining an exploratory power of 16% ($p < 0.0001$) for a combined neighborhood model (Table 7). However, the results show that only variables based on CN are significant.

In order to provide spatial results for the whole study area, the potential of satisfaction was mapped. By applying the regression parameters to a set of points resulting from a regular spatial sampling (300-m-side cells), the potential of satisfaction was estimated at all points according to the initial model (M). For each point, this consisted in measuring the frequency of (1) arable land within a 2555-m radius ($F_{AraCN2555}$), (2) residential built within a 105-m radius ($F_{BuiCN105}$), (3) residential built within a 1365-m radius ($F_{BuiCN1365}$). From these three variables, the satisfaction level (S) was evaluated by applying the following equation:

$$S = -1.63F_{AraCN2555} - 1.76F_{BuiCN105} - 13.70F_{BuiCN1365} + 0.65$$

Once the level of satisfaction (S) was determined for the set of points, a kriging interpolation method was used to evaluate the potential of satisfaction over the whole area (Fig. 7). Specifically, the resulting spatial pattern highlights an opposition between satisfying areas located in the north-east, north-west, south-east, and center of the study area and dissatisfying locations in the north, east, and south-west.

4. Discussion

The purpose of this paper was to compare the capacity of several neighborhood shapes and sizes to provide indicators relevant to

landscape satisfaction. The comparison was made on the assumption that satisfaction with the landscape could be influenced by (1) cognitive factors represented by CN, (2) spatial-practice indicators based on transportation networks (NN), and (3) spatial-practice indicators based on transportation networks and visibility (VN).

Given the r^2 associated with each statistical model, the corresponding neighborhood shapes were ranked. The results showed greater effectiveness for the models using CN than for those using NN and VN. By considering neighborhood shapes as indicators of individual-landscape relationships, these results might suggest that landscape satisfaction is primarily related to a neutral surrounding rather than to the factors depending on the accessibility of the residence. By providing an r^2 of 0.16, which is barely higher than the model based on CN, the result obtained from the combined neighborhood model could show at first sight that the different neighborhoods combine to provide a better explanation of satisfaction. However, given the correlation coefficients between certain pairs of landscape variables, the addition of variables describing the build elements using NN to the model based on CN induces colinearity, suggesting that the combination of neighborhood types proves to be irrelevant. Moreover, although the selected variables of this combined neighborhood model come from two types of neighborhood, suggesting that both provide relevant information likely to be integrated in the perception of the totality of landscape components, the analysis showed that only the variables based on CN were significant. In the perspective of building spatial indicators, the results do not argue in favor of using sophisticated neighborhood shapes, since the simplest model can explain a major part of landscape satisfaction by using a technique which is easy to implement. Such a result should be related to the grain (spatial and semantic resolutions) of the landscape data. Using a more precise description of landscape, it cannot be ruled out that landscape satisfaction results from a mix of what individuals see, do and know about their environment. For example, Luttik (2000) explores the effects of different environmental factors on house prices and shows that several environmental characteristics such as the view, the vicinity, and the contact with a given landscape feature provide additional effects.

Statistically, the analysis provides results with low explanatory powers, with correlation coefficients of less than 0.27, and regression models explaining 16% of the variance at best. Although the absolute values of these indicators are low, this explanatory level is similar to what is usually achieved in the modeling of landscape preferences (Ellis et al., 2006; Kweon et al., 2010). There are two

Table 4
The Pearson correlation coefficients between the dependent landscape variables.

Code	AraCN2555	GrassCN140	GrassCN2905	ForCN210	ForCN1715	BuiCN105	BuiCN1365	GrassNN35	ForNN315	BuiNN35	BuiNN2485	ForVN35
AraCN2555	1.00											
GrassCN140	0.17**	1.00										
GrassCN2905	0.77***	0.01	1.00									
ForCN210	-0.24**	-0.03	-0.24**	1.00								
ForCN1715	-0.57**	0.07	-0.74**	0.26**	1.00							
BuiCN105	0.11	-0.47**	0.13*	-0.37***	-0.22**	1.00						
BuiCN1365	-0.20**	-0.26**	0.11*	-0.07	-0.53**	0.13*	1.00					
GrassNN35	0.17**	0.98**	0.01	-0.04	0.07	-0.44**	-0.28**	1.00				
ForNN315	-0.24**	-0.11*	-0.17**	0.71**	0.15**	-0.25**	0.08	-0.11	1.00			
BuiNN35	0.05	-0.51**	0.11	-0.44**	-0.23**	0.90**	0.19**	-0.51**	-0.30**	1.00		
BuiNN2485	-0.13*	-0.30**	0.24**	-0.15*	-0.56**	0.22**	0.80**	-0.32**	0.09	0.30**	1.00	
ForVN35	0.07	0.17**	-0.01	-0.05	0.09	-0.25**	-0.26**	0.18**	-0.06	-0.23**	-0.25**	1.00

* $p < 0.05$.

** $p < 0.01$.

*** $p < 0.001$.

reasons for this: (1) objectively measuring an individual's satisfaction is difficult because of the multitude of factors involved in the individual's judgment; (2) modeling the landscape by including all of its physical components means using a large number of metrics to reflect the combination of all the features that make up a landscape. In particular, it would be interesting to take into account metrics related to the density or to the size of the landscape patches, as in previous studies (Cho et al., 2008, 2009; Lee et al., 2008). However, these metrics are usually computed in a circular neighborhood so that shape does not interfere with the meaning of the indicator. In this study, the use of such metrics was not compatible with the irregular shape of neighborhoods using NN and VN, and our results are concerned with landscape composition alone. For VN, several computations may be made to quantify the impact of visible elements, but only the visible surfaces are used in this paper. However, other metrics describing solid angles, i.e. the surface areas covered by an object on the retina (Domingo-Santos, de Villarán, Rapp-Arrarás, & de Provencs, 2011; Stamps, 2001) and the passive view, i.e. the potential to be seen from several locations (Joly et al., 2009) were tested. Since the various tests based on these computations failed to provide significant results, they have been omitted from this paper.

The analysis emphasizes the results for the different neighborhood distances. The shape of the correlation curves suggests the presence of two scale levels: short distances (less than 200 m) and long distances (between 1200 m and 2800 m). The existence of these levels indicates that individuals are sensitive to both their immediate neighborhood and the global context corresponding approximately to the municipality. The environmental preferences of individuals could be considered as the result of a double perception scale related to nearby and to broader neighborhoods. Such an interpretation could encourage the use of multilevel data models (Goldstein, 1995) to investigate the relationships between these neighborhood scales.

With regard to landscape categories, the analysis confirmed the positive role played by natural elements such as forests in contrast to artificial elements such as built areas, which generate dissatisfaction. These results are consistent with many studies showing individuals' attachment to the presence of green elements in their environment (Ellis et al., 2006; Kaplan & Austin, 2004; Kaplan & Kaplan, 1989; Kaplan, 1985, 2001; Kweon et al., 2010; Moranco, 2003; Tyrväinen & Miettinen, 2000). In the present study, grassland proves to be appreciated more than arable land even if such a finding has to be nuanced because of the low level of significance of the results. The most significant variable of the combined neighborhood model suggests that residential density is the main dissatisfaction criterion, confirming what is generally found in the literature, as mentioned by Schwanen and Mokhtarian (2004).

A sensitive issue of this research is the level of information captured by the data. By highlighting the sizeable effect of small distance scales on the level of satisfaction, the question of the grain of spatial information must be addressed. In particular, various studies have shown the importance of considering elements such as isolated trees (Cavaillès et al., 2009) or high-voltage power lines (Des Rosiers, Dubé, & Thériault, 2008) in the near neighborhood in explaining satisfaction. The analysis could therefore be improved by using high resolution landscape data. This could be done by using photos taken from the residential locations in order to enrich the information about the nearby landscape. However, despite its advantages, this method could not readily be reproduced.

When dealing with individual satisfaction, the model could be biased by the effects of personal characteristics. To verify this potentiality, an analysis of variance (ANOVA) was carried out between the residuals of the regression models and respondents' socio-economic characteristics. Like many studies revealing

Table 5
The results of multiple OLS regressions for each neighborhood shape.

Model	Variable	Coefficient	Standard coefficient	Student's <i>t</i>
CN <i>r</i> ² = 0.14 <i>p</i> < 0.0001	Constant	0.65		
	AraCN2555	−1.63	−0.15	−2.68**
	GrassCN140	−	−	−
	GrassCN2905	−	−	−
	ForCN210	−	−	−
	ForCN1715	−	−	−
	BuiCN105	−1.76	−0.23	−4.23***
	BuiCN1365	−13.70	−0.25	−4.40***
NN <i>r</i> ² = 0.09 <i>p</i> < 0.0001	Constant	0.25		
	GrassNN35	−	−	−
	ForNN315	0.00	0.13	2.17*
	BuiNN35	−0.00	−0.18	−2.86**
	BuiNN2485	0.00	−0.13	−2.18*
VN <i>r</i> ² = 0.01 <i>p</i> < 0.05	Constant	−0.01		
	ForVN35	0.00	0.12	2.04*

* *p* < 0.05.
 ** *p* < 0.01.
 *** *p* < 0.001.

statistical connections between neighborhood satisfaction and several personal characteristics (Lovejoy et al., 2010; Lu, 1999; Mohan & Twigg, 2007; Parkes et al., 2002), the ANOVA provided results suggesting a weak relationship between landscape satisfaction and only one personal characteristic common to the models.

Specifically, none of the socio-economic variables tested were significant except for those related to housing: tenants are less satisfied than owners although ownership is not necessary related to satisfaction. This finding is consistent with what Mohan and Twigg (2007) and Permentier, Bolt, and van Ham (2011) have reported.

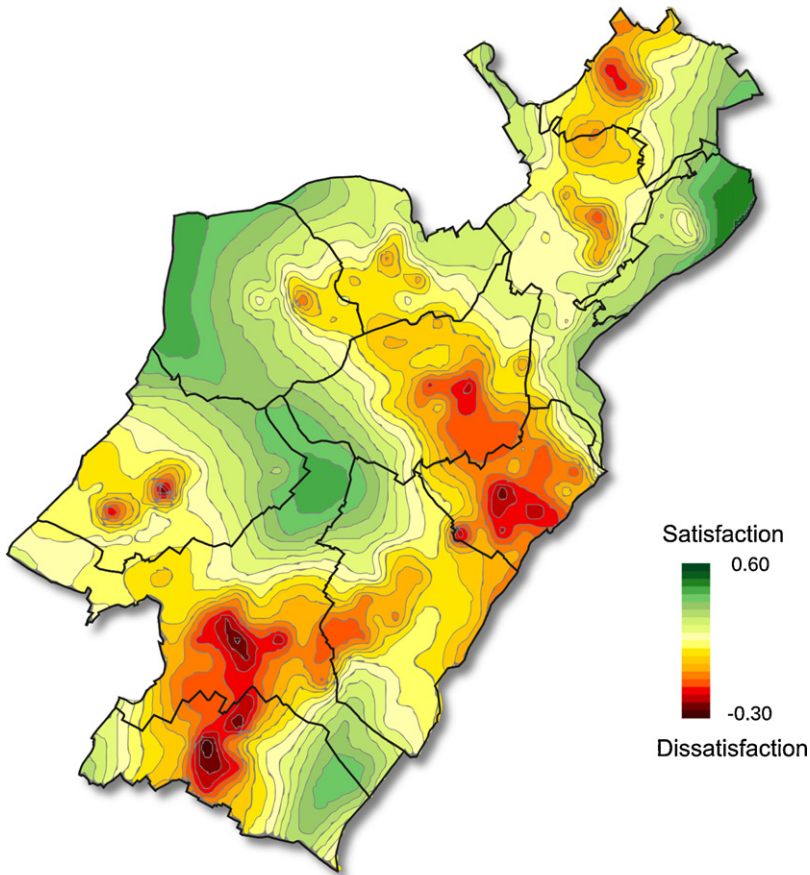


Fig. 7. The results of landscape satisfaction mapped using the combined neighborhood.

Table 6

Models combining several neighborhood shapes.

Models	r^2	AIC
Initial model M	0.143***	-674.93
M + GrassNN35	0.143***	-672.95
M + ForNN315	0.153***	-676.61
M + BuiNN35	0.143***	-673.12
M + BuiNN2485	0.152***	-676.31
M + ForVN35	0.143***	-672.94
M + ForNN315 + BuiNN2485	0.160***	-677.10

*** $p < 0.0001$.**Table 7**

The results of the regression for the combined neighborhood model.

Variable	Coefficient	Standard coefficient	Student's t	VIF
Constant	0.59			
AraCN2555	-1.44	-0.13	-2.33*	1.11
BuiCN105	-1.71	-0.22	-3.92***	1.15
BuiCN1365	-20.31	-0.36	-4.05***	2.81
ForNN315	0.00	0.10	1.74	1.14
BuiNN2485	0.00	0.14	1.57	2.86

* $p < 0.05$.** $p < 0.01$.*** $p < 0.001$.

5. Conclusions

The results of correlation and regression analysis alike reveal individual preferences for forest landscapes rather than built elements. They also seem to suggest clear preferences (negative and positive) for short distances for neighborhoods based on spatial practices (network and visible) and for long distances related to the neutral space represented by the isotropic neighborhood. The major finding from comparing neighborhood shapes is that the circular neighborhood proves to be sufficient to provide indicators of satisfaction from land cover data, although this shape is the crudest one used here. The hypothesis that sophisticated indicators are more significant is therefore invalidated.

Landscape composition was studied here as a variable influencing individual satisfaction. By using several neighborhood types, the analysis emphasized different perception levels depending on the effect of the environmental space. Such an approach might prove useful in urban planning by helping to define a zoning scheme of potential high satisfaction. This approach could be incorporated into urban development projects by using spatial simulations and mapping. A better understanding of individual perception and satisfaction seems relevant to the development of urban planning policies adapted to the needs and aspirations of the population.

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