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► **To cite this version:**

Samy Youssoufi, H el ene Houot, Gilles Vuidel, Sophie Pujol, Frederic Mauny, et al.. Combining visual and noise characteristics of a neighborhood environment to model residential satisfaction. *Landscape and Urban Planning*, 2020, 204, pp.103932. 10.1016/j.landurbplan.2020.103932 . hal-02939288

HAL Id: hal-02939288

<https://hal.science/hal-02939288v1>

Submitted on 18 Sep 2020

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COMBINING VISUAL AND NOISE CHARACTERISTICS OF A NEIGHBORHOOD ENVIRONMENT TO MODEL RESIDENTIAL SATISFACTION: AN APPLICATION USING GIS-BASED METRICS

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This is a postprint version, the definitive version of this paper is :

Samy Youssoufi, H el ene Houot, Gilles Vuidel, Sophie Pujol, Frederic Mauny, et al.. Combining visual and noise characteristics of a neighborhood environment to model residential satisfaction: An application using GIS-based metrics. *Landscape and Urban Planning*, Elsevier, 2020, 204, pp.103932. (<[10.1016/j.landurbplan.2020.103932](https://doi.org/10.1016/j.landurbplan.2020.103932)>).

Highlights

- Landscape visible features and traffic noise influence residential satisfaction.
- The use of PLS-PM allows setting up an integrated model to assess satisfaction.
- Visible and acoustic metrics combine to provide more explanations of satisfaction
- The use of digital data and GIS methods allows mapping distribution of satisfaction
- The approach can lead to a decision-making tool for urban planning and development

Abstract

This paper focuses on the combined impact of sound and visibility features on residential satisfaction in a suburban context. Based on a modeling approach, the study presents an integrated analysis here a set of spatial metrics, describing visibility of landscape features and road-traffic noise, are associated with data from a survey of neighborhood satisfaction. This survey was conducted on a sample of 845 inhabitants living in a medium-size French city. Using a PLS path model, the main objective of this paper is to assess how visual and sound metrics combine to provide complementary explanations of neighborhood satisfaction. Moreover, the analysis focuses on assessing the extent to which a part of the heterogeneity of the residents' neighborhood perception is due to their socio-economic position or to their neighborhood's characteristics. The results show that visual and sound criteria influence residential satisfaction cumulatively, and that sensitivity to these criteria varies according to the socio-economic position of individuals, opposing specifically homeowners and tenants. By using digital spatial data and GIS methods, an integrated indicator is produced to map the spatial distribution of neighborhood satisfaction for all residential locations of the study area. In an urban planning context, such a spatially oriented approach can be considered as a decision-making tool for planning and development to identify high-stakes zones in order to improve the inhabitants' quality of life.

1. INTRODUCTION

Cognitively, residential satisfaction is usually defined as the gap between a household's desired housing and its actual neighborhood situation (Amérigo, 2002; Galster, 1987; Galster & Hesser, 1981; Jiang, Feng, Timmermans, & Li, 2017). A key component of residential satisfaction is neighborhood satisfaction (Sirgy & Cornwell, 2002), which encompasses the physical, social, and economic characteristics of the surrounding environment (Boeckermann, Kaczynski, & Child, 2017; Huang & Du, 2015; Permentier, Bolt, & van Ham, 2011). Among these characteristics, visual and acoustic features are major environmental components (Ellis, Lee, & Kweon, 2006; Hur, Nasar, & Chun, 2010; Jeon & Jo, 2020; Kweon, Ellis, Leiva, & Rogers, 2010; Lee, Ellis, Kweon, & Hong, 2008), the perception of which strongly affects well-being (Botteldooren, Dekoninck, & Gillis, 2011; Braubach, 2007; Guite, Clark, & Ackrill, 2006), quality of life (Mohan & Twigg, 2007), and mental health (Braubach, 2007; de Jong, Albin, Skärbäck, Grahn, & Björk, 2012; Dratva et al., 2010; Leslie & Cerin, 2008).

Several studies investigate the influence of visible landscape attributes of neighborhood on residential satisfaction. They mainly focus on evaluating how landscape features such as natural/artificial types of land use (Ellis et al., 2006; Hur et al., 2010; Kaplan, 1985; Kweon et al., 2010; Lee et al., 2008; Talbot, 1988; Youssoufi & Foltête, 2013), or openness (Hur et al., 2010; Sahraoui, Youssoufi, & Foltête, 2016) impact satisfaction levels. Other studies assess the influence of different landscape features depending on geographical context and spatial scale (Youssoufi & Foltête, 2013).

Yet other studies deal with the relationship between acoustic characteristics and neighborhood satisfaction (Botteldooren et al., 2011; Kroesen et al., 2010; Schreckenberg, Meis, Kahl, Peschel, & Eikmann, 2010; Urban & Máca, 2013; von Lindern, Hartig, & Lercher, 2016). These studies focus on transportation noise only and mainly endeavor to better understand the causal connection between noise annoyance, global evaluation of the neighborhood, and noise-level exposure. Hence, only unwanted sounds are considered in these studies, which are mostly carried out from a health perspective. Several complementary studies emphasize on soundscapes quality and investigate relationships between noise level exposure and soundscape perception and evaluation (Berglund & Nilsson, 2006; Brambilla et al., 2013; Yu & Kang, 2014), with many potential applications in urban and housing design, and landscape planning and management (Brown et al., 2011).

Using a modeling approach focusing on visual features, Sahraoui et al. (2016a) report that a part of unexplained (i.e. residual) satisfaction could be due to noise pollution. This argues in favor of integrated analyses of the physical attributes of neighborhoods. However, visual and acoustic features are usually considered separately and very few studies have investigated the combined impact of sound and visibility features on residential satisfaction. Based on the European housing and health status (LARES) study, Braubach (2007) studies the influence of various residential environment characteristics on satisfaction with the residential environment including noise from the surrounding area, traffic noise, and vegetation along streets. A study by Gille, Marquis-Favre and Lam (2017) proposes a noise annoyance model including noise exposure level, dwelling satisfaction, and visibility of the noise source variables. Judging from the review by Van Renterghem (2019) seeking insight into interactions between vegetation, sound environment, and annoyance associated with unwanted sound, most combined studies focus on visible vegetation. More broadly, most integrated approaches deal with the association between visible landscape and individuals' perceptions and preferences from a soundscape ecology perspective (Ge & Hokao, 2005; Liu, Kang, Behm, & Luo, 2014; Viollon, Lavandier,

& Drake, 2002; Watts, Chinn, & Godfrey, 1999; Watts & Pheasant, 2015; Yu & Kang, 2009) but no relationship with residential satisfaction is investigated in these works.

On the regional and urban planning side, satisfaction with the visual and acoustic environment is of major concern for planners and decision-makers seeking to limit urban sprawl and promote the residential attractiveness of their areas. One of the reasons is that residential satisfaction is an important “push factor” in the residential migration process (Jiang et al., 2017; Speare, 1974; Tannier et al., 2016), especially the environmental quality of the surrounding housing (Kahlmeier, Schindler, Grize, & Braun-Fahrländer, 2001; Wolpert, 1966). Noise exposure and residential satisfaction are also related to the attractiveness of residential areas (Schreckenberget al., 2010) and visible landscape is often considered an important factor of residential choice, in particular for high-income households (Fernandez, Brown, Marans, & Nassauer, 2005). From this perspective, analyzing the effect of visual and acoustic features on neighborhood satisfaction could be helpfully based on the combination of perceptual surveys and digital spatial data in GIS tools to provide systematic diagnoses and serve as a decision-making tool for planning and development. As concerns visual features, digital data have already been used to characterize the proximity of households to wooded landscape from satellite imagery (Ellis et al., 2006; Lee et al., 2008) or from land-cover maps (Hur et al., 2010; Kweon et al., 2010), but these studies do not aim to generalize perceptual data to the whole study area. Such a spatially oriented approach was recently used to map neighborhood satisfaction (Yousoufi & Foltête, 2013) and the aesthetic potential of landscape (Sahraoui, Clauzel, & Foltête, 2016) using visibility metrics relying on digital data. The use of this modeling approach to visibility is also supported by studies showing the importance of the view of natural features against the proximity to green spaces (Kearney, 2006) and outlining the effect of visual attributes on the “pricing” of landscape (Cavallès et al., 2009; Joly et al., 2009). In a similar vein, acoustic metrics were introduced in a GIS tool in order to map neighborhood quality areas determined from the predicted annoyance impacts for residents (Klæboe, Engelién, & Steinnes, 2006). Such metrics are also used to explain the spatial differences in house prices (Chasco & Le Gallo, 2013; Montero, Fernández-Avilés, & Mínguez, 2011). From a soundscape evaluation perspective, Hewlett, Harding, Munro, Terradillos and Wilkinson (2017) develop a GIS modeling approach to assess and map tranquility perception at a neighborhood scale. However, no integrated tool has yet been designed to predict and map the potential level of satisfaction at the urban or regional scales.

In this paper, we propose an integrated analysis to explore how visual features and environmental noise combine to affect neighborhood satisfaction. We associate a set of spatial metrics describing visibility of landscape features and road-traffic noise with data from a survey of residential satisfaction conducted in the suburban area of Besançon, eastern France and reported in earlier research (Yousoufi & Foltête, 2013). Our main hypothesis is that visual and acoustic metrics provide complementary explanations of neighborhood satisfaction and that both dimensions are required to map the potential level of satisfaction accurately. In addition, we suppose that individual characteristics also influence neighborhood satisfaction, leading us to investigate the sensitivity of the statistical models to the socio-economic position of the respondents.

2. MATERIAL AND METHODS

2.1. Study area and measurement of neighborhood satisfaction

The study was conducted in the urban area of Besançon, a medium-sized French city where suburbanization has been ongoing since the 1970s. Currently, a suburban area of about 75,000 inhabitants surrounds the central city of 120,000 inhabitants. The chosen study area is a set of 10 administrative districts (*communes*) located in the northwestern periphery of Besançon, where significant suburbanization has occurred. The study area has just over 18,000 inhabitants. It is crossed from east to west by the A36 highway and from north to south by the RN57 expressway. Railway line No. 852 runs south of the study area (Fig. 1).

The degree of neighborhood satisfaction was evaluated from a survey conducted in June 2009 and presented in Youssoufi and Foltête (2013). A sample of 845 people was stratified by population size of the administrative districts. Each respondent answered a set of questions about their residential environment and was GIS-referenced based on the postal address. The survey covered four main topics: (1) evaluation of the surroundings through the assessment of visible and audible elements of the neighborhood, (2) access to various urban amenities, (3) perception of the residential built environment in terms of aesthetics and density, and (4) evaluation of individual and public transport conditions. Individuals were invited to assess the visible landscape on Lickert scales and to respond to a series of assertions by saying whether they agreed with them.

A multiple correspondence analysis (MCA) (Tenenhaus & Young, 1985) was performed to synthesize the responses in the form of factorial axes. The interpretation was used to identify the first factor (the only one considered in the present article) as the neighborhood satisfaction gradient varying from dissatisfied to satisfied. It corresponds to a multidimensional evaluation of two physical features of the surrounding environment: visible landscape and noise environment. As in Youssoufi and Foltête (2013) and Sahraoui et al. (2016a), the coordinates of individuals on this axis form the target variable of the analysis that we seek to explain by explanatory variables, namely visual and acoustic metrics in this paper.

2.2. Spatial data and residential environment modeling

The land-use data come from a 2012 vector database (BD Topo IGN) used for characterizing (1) forests, (2) grasslands and croplands, (3) artificialized spaces (built environment, secondary roads), (4) residential openspaces around housing, and (5) major transport infrastructures (railways and highways). It was digitized at 5 m resolution to obtain a five-category digital land-cover model (LCM). A 5 m resolution digital terrain model (DTM) and a 5 m resolution digital elevation model (DEM) were also used to estimate the altitude of every location on the surface and the height of the land-cover elements (Fig. 1).

2.3. Visible landscape modeling

This study relies on the modeling of landscape visibility in tangential view, i.e. as an observer could actually observe it from any location, using PixScape software (Sahraoui, Vuidel, Joly, & Foltête, 2018).

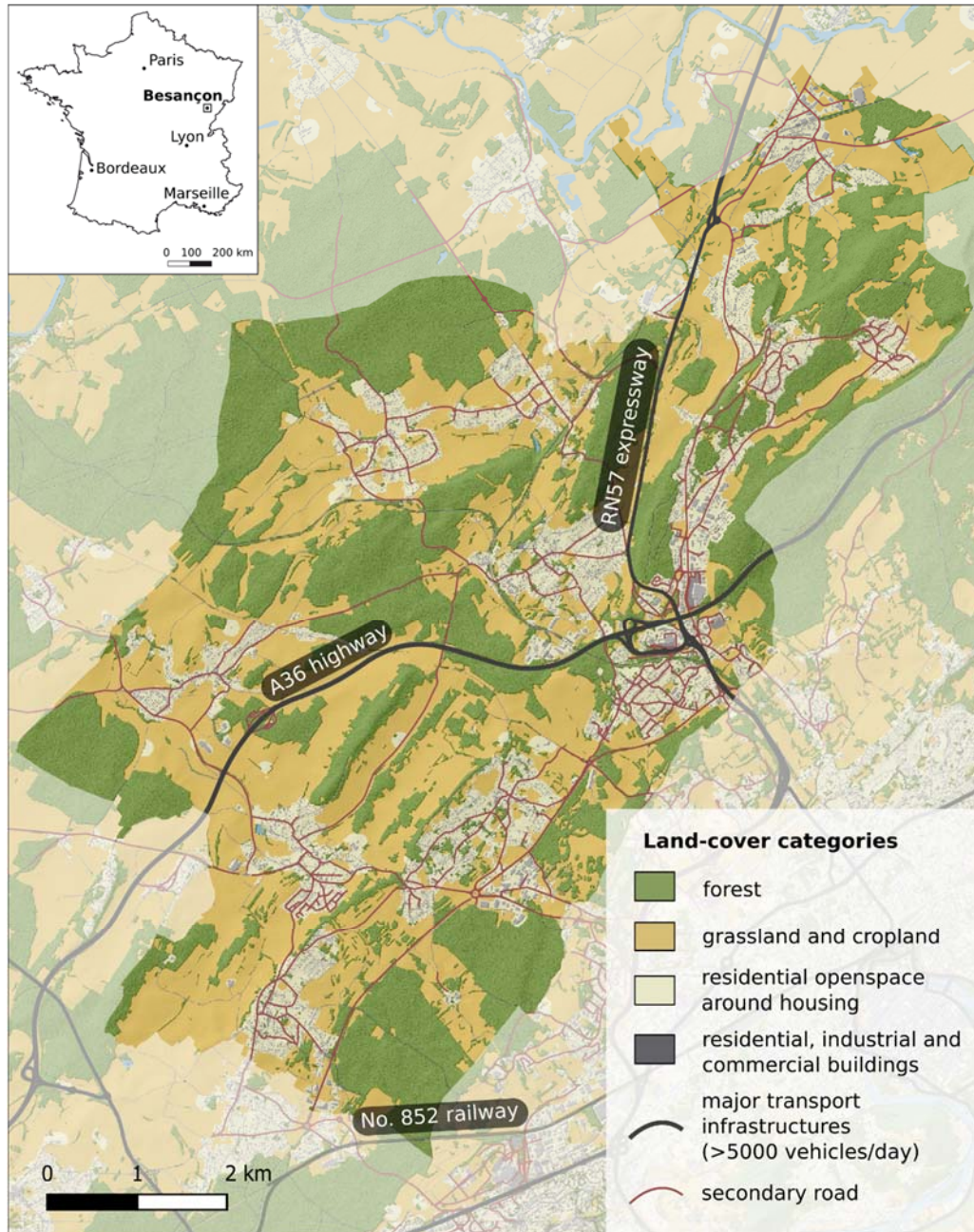


Figure 1 : The study area and the spatial data used (LCM, DTM, DEM) with a resolution of 5 x 5 m. The study area is located in the northwestern periphery of Besançon (France) and has about 18,000 inhabitants.

A synthetic image of the potentially visible landscape was built from any observation point using the LCM, DTM, and DEM spatial data. It relies on the calculation of angular surface areas to quantify the vertical development of the landscape elements, to take into account the height and width of the objects and their distance from the observation point as on the retina of a virtual observer (Bishop, 2003; Domingo-Santos, de Villarán, Rapp-Arrarás, & de Provencs, 2011). The visible surface areas are

thus expressed in square angles, i.e. a unit considered to be close to the landscape actually observed. Five metrics commonly used in landscape visibility analysis were calculated from each synthetic image:

(1) the proportion P of visible area a of a land-cover category i in the total visible area A defined as:

$$P_i = \frac{a_i}{A};$$

(2) the interspersion and juxtaposition index (IJI) (McGarigal & Marks, 1995) measures the patch adjacencies, i.e. the extent to which patches of land-cover categories are interspersed. It is defined as:

$$IJI = 100 \frac{-\sum_{i=1}^m \sum_{k=i+1}^m [(\frac{e_{ik}}{E}) \ln(\frac{e_{ik}}{E})]}{\ln(0.5[m(m-1)])}$$

where e_{ik} is the total length of adjacencies between land-cover categories i and k , E the total length of adjacencies, and m the number of land-cover categories. The values are close to 0 if the land-cover categories exhibit some pattern and close to 100 if no regularity is observed.

(3) The standardized Shannon diversity index S measures the diversity of a visible landscape in terms of distribution of visible land-cover categories in the landscape scene, defined as:

$$S = -\frac{1}{\log(n)} \sum_{i=1}^n \frac{A_i}{A} \log\left(\frac{A_i}{A}\right)$$

where A is the total visible area and n is the number of land-cover categories. A value of 0 indicates that only one land-cover category is visible and a value of 1 indicates that all land-cover categories are distributed equitably in the visible scene.

Two additional indices were used to quantify the degree of openness of the visible landscape.

(4) the first one measures the maximum distance between the observation point and the visible locations. It is defined as $DM = \max\{d_i \mid i \in [1; k]\}$;

(5) the second one measures the average distance between the observation point and the visible locations. It is defined as $DA = \frac{1}{k} \sum_{i=1}^k d_i$ where d_i represents the Euclidean distance from the observation point to the visible pixel i and k is the total number of visible pixels.

2.4. Noise modeling

Noise levels were calculated according to the European Commission's Environmental Noise Directive 2002/49/CE using MITHRA-SIG v.3.3.7 noise-prediction software application developed by Geomod and the French Scientific and Technical Centre for Building (CSTB) and already used in several studies (e.g., Pujol et al., 2014; Tenailleau et al., 2015). Two types of noise sources were considered: road traffic and rail traffic. The inputs of the model were topographic data, including buildings, roads, and railways (French National Geographical Institute database, BD TOPO 2012 or 2016), meteorological data (French National Meteorological Service), and traffic data for each rail and road section.

Three noise maps were calculated in a 2 x 2 m raster grid covering the study area in order to consider time differences in noise levels over a 24 h period. The noise metrics were based on the annual outdoor equivalent continuous A-weighted sound levels (LAeq, in dB) during the day (L_{Day} 06:00–18:00), the evening (L_{Evening} 18:00–22:00), and at night (L_{Night} 22:00–06:00).

Because a highway and high-traffic roads crossing the study area generate significant background noise, an original noise metric was calculated: the major roads noise level (L_{MR}). Only the highway and national roads with more than 5000 vehicles per day were considered when assessing

this background noise level during the day ($L_{MR,Day}$ 06:00–18:00), the evening ($L_{MR,Evening}$ 18:00–22:00), and at night ($L_{MR,Night}$ 22:00–06:00). Figure 1 shows the major roads and the secondary road network location.

To quantify the difference between the day or evening and night noise levels, the day/night noise level contrast (L_{DNC}) was also calculated as follows :

$$L_{DNC} = L_{Day} - L_{Night}$$

2.5. Spatial aggregation of metrics at three scales of neighborhood

Several spatial scales of neighborhood can be considered when characterizing the residential environment (Klæboe et al., 2006; Youssoufi & Foltête, 2013). To take into account this environment without focusing exclusively on a given spatial scale, the respondents' neighborhood was considered at three levels supposedly characterizing their living environment and their neighborhood spatial practices. Thus, the residential environment was considered (1) from each respondent's residential building by taking into account the area immediately adjacent to the building, (2) from the entire housing plot on which the building is located so as to take into account the residents' external private space, and (3) from the roads surrounding the residential building, assumed to be used for daily spatial practices.

Consequently, the visual and acoustic metrics were initially computed for each cell of the raster layers of 5 x 5 m and 2 x 2 m respectively, and the resulting values were then aggregated at three spatial scales. At the building scale, each metric was averaged from the values of the pixels representing the residential building of a given respondent, to characterize what could be perceived from home. At the parcel scale, the averaging was applied with all pixels of the housing plot, corresponding generally to open spaces (i.e. gardens) around the building. At the road network scale, the metrics were averaged by including all pixels of surrounding roads up to a network distance of 500 m from the dwelling, using a similar approach to that of Botteldooren et al. (2011). This scale was intended to represent what could be perceived when traveling around home, for example by taking a 20-minute walk (Hoshino, 2011; Kweon et al., 2010). Finally, we obtained a table containing 27 landscape metrics and 21 noise metrics (table 1).

2.6. Statistical analysis

Assuming that the perception of the neighborhood environment is performed synoptically rather than by segments, the analysis aimed at explaining the level of satisfaction of individuals from the combination of multiple visible and audible features across several spatial scales by using a multivariate causal model. To this end, we used partial least square path modeling (PLS-PM) (Tenenhaus, Esposito Vinzi, Chatelin, & Lauro, 2005) to estimate complex multivariate relationships among observed (i.e. manifest) and non-directly observed (i.e. latent) variables while developing a global model of cause-effect relationships among latent variables. In this statistical modeling, each link between a manifest variable and a latent variable is quantified by a linear correlation coefficient, termed here a "loading" (Sanchez, 2013).

In the present case PLS-PM allowed us to model relationships between the inhabitants' level of satisfaction (considered as a single latent variable) and the visual and acoustic attributes of their

neighborhood environments. The visual and sound metrics were thus considered as manifest variables and grouped for shaping latent variables when similar in meaning and when their loading was greater than 0.7, as recommended by Sanchez (2013). After several episodes of trial and error, seven visual latent variables were defined for the visual landscape: forest landscape, grassland and cropland, residential openspace (Jones & Reed, 2018), artificialized landscape, view of major infrastructures, landscape heterogeneity, and landscape openness. Because sound metrics were less varied, only three acoustic latent variables were defined: noisy environment, background noise, and night/day noise contrast. We applied PLS-PM first from visual metrics, second from sound metrics, and third from both types of metrics. The PLS-PM analyses were carried out in R using the *plspm* package (Sanchez, 2013). Once computed, the weight coefficients defining the latent variables from the manifest variables and the path coefficients linking the latent variables were used to estimate the satisfaction level at any pixel of the study area and finally to map potential residential satisfaction.

The construction of a global PLS-PM including the full sample of respondents (i.e. 845 individuals) relies on the assumption of relative congruence in the perception of the neighborhood environment. At the same time, we hypothesize that a part of the heterogeneity in this perception is due to individuals' socio-economic status. In order to identify specific groups expressing similar preferences, an unsupervised segmentation process of the global PLS-PM (Vinzi, Trinchera, Squillacioti, & Tenenhaus, 2008) was applied with the socio-economic characteristics of individuals. This involved developing an automated binary decision tree of path models where each node contained a sub PLS-PM with its own setting, using the *pathmox* algorithm (Lamberti, Aluja-Banet, & Sanchez, 2016, 2017).

	Spatial	Metrics	
Landscape metrics	building	P1 _b	proportion of forest seen from building
		P2 _b	proportion of open space seen from building
		P3 _b	proportion of built and secondary road seen from building
		P4 _b	proportion of residential area seen from building
		P5 _b	proportion of major infrastructures seen from building
		DA _b	average distance of visible space from building
		DM _b	maximum distance of visible space from building
		S _b	landscape Shannon diversity index from building
		IJI _b	landscape patch adjacencies from building
	parcel	P1 _p	proportion of forest seen from parcel
		P2 _p	proportion of open space seen from parcel
		P3 _p	proportion of built and secondary road seen from parcel
		P4 _p	proportion of residential area seen from parcel
		P5 _p	proportion of major infrastructures seen from parcel
		DA _p	average distance of visible space from parcel
		DM _p	maximum distance of visible space from parcel
		S _p	landscape Shannon diversity index from parcel
		IJI _p	landscape patch adjacencies from parcel
	road	P1 _r	proportion of forest seen from road
		P2 _r	proportion of open space seen from road
		P3 _r	proportion of built and secondary road seen from road
		P4 _r	proportion of residential area seen from road
		P5 _r	proportion of major infrastructures seen from road
		DA _r	average distance of visible space from road
		DM _r	maximum distance of visible space from road
		S _r	landscape Shannon diversity index from road
		IJI _r	landscape patch adjacencies from road
building	L _{Day,b}	daily noise level at building	

Sound metrics		L _{Evening,b}	evening noise level at building
		L _{Night,b}	night noise level at building
		L _{MR,Day,b}	daily background noise level at building
		L _{MR,Evening,b}	evening background noise level at building
		L _{MR,Night,b}	night background noise level at building
		L _{DNC,b}	contrast day-night noise level at building
	parcel	L _{Day,p}	daily noise level at parcel
		L _{Evening,p}	evening noise level at parcel
		L _{Night,p}	night noise level at parcel
		L _{MR,Day,p}	daily background noise level at parcel
		L _{MR,Evening,p}	evening background noise level at parcel
		L _{MR,Night,p}	night background noise level at parcel
	road	L _{DNC,p}	contrast day-night noise level at parcel
		L _{Day,r}	daily noise level from road
		L _{Evening,r}	evening noise level from road
		L _{Night,r}	night noise level from road
		L _{MR,Day,r}	daily background noise level from road
		L _{MR,Evening,r}	evening background noise level from road
			L _{MR,Night,r}
		L _{DNC,r}	contrast day-night noise level from road

Table 1: The landscape and noise metrics

In order to determine whether the individuals of each group express a degree of satisfaction related more to their socio-economic position than to the characteristics of their residential location, an analysis of variance (ANOVA) based on a Bonferroni pairwise comparison test was conducted.

3. RESULTS

Analysis of the results of this study is presented in three steps: first we highlight the results of the three PLS-PM analyses, then we focus on the cartographic outcomes of the potential level of satisfaction, and finally we present the results of the segmentation process.

3.1. PLS-PM analyses

The first model based on visible metrics (Fig. 2) leads to an overall average performance (goodness-of-fit = 0.41) with a relatively low ($r^2 = 0.11$) explanatory power. Forest landscape, residential openspace, and landscape openness have a positive and statistically significant effect on inhabitants' satisfaction. Landscape heterogeneity, grassland and cropland, which are also quite closely linked, also have a positive but small effect on the degree of satisfaction. The view of artificial features such as buildings, secondary roads, or major transport infrastructure does not seem to affect inhabitants' satisfaction.

The second model based on noise metrics also has an average overall performance (goodness-of-fit = 0.40) and the r^2 coefficient is low (0.08). The graph (Fig. 3) shows that the general noise level negatively affects the degree of satisfaction while the difference between daytime and nighttime noise

is favorably perceived. Since the background noise contributes by definition to the overall noise level, it is not surprising to note a significant relationship between these two variables. The background noise, however, does not directly influence the inhabitants' degree of satisfaction.

The third model combines both visual and acoustic metrics (Fig. 4). Note that only the latent variables were represented since the associated manifest variables are the same as in the two previous models. The overall performance is slightly higher (GoF = 0.44) and the r^2 associated with the degree of satisfaction reaches 0.15. Although the results are substantially the same as those presented above, some differences can be noted. Landscape heterogeneity, which had a weak but positive effect in the first model, is no longer statistically significant at the 5% threshold in the combined model. In addition, certain relationships between audible and visible elements of the landscape have been established. In particular, we note that the view of major infrastructure and artificial landscapes significantly impacts the overall noise level, contrary to landscape openness.

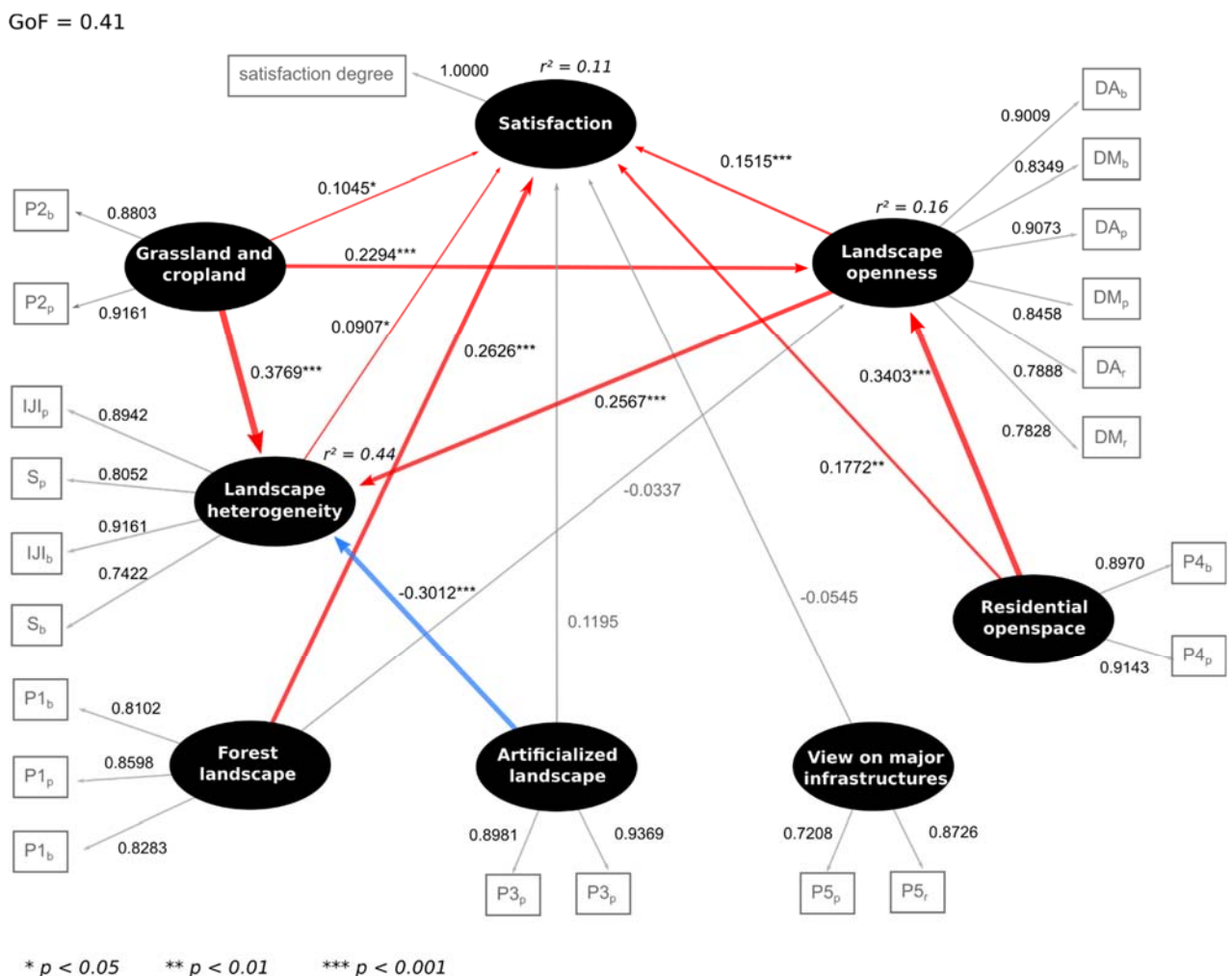


Figure 2 : The visible landscape PLS-PM model. The arrows between the latent variables (non-directly observed) indicate the intensity (thickness) and the direction (color) of the relationship. A red arrow indicates a positive relationship, a blue arrow indicates a negative relationship and a gray arrow indicates an insignificant relationship at a 5% threshold. The links between the latent and manifest (observed) variables are interpreted as the contribution of a manifest variable to its latent variable.

3.2. Spatial potential of satisfaction level

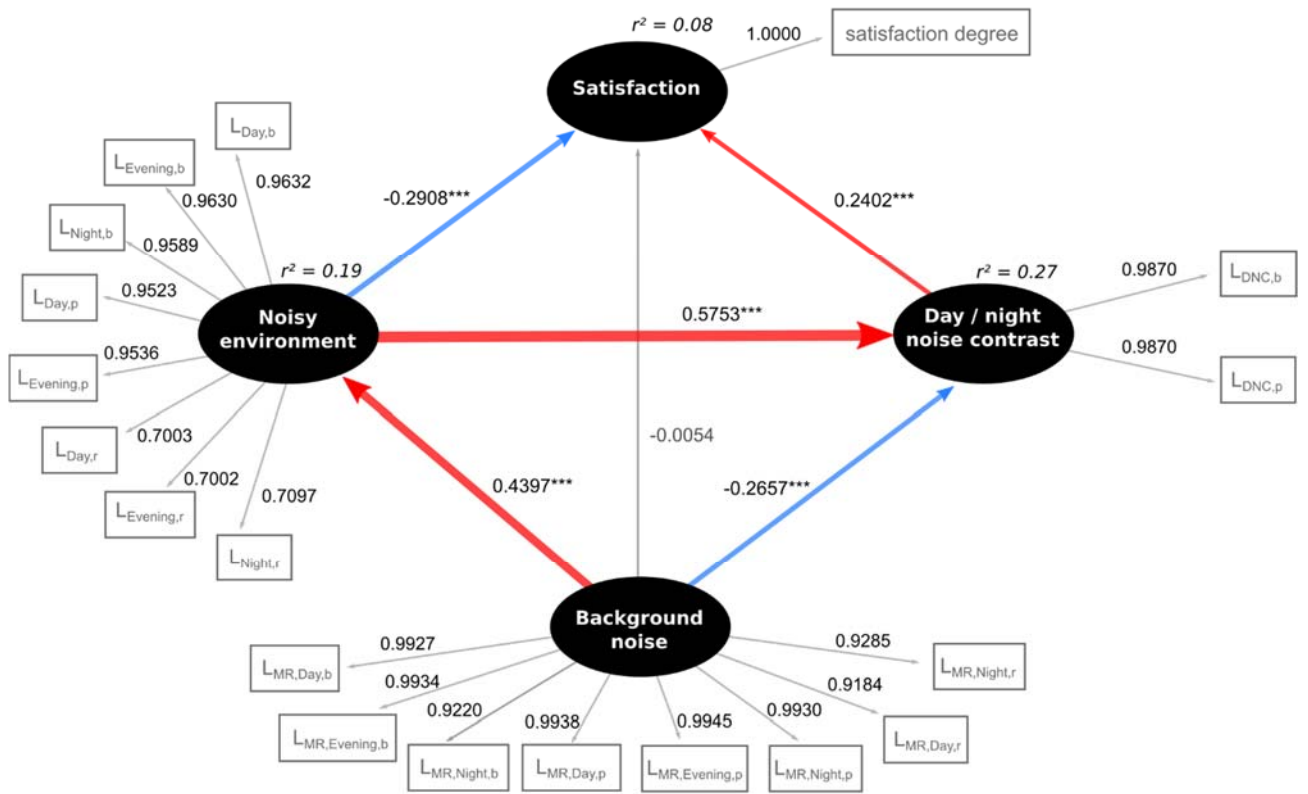
Metrics were calculated for the three spatial scales of neighborhoods and related to all residential lots in the study area. Figures 5a and 5b show the estimated satisfaction potential for the visible landscape model and the noise level, respectively, while Figure 5c shows the satisfaction potential for the combined model.

In terms of satisfaction with the visible landscape (Fig. 5a), the results show a center–periphery gradient along which the centers of the residential areas are generally unsatisfactory, notably because of an obstructed view, while the peripheries score higher because of the open landscape and the view of forest areas.

The major transport infrastructures have a negative effect on the degree of satisfaction (Fig 5b). More specifically, we note that areas near highways (east–west route and north–south route) and near the railway line (south of the zone) are negatively impacted.

The summary of satisfaction levels (Fig. 5c) exhibits a fairly marked contrast between the center plus some parcels in the south of the study area, where the satisfaction scores are quite low, and the north of the zone, where the satisfaction scores are globally higher. We note the advantage of using a combined model since this map merges the two previous spatial structures and leads to a greater diversity of spatial satisfaction structures than in Figures 5a and 5b. The center–periphery gradient effect persists but combines with the effect of proximity to major transport infrastructures, which causes a shift in the potential of dissatisfaction in certain areas (Fig 5c'). In some cases, it can also be noted that locations where the degree of satisfaction with the visible landscape is low and the degree of satisfaction with overall noise level is high (and vice versa) are relatively neutral in the combined model. This reflects the compensatory nature of the combined model in which the negative influence linked to an environmental determinant can be offset by the positive influence to another environmental determinant.

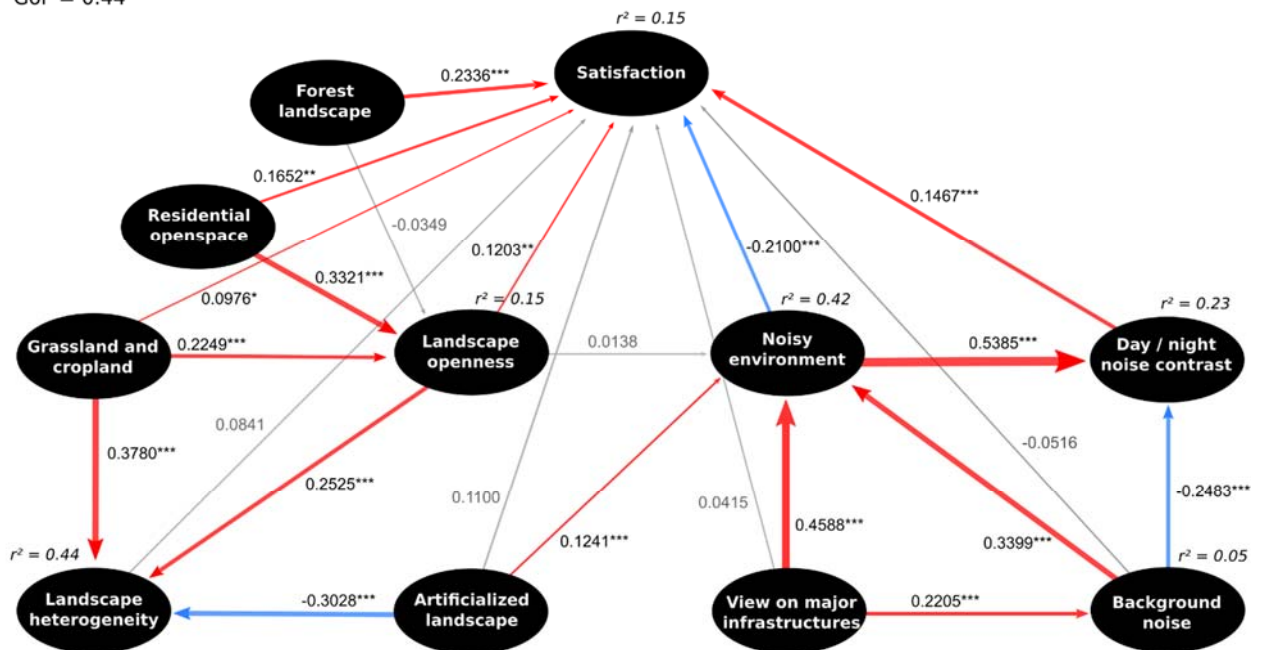
GoF = 0.40



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

Figure 3 : The noise PLS-PM model. The description of the arrows is identical to that of Fig. 2.

GoF = 0.44



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

Figure 4 : The combined PLS-PM model. The description of the arrows is identical to that of Fig. 2.

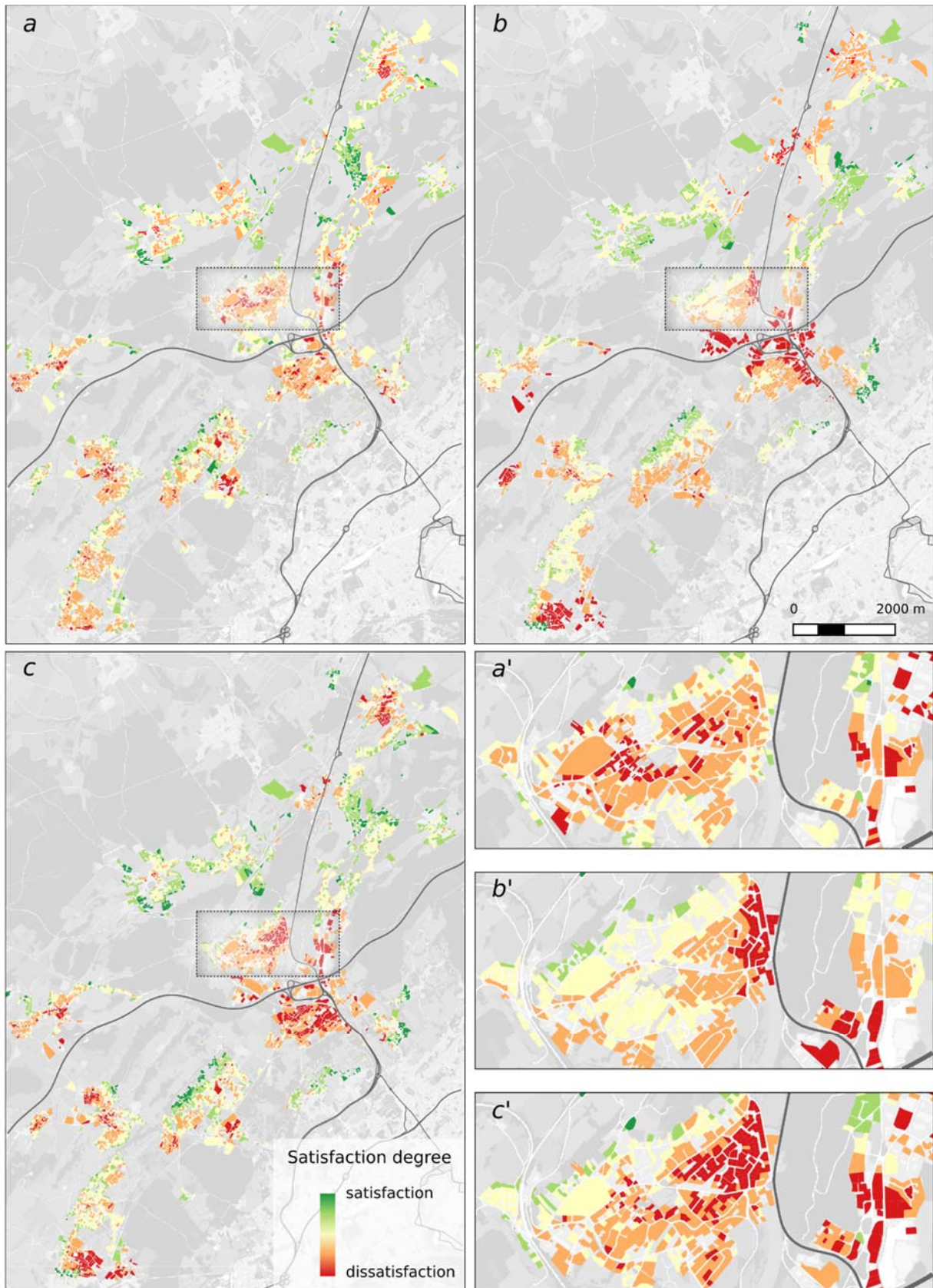


Figure 5 : The spatial potential of level of satisfaction of the residential lots. All maps are based on the use of the same discretization method and thresholds. Maps a, b and c show the estimated satisfaction potential for the visible landscape, the noise level and the combined model respectively. Maps a', b' and c' allow to focus on an urbanized area where the potential of satisfaction changes significantly depending on the model used.

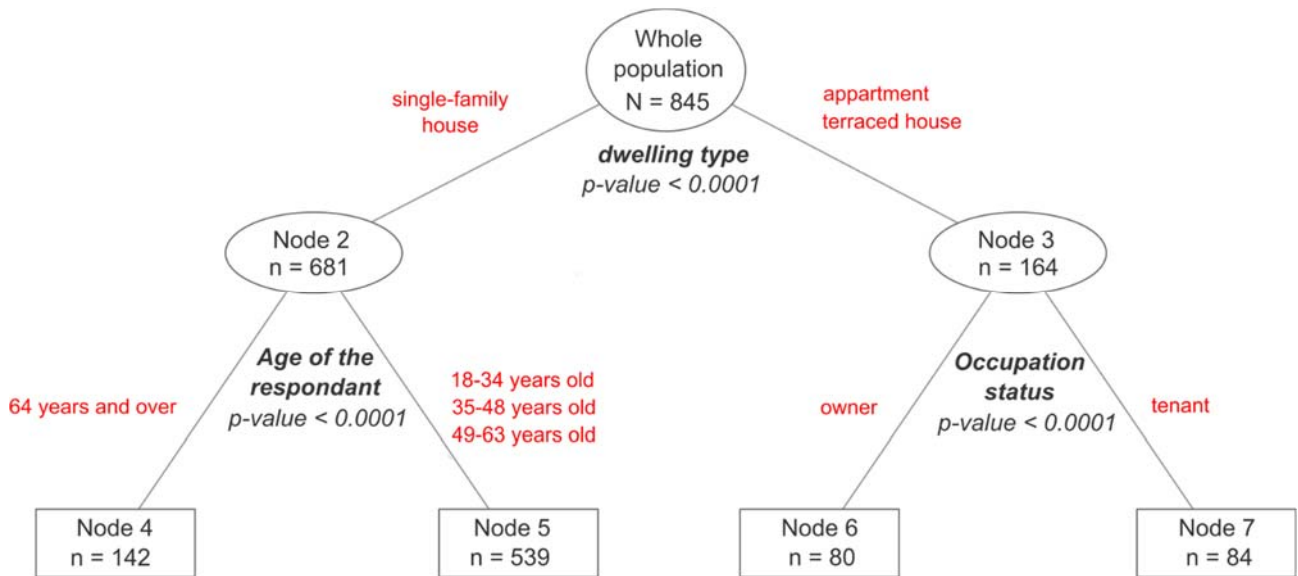


Figure 6 : The binary decision tree generated by the segmentation process of the pathmox algorithm.

3.3. Segmentation process according to socio-economic status

The decision tree resulting from the segmentation process includes two levels (Fig. 6). The first level refers to the respondents' dwelling type, separating individuals living in single-family houses and those living in apartments or terraced houses. At the second level, individuals living in single-family houses were distinguished by age (under 64 and over 64) while individuals living in apartments or terraced houses were divided according to their occupancy status, namely owner-occupier or tenant. Finally, the segmentation process produces four groups of unequal sizes.

Respondents living in single-family homes (nodes 4 and 5) are the most satisfied, with a mean level of satisfaction of 0.03 (Fig. 7) while those living in apartments or terraced houses (nodes 6 and 7) are more dissatisfied (from -0.19 to -0.20) (Fig. 8). For over 64-year olds living in single-family homes, only the view of forest areas seems to have a positive effect on satisfaction ($\beta_{\text{for. land.} - \text{sat.}} = 0.46$, $r^2 = 0.15$). The other variables do not have statistically significant impacts. The corresponding spatial potential of satisfaction exhibits a gradient corresponding to the amount of forest that can be seen from the residential lots of the study area. According to the preferences of this group of people, the model shows that several residential lots in the west of the study area are rather negatively evaluated, whereas residential lots in the east are more satisfactory, which partly corresponds to the distribution of forest areas, more present in the east of the area while the west is more dominated by grassland and cropland (Fig. 1). Node 5, made up of under 64-year olds living in single-family homes, reflects a preference for the view of forest areas ($\beta_{\text{for. land.} - \text{sat.}} = 0.25$), of residential openspaces ($\beta_{\text{res. land.} - \text{sat.}} = 0.18$), and a sensitivity to the noise contrast between day and night ($\beta_{\text{day/night noise cont.} - \text{sat.}} = 0.18$). These residents also express dissatisfaction with the noise level of their living environment ($\beta_{\text{noisy envir.} - \text{sati.}} = -0.23$). The r^2 associated with the "satisfaction" variable is 0.12. Based on the statistical parameters of the PLS-PM model of node 5, the cartographic extrapolation mainly highlights a gradient between residential lots located near the major transport infrastructures, which are negatively evaluated, and those further afield, which are more positively evaluated.

Owner-occupiers of apartments or terraced houses (Node 6) express dissatisfaction with the background noise ($\beta_{\text{backgr. noise} - \text{sat.}} = -0.42$, $r^2 = 0.32$). More than in the previous case, the map reveals a marked contrast between residential lots near the major transport infrastructures and those where

traffic background noise is lower. Tenants of apartments or terraced houses (Node 7) are the most dissatisfied group of people (mean level of satisfaction of -0.020). Only grassland and cropland landscapes seem to have a positive influence ($\beta_{\text{grass. cropland. - sat.}} = 0.39$, $r^2 = 0.17$). Extrapolation of the results of this model reveals that most residential lots are little appreciated if at all, whereas only a few are evaluated very positively.

The ANOVA consisted in comparing the means of the estimated score of each of the six significant latent variables (forest landscape, residential openspace, grassland and cropland, noisy environment, day/night noise contrast, background noise) for individuals in each of the four groups (Table 2). However, the results should be interpreted cautiously because of the imbalance among the four groups of individuals.

From the results, we note that the presence of forest landscapes does not differ statistically across the groups studied ($F_{(3,841)} = 0.517$, $p = 0.670$), making it possible to affirm that people living in single-family houses are more receptive than the other inhabitants to this type of visible landscape. Conversely, the analysis reveals that individuals in group 5 (who express a positive degree of satisfaction with residential openspace) are statistically those for whom this type of landscape is most present. We also note that the individuals in group 7 are the only ones satisfied with the presence of grassland and cropland in their neighborhood although this group is that for which the presence of grassland and cropland is weakest.

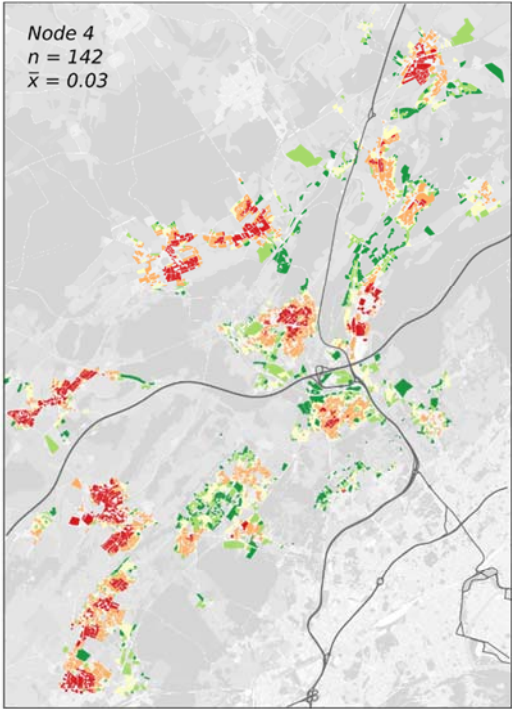
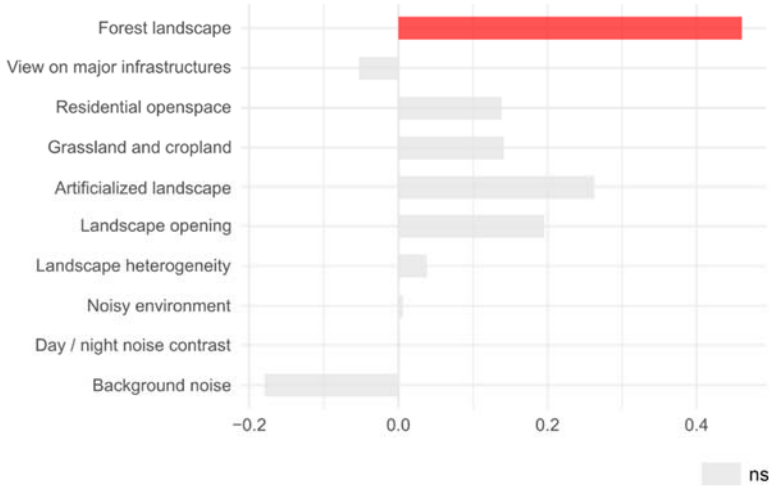
Mean values of the noisy environment latent variable present significant differences depending on the group of individuals ($F_{(3,841)} = 17.918$, $p < 0.0001$). Specifically, individuals living in apartments or terraced houses (nodes 6 and 7) are subject to significantly higher noise levels than those living in single-family houses and aged 18 to 64 years (node 5). However, only individuals in this group express discomfort with the level of noise, although it is the least exposed group. Therefore, it can be hypothesized that people under 64 living in single-family houses have a strong preference for peace and quiet in their residential environment. Noise contrast between day and night does not differ statistically ($F_{(3,841)} = 1.473$, $p = 0.220$) and only people under 64 living in single-family houses express a positive degree of satisfaction, which is consistent with the previous finding. While owner-occupiers of apartments or terraced houses are not significantly more exposed than other residents, they express a degree of dissatisfaction with background noise. They may be considered to attribute more importance than other inhabitants to the level of background noise in their living environment.

4. DISCUSSION

Although weak, the explanatory power of the combined model is greater than for the visible landscape model and the noise model taken separately. Furthermore, the spatial distribution of the potential of residential satisfaction predicted by each model is quite different, suggesting that perception of the quality of a place is highly dependent on the variable being measured. It can be thus assumed that each model provides its own information. These results tend to prove the value of combining the visible and audible approaches to produce an integrated indicator in the assessment of neighborhood satisfaction. Due to their non-redundancy, the hypothesis that visual and noise metrics provide complementary explanations for neighborhood perception and satisfaction is confirmed. This is all the more important because few studies examine this question but focus instead on the links between visible vegetation and noise perception (Liu et al., 2014; Watts et al., 1999), the use of urban green space, noise perception, and satisfaction (Rey Gozalo, Barrigón Morillas, Montes González, &

Atanasio Moraga, 2018), or dwelling satisfaction and visibility of noise sources (Gille et al., 2017). Combined features such as open landscape, forest landscape and low noise level have a positive effect on satisfaction level. Conversely, neighborhood dissatisfaction can be explained by high road noise level but can be balanced by view on forest landscape. These results are consistent with the review of Van Renterghem (2019) which highlights the positive influence of visual scenes containing vegetation and natural elements on noise annoyance reduction.

Path coefficient on satisfaction – Node 4 - ($r^2 = 0.15$)



Path coefficient on satisfaction – Node 5 - ($r^2 = 0.12$)

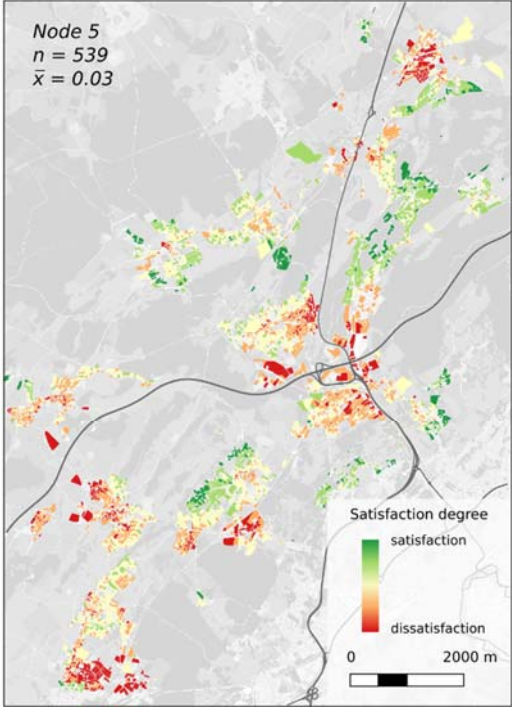
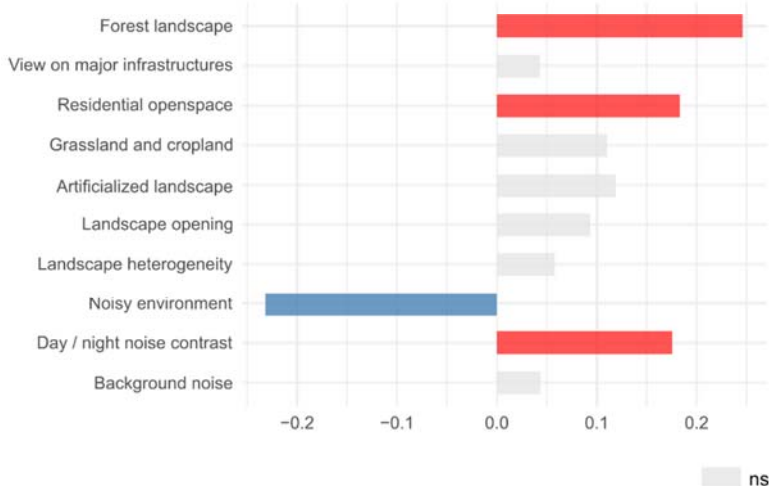
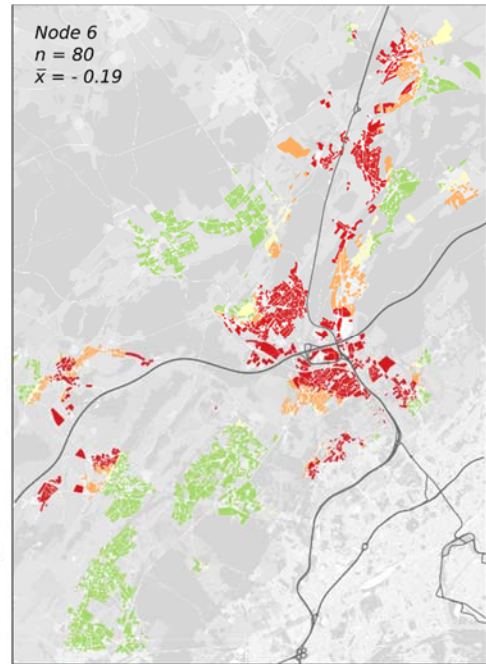
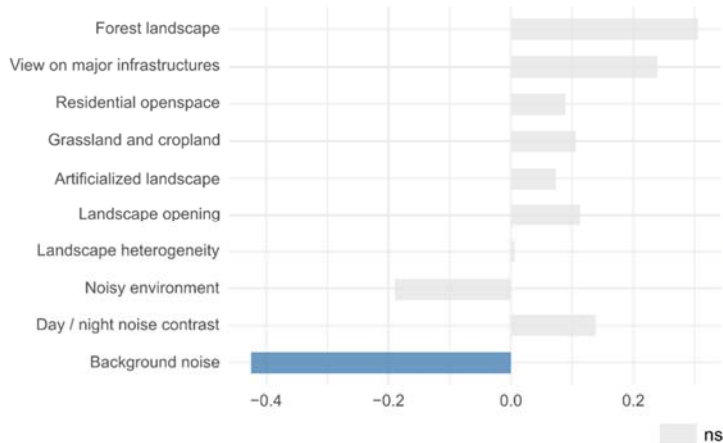


Figure 7 : The values of the path coefficients between satisfaction and other latent variables for nodes 4 and 5. Following the approach explained above, spatial extrapolations are also mapped using the same discretization method and thresholds as in Fig. 5.

Besides explaining and predicting a target variable, PLS path models can identify relationships between latent variables (Tenenhaus et al., 2005). Although indirect or mediating effects between latent variables could also have been analyzed, this study focuses exclusively on direct effects, which have a stronger influence on statistical models. The identification of a correlation between artificialized landscape and overall noise level is relatively coherent as the most heavily urbanized sectors are near the major road infrastructures. This is in line with soundscape ecology studies that find close relationships between landscape and soundscape compositions (e.g., Fuller, Axel, Tucker, & Gage, 2015).

Path coefficient on satisfaction – Node 6 - ($r^2 = 0.32$)



Path coefficient on satisfaction – Node 7 - ($r^2 = 0.17$)

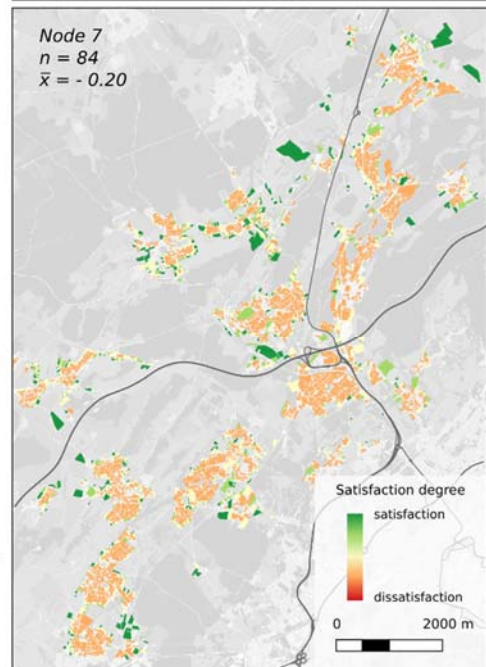
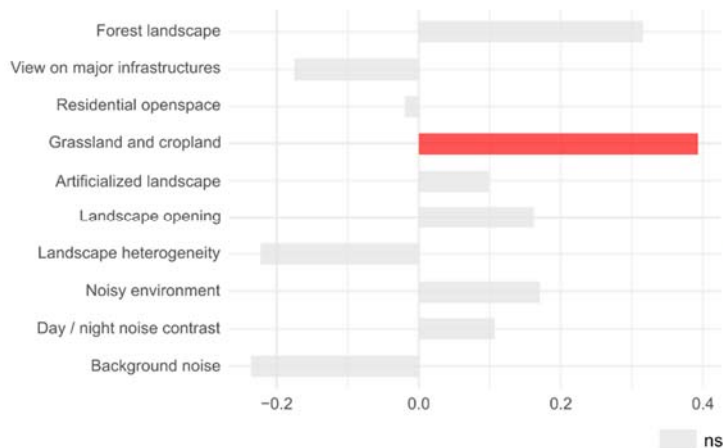


Figure 8 : The values of the path coefficients between satisfaction and other latent variables for nodes 6 and 7. Following the approach explained above, spatial extrapolations are also mapped using the same discretization method and thresholds as in Fig. 5.

Grassland, cropland, residential openspace, and especially forest are valued, which is consistent with the results of several studies finding that the presence of trees and wooded landscapes has a positive effect on neighborhood satisfaction (Ellis et al., 2006; Hur et al., 2010; Kaplan, 1985; Kweon et al., 2010; Lee et al., 2008; Talbot, 1988; Yousoufi & Foltête, 2013), fitting more broadly with the impact of naturalness (Hur et al., 2010) and the amount of green features (Hadavi & Kaplan, 2016). Conversely, most studies show that densely built-up neighborhoods are often negatively perceived and more specifically in the case of commercial buildings (Kweon et al., 2010; Sahraoui et al., 2016a; Yousoufi & Foltête, 2013), even though this negative perception can be mitigated by the presence of trees (Ellis

et al., 2006). In this study, artificialized landscape does not significantly influence the inhabitants' perception. This can be explained by the specific residential environment of the study area, located in a suburban area where mainly single-family homes usually surrounded by trees do not give a feeling of landscape saturation. Landscape openness is positively evaluated, confirming people's preferences for non-dense landscapes.

Latent variable	Source	df	SS	MS	F	Pr > F	Contrast	Diff.	Std. diff.	Pr > Diff	Sig.
<i>forest landscape</i>	Model	3	1.557	0.519	0.517	0.670	N7 vs N6	0.187	1.194	0.233	No
	Error	841	843.443	1.003			N7 vs N4	0.082	0.597	0.551	No
	Corrected total	844	845.000				N7 vs N5	0.062	0.529	0.597	No
							N5 vs N6	0.125	1.039	0.299	No
							N5 vs N4	0.020	0.213	0.831	No
							N4 vs N6	0.105	0.747	0.456	No
	Corrected level of significance : 0.008										
<i>residential openspace</i>	Model	3	101.989	33.996	38.48	< 0.0001	N5 vs N6	0.962	8.546	< 0.0001	Yes
	Error	841	743.011	0.883			N5 vs N7	0.831	7.541	< 0.0001	Yes
	Corrected total	844	845.000				N5 vs N4	0.145	1.634	0.103	No
							N4 vs N6	0.818	6.222	< 0.0001	Yes
							N4 vs N7	0.687	5.307	< 0.0001	Yes
							N7 vs N6	0.131	0.892	0.372	No
	Corrected level of significance : 0.008										
<i>grassland and cropland</i>	Model	3	11.675	3.892	3.928	0.008	N4 vs N7	0.405	2.956	0.003	Yes
	Error	841	833.325	0.991			N4 vs N6	0.357	2.562	0.011	No
	Corrected total	844	845.000				N4 vs N5	0.153	1.632	0.103	No
							N5 vs N7	0.252	2.156	0.031	No
							N5 vs N6	0.203	1.705	0.089	No
							N6 vs N7	0.048	0.311	0.756	No
	Corrected level of significance : 0.008										
<i>noisy environment</i>	Model	3	50.765	16.922	17.918	< 0.0001	N7 vs N5	0.791	6.937	< 0.0001	Yes
	Error	841	794.235	0.944			N7 vs N4	0.685	5.120	< 0.0001	Yes
	Corrected total	844	845.000				N7 vs N6	0.413	2.722	0.007	Yes
							N6 vs N5	0.377	3.242	0.001	Yes
							N6 vs N4	0.272	1.999	0.046	No
							N4 vs N5	0.106	1.156	0.248	No
	Corrected level of significance : 0.008										
<i>day / night noise contrast</i>	Model	3	4.418	1.473	1.473	0.220	N7 vs N5	0.184	1.566	0.118	No
	Error	841	840.582	1.000			N7 vs N6	0.147	0.940	0.347	No
	Corrected total	844	845.000				N7 vs N4	0.029	0.210	0.834	No
							N4 vs N5	0.155	1.641	0.101	No
							N4 vs N6	0.118	0.844	0.399	No
							N6 vs N5	0.037	0.308	0.758	No
	Corrected level of significance : 0.008										
<i>Background noise</i>	Model	3	14.305	4.768	4.827	0.002	N7 vs N5	0.379	3.255	0.001	Yes
	Error	841	830.695	0.988			N7 vs N4	0.349	2.551	0.011	No
	Corrected total	844	845.000				N7 vs N6	0.103	0.666	0.506	No
							N6 vs N5	0.276	2.319	0.021	No
							N6 vs N4	0.246	1.768	0.077	No
							N4 vs N5	0.030	0.325	0.745	No
	Corrected level of significance : 0.008										

Table 2: The results of the ANOVA analysis

Findings from several studies show that spatial and temporal variation in the noise environment influence the noise perception level (Quintero, Romeu, & Balastegui, 2019; Rey Gozalo, Barrigón Morillas, & Gómez Escobar, 2014; Romeu, Genescà, Pàmies, & Jiménez, 2011), noise annoyance (Klæboe et al., 2006), and neighborhood satisfaction (Botteldooren et al., 2011). In this study, an analytic description of the noise environment takes into account the articulation between spatial and temporal scales through manifest variables. The combination of those manifest variables in three latent variables produces an original and synthetic description of the noise environment which seems appropriate for explaining residential satisfaction in both the noise model and the combined model. Indeed, the environmental noise level is the most significant variable correlated with residential satisfaction, in line with studies of the relationship between sound characteristics and neighborhood satisfaction (Botteldooren et al., 2011; Kroesen et al., 2010; Schreckenberget al., 2010; Urban & Máca, 2013; von Lindern et al., 2016). The day/night noise contrast variable may be complementary as it has a significant effect in both the noise model and the combined global model. The influence of background noise is observed only for people living in apartments or terraced houses. This result may be explained by the specific spatial pattern of dwellings of this type, which are significantly slightly clustered and mainly located near the major road infrastructures (highway and expressway). This difference in residential location results in a significant difference in noise exposure as confirmed by the significant values of exposure to noisy environments for people living in apartments or terraced houses and even to background noise for those who are tenants.

Many studies have assessed the relationships between individual characteristics and neighborhood satisfaction (Amérigo & Aragonés, 1997; Huang, Du, & Yu, 2015; Ibem & Aduwo, 2013). In this study, some of these links were highlighted. For example, the ANOVA pointed out that people under 64 and living in single-family houses seem more receptive than other categories of people to the view of forest and value the peace and quiet of their living environment more highly. Among this group, over 92% also own their homes. In addition, the study highlights that owner-occupiers of apartments or terraced houses attach more importance to the level of ambient background noise than tenants do. It can thus be seen that owner-occupiers, regardless of the type of housing people live in, form a group that is relatively sensitive to the ambient noise level (noisy environment or background noise depending on the case) with the exception of elderly people living in single-family houses who are mostly owners but who do not express any discomfort with the noise level. A significant association between home ownership and noise sensitivity can, however, be established in this study, which is consistent with the results of Brink et al. (2019), Miedema and Vos (1999) and Kroesen et al. (2010) who deal with the effects of aircraft noise on residential satisfaction. This is also in line with the study of Hamersma et al. (2015) showing that specific sensitivity of homeowners to noise and barrier-effect annoyance may be explained by concerns about the consequences of nuisances on house prices.

However, the study also shows that housing characteristics may partly explain how satisfied or dissatisfied residents are with their living environment. Thus, people living in single-family house benefit from an environment strongly marked by the presence of residential openspace (namely trees, private gardens, public parks) and tend to value this type of land use positively. In addition to the significantly greater amount of residential openspaces, we assume that the private use of residential openspaces may contribute to increase satisfaction of single-family house residents. Conversely, the least satisfied people are tenants living in apartments or terraced houses and for whom the ambient noise level is the highest and the presence of grassland and cropland is the lowest.

Finally, our paper shows that visual and acoustic metrics provide complementary explanations of neighborhood satisfaction. In regional and urban planning and design contexts, it seems worth using a model combining visual and acoustic metrics to accurately map the potential level and to take into account possible compensatory effects. Nevertheless, our explanatory approach was based on a large set of environmental descriptors grouped into latent variables, that can be viewed as a hurdle for easily reproducing the method. However, from this perspective, a simplified version of the statistical model could be designed without significant loss of predictive power. One strength of this modeling approach is that it is possible to map the spatial distribution of residential satisfaction of the entire regional or urban area, which could lead to the identification of high-stakes zones. In such zones, decision-makers may conduct further studies to confirm and better understand local issues. For instance, participatory approaches with a large range of stakeholders (local authorities, associations, professional organizations, etc.) and residents may be adopted, such as those developed by Hewlett et al. (2017) for the tranquility of areas. In our study, the sound dimension focuses on traffic noise sources only. More qualitative combined approaches such as those proposed from a soundscape ecology perspective might also be considered in the high-stakes zones (Pijanowski, Farina, Gage, Dumyahn, & Krause, 2011). Building a planning framework like the one suggested by Margaritis and Kang (2017) is another promising direction to move in. It might also be useful to introduce sound quality indicators in the neighborhood predictive model in order to consider this soundscape dimension at regional and urban scales. In this context, the application of soundscape maps modeled with geo-referenced data might be appropriate (Lavandier, Aumond, Gomez, & Domingùès, 2016).

5. CONCLUSION

This study focuses on the inclusion of visual and noise metrics in a combined model to assess residential satisfaction. The analyses show that these two types of metrics combine and provide a quite low but greater explanatory power about the degree of satisfaction than if considered separately. In this sense, we can consider that our hypothesis is partly validated. By using spatial data and GIS methods, this study relies on the mapping of the spatial distribution of residential satisfaction for all residential locations in the study area. In an urban planning context and using complementary studies, such an approach could help decision-makers identify high-stakes zones that need to be protected from future development, or on the contrary, zones where effort must be made to improve the inhabitants' quality of life.

Another hypothesis of this study consisted in checking whether a part of the heterogeneity of the residents' perception of their neighborhood was due to their socio-economic position. Using an original classification method, we were able to identify groups of individuals expressing similar preferences. It has been shown, for example, that home ownership seems to be accompanied by a greater sensitivity to the noise level of the neighborhood and that people living in single-family homes are more sensitive to the view of the forest.

Recently, the same survey was conducted on a subset of individuals from the original sample. By building a set of visual and noise metrics based on current spatial data, a future study will focus on assessing the extent to which change in the residential environment influences changes in individual satisfaction over time.

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