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SPATIAL MODELLING OF LANDSCAPE AESTHETIC POTENTIAL IN URBAN-RURAL FRINGES

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Abstract

The aesthetic potential of landscape has to be modelled to provide tools for land-use planning. This involves identifying landscape attributes and revealing individuals' landscape preferences. Landscape aesthetic judgments of individuals (n=1420) were studied by means of a photo-based survey. A set of landscape visibility metrics was created to measure landscape composition and configuration in each photograph using spatial data. These metrics were used as explanatory variables in multiple linear regressions to explain aesthetic judgments. We demonstrate that landscape aesthetic judgments may be synthesized in three consensus groups. The statistical results obtained show that landscape visibility metrics have good explanatory power. Ultimately, we propose a spatial modelling of landscape aesthetic potential based on these results combined with systematic computation of visibility metrics.

Highlights

- We define several groups of landscape aesthetic judgments from a photo-based survey
- We compute visibility metrics with which to model landscape structure from spatial data
- Aesthetic judgments are explained by visibility metrics based on statistical analysis
- Visibility metrics can be used to provide maps of landscape aesthetic potential

Keywords

Landscape aesthetics; Photo survey; Judgment consensus; Visibility analysis; Landscape metrics.

1. Introduction

Landscape quality, defined as 'the relative aesthetic excellence of a landscape' (Daniel, 2001), has recently become an important dimension of public policies. The European Landscape Convention sets out recommendations for landscape quality issues and encourages public authorities to consider the aspirations of inhabitants regarding the landscape features of their environment (Concil of Europe, 2000). Landscape aesthetics is indeed recognized as a cultural ecosystem service that influences human well-being (de Groot et al., 2010; Millenium Ecosystem Assessment, 2003). Several scientific studies have shown for example that landscape is a significant component of residential satisfaction for inhabitants in urban and suburban areas (Hur et al., 2010; Kweon et al., 2010). But defining landscape quality involves assessing landscape preferences. Such preferences result from the interaction between landscape attributes and the characteristics of the observers.

Scientific research into landscape preferences has long focused on consensus among individuals about landscape quality (Van den Berg et al., 1998). Hagerhall (2001) has shown that such consensus is more important for pleasing landscapes than for ones that are judged less aesthetic. The similarities or consensus as to landscape preferences are part of evolutionary theories (Appleton, 1975; Kaplan and Kaplan, 1989; Wilson, 1984). These theories hold that landscape aesthetic preferences are formed by the common evolutionary history of humans who react positively to landscape features that supposedly ensure their survival and improve their well-being. Among these theories, the *biophilia* hypothesis (Fromm, 1964; Kellert and Wilson, 1993; Wilson, 1984) shows the influence of exposure to natural environments on psychological well-being. At the same time, studies about restorative environments demonstrate that individuals' health is directly linked to environmental characteristics. In this context, two fields of study have emerged (Van den Berg et al., 2014), focusing on the influences of the natural environment (1) on affective states (*Stress Recovery Theory*) (Ulrich, 1979) and (2) on the restoration of attention (*Attention Restoration Theory*) (Kaplan and Kaplan, 1989). Cognitive aspects of the environmental configuration have also been widely explored through *prospect-refuge theory* (Appleton, 1975) and information processing theory (Kaplan and Kaplan, 1989). In the first

case, Appleton (1975) states that the development of humanity has led people to prefer places where they can have a wide view (*prospect*), while remaining concealed (*refuge*). In the second case, (Kaplan and Kaplan, 1989) show that the combination of four informational factors (complexity, consistency, clarity and mystery) through a landscape preference matrix is likely to influence individual preferences. Starting from the premise that landscape quality is the same for all individuals, expert-based approaches to landscape assessment have largely dominated environmental management practices. They assume that the value to be ascribed to a landscape may depend directly on its visual attributes. Experts can therefore supposedly assess the quality of a landscape objectively (Karjalainen and Tyrva, 2002; Vouligny et al., 2009).

Unlike evolutionary theories, cultural theories (Carlson, 2001; Tuan, 1974) suggest that landscape preferences are constantly changing, shaped by individuals' personal and cultural experiences (Lindemann-Matthies et al., 2010). These perceptive approaches are based on a cognitive judgment of landscape characteristics (Daniel and Vining, 1983) and focus on landscape 'through the eye of the beholder'. Lothian (1999) asserts that 'the paradox is that in common usage, the landscape is taken to be beautiful but in actuality this beauty is literally a fragment of the imagination, a product of the viewer's own cultural, social and psychological constitution'. In this context, several studies demonstrate that landscape preferences may vary with individuals' socioeconomic, demographic or cultural characteristics (Stamps, 1999; van Zanten et al., 2014). Differences have been noted depending on age (Howley et al., 2012; Sevenant and Antrop, 2010; Van den Berg and Koole, 2006), sex and place of residence (Kalivoda et al., 2014), income (Campbell, 2007) and degree of knowledge or expertise about landscape (Rogge et al., 2007; Stumse, 1996; Tveit, 2009).

This opposition between (1) evolutionary approaches based on expert assessments and (2) cultural approaches based on perceptive evaluations still prevails. It relates directly to the objectivist (physical) and subjectivist (psychological) paradigm presented by Lothian (1999). However, other studies (Bourassa, 1991; Fry et al., 2009; Norton et al., 1998; Tress et al., 2001) have shown that evolutionary and cultural determinants jointly influence individuals' landscape preferences.

The approach focusing on consensus among individuals from an evolutionary perspective seems reductive to a fault and may omit some of the variability among individuals' judgments. Conversely, the exploration of individual preferences restricts the potential spatial modelling for designing decision support tools for land-use planning. However, the consideration of the

landscape aesthetic preferences is an important issue for spatial planning. Landscape is a component of the living environment of people, and land use planning can lead to change this landscape. Although public policies clearly call for maintaining the visual quality of the landscape, this quality is never really defined.

In this paper, we therefore seek to propose a way to define this landscape quality through the eyes of the observers, with the aim to guide land use policies. Although landscape aesthetic preferences are the outcome of a complex process of perception, we assume that (1) there are similarities between aesthetic judgments of certain groups of individuals, and (2) these aesthetic judgments can be explained by some combination of landscape visibility metrics. The objective of this study is thus to model landscape aesthetic potential by arranging individual landscape preferences into a limited number of aesthetic judgment groups.

For this purpose, we develop a five-step modelling approach: (1) construction of a perception survey based on a corpus of landscape photographs, (2) computation of landscape visibility metrics from spatial data, (3) definition of homogeneous groups of landscape aesthetic judgments, (4) analysis of statistical relationships between aesthetic judgments and landscape metrics, and (5) spatialization of landscape aesthetic potential and identification of areas of consensus and disagreement.

This study is conducted in urban-rural fringes. These areas where town meets countryside (Scott et al., 2013) are particularly affected by agricultural changes, including intensification and scale enlargement, or conversely agricultural abandonment (van Zanten et al., 2014), and by urban sprawl that has been occurring in all European cities since the 1960s (European Environment Agency, 2006). Such development is characterized by the rapid extension of commercial areas and the construction of uniform and monotonous residential areas (Friedberger, 2000). This is mainly due to the desire of households to move into the peaceful environment of a semi-rural area while being able to enjoy the benefits offered by an urban area nearby (Daniels, 1998; Sullivan and Lovell, 2006). Although continuous physical transformations of these areas could affect the living environment of their inhabitants, urban-rural fringes have been neglected by land-use planning for decades (Gallent et al., 2004).

2. Methodological background

2.1. Landscape photo-based survey

Within the framework of the evolutionary and cultural approaches, landscape photographs are commonly used. They are considered an interesting medium for evaluating landscape preferences (Arriaza et al., 2005; Natori & Chenoweth, 2008; Wherrett, 2000). Although they cannot replace *in situ* observations, they do provide a holistic representation of landscape using visual stimuli that can approximate an actual experience of landscape (Barroso et al., 2012). These stimuli allow the mind to associate the visual information of landscape with other sensory knowledge and activate an intuitive recognition of its aesthetic quality (Bell, 2001). Two main groups of methods exist in photo-based landscape preference assessment. The methods by attitude scale, or "Scenic Beauty Estimation Method" (e.g. Daniel & Boster, 1976) involve evaluating each photo independently by assigning it a score, usually on a 5-point Likert scale (e.g. Cañas, Ayuga, Ayuga, & Canas, 2009; Dramstad, Tveit, Fjellstad, & Fry, 2006; Ives & Kendal, 2013). The ranking methods or "Law of Comparative Judgment" (e.g. Buhyoff & Leuschner, 1978) consist in ranking a set of photos according to the quality of the landscape represented, either in order of preference (e.g. Arriaza et al., 2004) or by pairwise comparisons (e.g. Tahvanainen, Tyrväinen, Ihalainen, Vuorela, & Kolehmainen, 2001). These judgments are then compared and contrasted with indicators relating to the landscapes represented in order to gain insight into individuals' landscape preferences.

2.2. Landscape visibility analysis

The construction of landscape indicators is an essential step in landscape preference assessment. Such indicators serve as a measuring basis by converting the visual perception of the physical landscape into quantifiable criteria (Sang et al., 2008). These indicators can be obtained by *in situ* observations (Arriaza et al., 2004; Otero Pastor et al., 2007) or by GIS modelling (Cavailhès et al., 2009; Sang et al., 2008; Schirpke et al., 2013). The first approach provides a wealth of information but is restricted to a limited area. The second approach, based on digital spatial data, allows the landscape analysis to be extended to the entire study area (Schirpke et al., 2013; Youssoufi and Foltête, 2013).

Landscape visibility analyses can be used to study individuals' landscape preferences (de la Fuente de Val et al., 2006; Lee et al., 2008). They can be split into two main methods. The sight-line method (Fisher, 1996; Joly et al., 2009) entails characterizing the visible landscape by counting the pixels seen from a virtual viewpoint. The solid angles method (Domingo-Santos et al., 2011; Germino et al., 2001) involves using trigonometric calculations to quantify the surface areas of the observer's retina occupied by landscape features (Llobera, 2003). Several

types of landscape visibility metrics can be computed using these approaches. First, composition metrics quantify the area of each element within a viewshed to take account of the visual contents of landscapes (Joly et al., 2009; Miller, 2001). Second, configuration metrics adapted from landscape ecology quantify the fragmentation of the visible landscape. In most studies, configuration metrics are calculated from a zenithal view within the viewshed (Dramstad et al., 2006; Palmer, 2004; Schirpke et al., 2013).

3. Methodology

3.1. Study areas

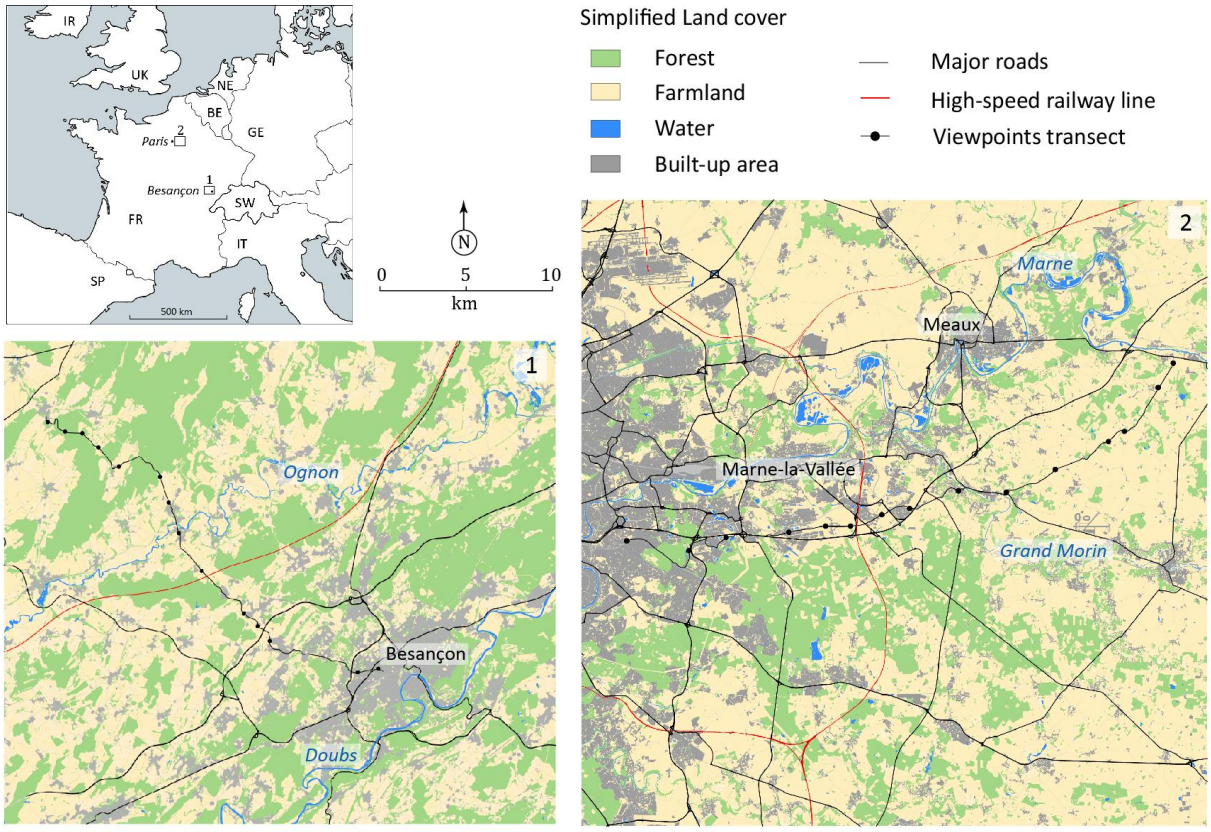


Fig. 1. Location of the two French study areas and of the shooting viewpoints used in the perception survey. The land cover was simplified into four classes to make the map easier to read.

The study areas are two French urban fringes (**Fig. 1**) representing a medium sized city and a large metropolis that differed in their urban density and their dynamics of urban sprawl. The selection of cities was guided by the availability of land cover data. The first study area (700 km²) includes the metropolitan area of Besançon and its north-eastern urban fringes. The landscape is dominated by forest (41%) and farmland (39%), while urbanized areas represent less than 5% of the land cover. The area is crossed by the Ognon valley in the north and Doubs

valley in the south. The steep hills and rugged terrain south of the city of Besançon have not been amenable to urban expansion. The area is crossed by several major transport infrastructures, including a motorway and a high-speed railway line. The second area (2025 km²) is located in the eastern part of the metropolitan area of Paris. Farmland covers 48% of this area and urbanized areas 19%, especially in the western part. Two valleys (the Marne and the Grand Morin) cross the area, which is also dissected by many transport infrastructures. These two areas have both been affected by urban sprawl since the 1970s due to their residential attractiveness, but with different dynamics because of the greater urban expansion of Paris.

2.2. Perception survey

2.2.1. Shooting protocol

The stimuli used in the landscape preferences analysis were a corpus of representative photographs of urban-fringe landscapes. The photographs were taken along two roads heading away from the dense urban areas towards rural areas over a total length of 25 km in zone 1 and 45 km in zone 2. In the same way as in Medley et al. (1995), the roads were used as transects along an urban-rural gradient and therefore cross a wide variety of landscapes. They were selected by avoiding major roads, not suitable for the shooting protocol. The shooting viewpoints were then spatially sampled along the two transects. Fifteen points were picked at random along each transect, with a reticular distance of at least 0.5 km between any two points (**Fig. 1**).

We took one to three photographs at each point using a Nikon D800 with a 35mm focal length as in (Kalivoda et al., 2014). This focal length provides a horizontal opening of 60° and a vertical opening of 50°, which values are considered closest to human binocular vision. This viewing angle allows for good discrimination of landscape colours and shapes (Pinker, 1986). The horizontal stability and constant shot height of 1.75 m were ensured by mounting the camera on a tripod fitted with a spirit level. The geographical coordinates and the orientation of each shooting viewpoint were also noted using a GPS and a magnetic compass. All photographs were taken by a researcher over two days in early autumn 2014, in identical weather conditions. Photographs of poor quality or that duplicated others in terms of landscape composition and configuration were removed. In the end, 30 photographs (15 per zone) were kept (**Fig. 2**). They were not subsequently altered in any way.

Fig. 2. Examples of photographs representing a wide variety of landscapes in urban fringes. The perception survey counted 30 photographs in all.

2.2.2. Construction of the survey

Landscape preferences were evaluated through an internet-based survey using the selected photographs. Several studies (Bishop, 1997; Wherrett, 2000, 1999) have highlighted the value of such surveys. Internet-based surveys can enrol many participants quickly and cheaply, while minimizing bias that may arise from the organization of the experiment (Reips, 2002; Roth, 2006). The survey was constructed using the open-source online survey *LimeSurvey* (www.limesurvey.org). An email was sent in November 2014 to several French government departments, both at national level (Ministry of Environment and Regional Planning) and at the level of departments and districts (regional authorities of environment and regional planning, urban and landscape planning agencies, etc.), to agencies or associations involved in urban and regional planning, and to a mailing list of French-speaking academic geographers. This email set out the aims of the study and gave the URL for the survey. It also asked the recipients to forward the survey to their own contacts. The survey was thus distributed by intentional sampling (Kvale, 1996) followed by a snowball effect from key informants (Barroso et al., 2012). Respondents can be “novices” in landscape assessment or “experts” (e.g. landscape architects, landscape researchers). They were asked to specify it at the end of the questionnaire.

The survey was based on a pairwise comparison, according to the method proposed by (Saaty, 1977). The photographs were first mixed, then drawn randomly and labelled in order by 1, 2,..., *m*. Given the total number of photographs, it would have been impossible to evaluate all existing comparisons within a reasonable time in the context of a survey. Accordingly, the analysis was

reduced to 60 pairs of photographs. First, 30 pairs were defined so that photograph 1 was compared with 2, 2 with 3, ..., *m* with 1. Then 30 other pairs were formed so that photograph 1 was compared with 3, 2 with 4, ..., *m* with 2. The order of the 60 pairs of photographs within the questionnaire was determined so that no photograph could appear more than once in every 10 pairs. Participants were invited to choose their favourite photograph at each step by the prompt: 'Select the scene you prefer'. The location of the photographs did not deliberately disclosed to the respondents of the survey to not influence them. It was just stated at the beginning that all the photographs 'were taken in urban fringes of French agglomerations'.

We then constructed a matrix A=$[a_{ij}]$ comparing *n* by *n* photographs as $a_{ij} > 0$ for any *i,j* $= 1, \dots, n$. This positive matrix respects the reciprocity $a_{ji} = 1/a_{ij}$. For each pair of photographs, we assigned a value of 2 to the selected photograph, and a value of ½ to the other. Matrix entries left blank were iteratively replaced by the product of geometric means of the existing entries in the respective rows and columns according to the formula proposed by (Koczkodaj et al., 1999):

$$a'_{ij} = \sqrt[n_i]{\prod_{k=1}^{n_i} a_{ik}} \sqrt[n_j]{\prod_{k=1}^{n_j} a_{kj}}$$

The additional information of these entries minimized the inconsistency of the matrix corresponding to each respondent. The calculation of the eigenvector (Saaty, 1990) of the response matrix for each respondent gave the weight ω of each photograph. This method provided a quantitative variable for each photograph from relative qualitative rankings, reflecting the aesthetic judgment of each individual.

2.3. Visibility analysis

2.3.2. Spatial data

Land Cover

For zone 1, land cover data were obtained by combining two vectorial databases. (1) The BD Topo provided by IGN (2010) contained forests, aquatic areas, artificialized areas, buildings and transport infrastructures. (2) The BD Agreste (2010) contained agricultural areas, by distinguishing grassland and cropland. Areas non informed by these two data sources were counted as green spaces after a photo-interpretation step. This was particularly the case alongside transport infrastructures or in intra-urban spaces (parks and gardens).

For zone 2, the land cover data were provided by the Institute for Urban Planning and Development of the Region Ile-de-France (IAU-IDF, 2012). The vectorial database was very

detailed and contained 83 land cover and land use categories including several types of forests (woods, plantations, etc.), green spaces (parks, gardens, golfs, etc.), aquatic areas, agricultural areas, artificialized areas and main transport infrastructures. This information was supplemented by the BD Topo provided by IGN (2012) for buildings and secondary roads.

For each zone, vector data were combined and grouped into nine land cover categories (**Tab. 1**) to allow comparison of the two study areas. These nine categories were identified in the literature as key elements likely to affect individual landscape preferences. The two vector maps were then converted into two raster layers with a 5 m spatial resolution.

DEM

Digital elevation models (DEM) are important in modelling the visible landscape because they represent its physical shape. For each area, a 50 m spatial resolution DEM was provided by the French National Geographic Institute (IGN). The two DEM were re-sampled and interpolated by the regularized splines method (Franke, 1982; Mitas and Mitasova, 1988) to give the same resolution as on the land cover maps.

DSM

Information about the height of the landscape elements that may obstruct views was required (Joly et al., 2009). So, for each zone, a digital surface model (DSM) of 5 m spatial resolution was constructed by specifying a height mask only for the elements that have in reality a quite sufficient height to block the view (buildings and forest elements). BD Topo provided accurate information about the height of each building (**Tab. 1**), measured by photogrammetry from aerial images. A random height between 15 m and 25 m was assigned for forest elements, corresponding to the approximate height of tree species in the two study areas. The height of other elements, being relatively flat, was set to zero.

Table 1. Land cover categories and height of the elements for each category.

	Land cover categories	**Height**
1	Forest	Random values [15; 25]
2	Green spaces	0
3	Arable	0
4	Grassland	0
5	Water	0

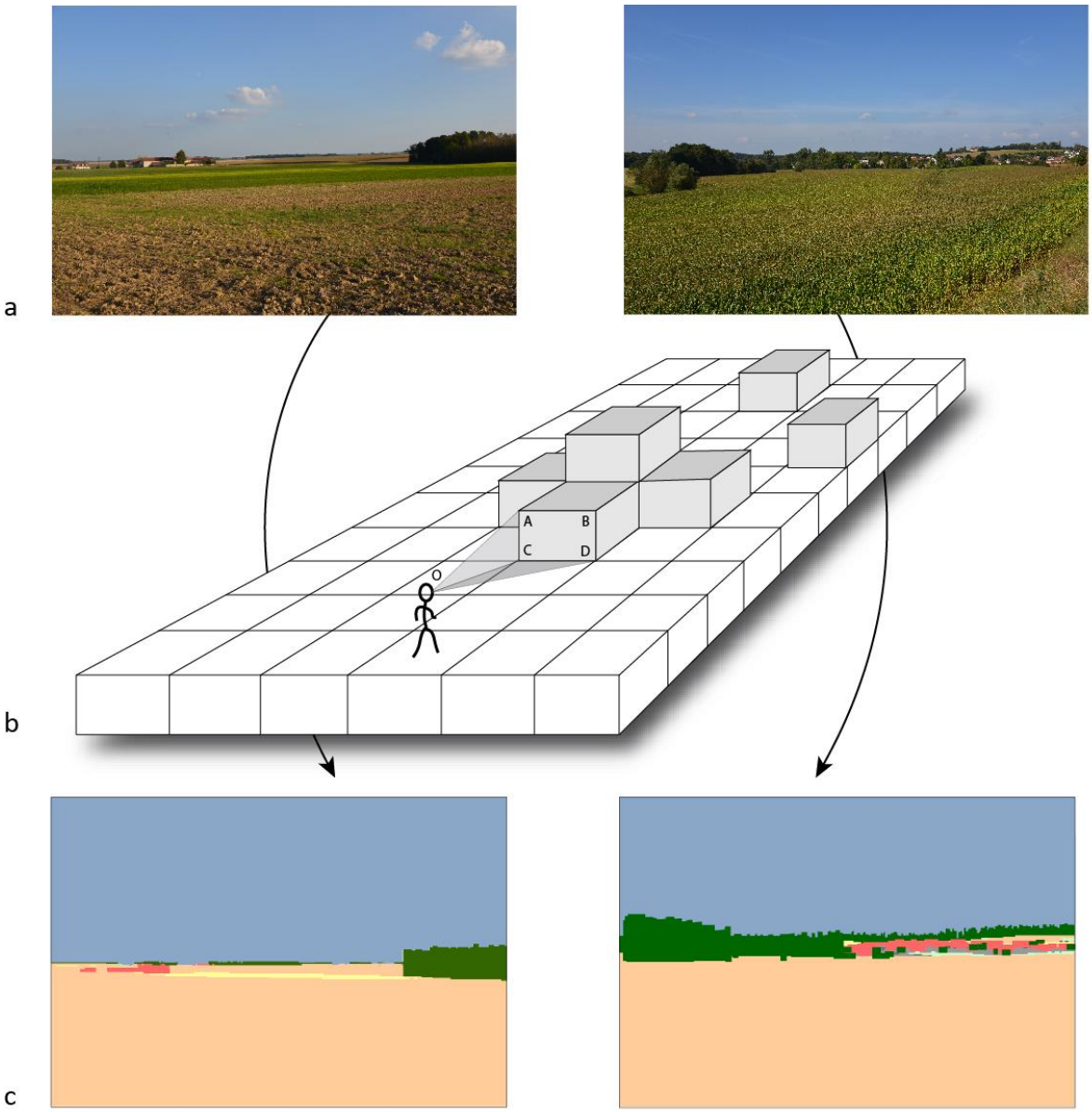
6	Artificial	0
7	Residential buildings	Real values *(source : IGN)*
8	Retail buildings	Real values *(source : IGN)*
9	Roads	0

2.3.3. Computation of visibility metrics

In this study, the visible landscape was modelled using the solid angles method quantifying landscape composition and configuration on the retina of a potential observer. This involved using a *sight line* method creating a 2D image synthesis of a modelled environment from 2.5D spatial data (land cover, DEM and DSM) (**Fig. 3**). Several metrics can be computed from this image (see Appendix 1 for details).

For a given viewpoint, composition and configuration metrics were calculated in an area corresponding to the view represented in the photograph. Computations were launched from geolocated points in the same direction as the photographs and at a height of 1.75 m. These analyses were limited to a horizontal angle of 60° and a vertical angle of 50°. Consequently, they quantified precisely the landscape characteristics visible in each photograph.

Composition metrics were used to quantify each visible element from the nine land-cover categories to characterize the visual content of landscapes (Joly et al., 2009; Miller, 2001). In addition, configuration metrics allowed to measure the diversity of the visible landscape (SCOMP), its degree of aggregation or fragmentation (CONTAG and IJI), its openness (SUM and AVE), its texture (SDIST and DEPTHLINE), and the shape of the skyline (SKYLINE), which can be more or less rough according to the relief or the presence of elevated elements. The Appendix 2 presents the descriptive statistics of variables.



Composition metrics		Configuration metrics	
Forest	2.104	SCOMP	0.209
Green	0.008	CONTAG	88.781
Cropland	45.438	IJI	49.805
Grassland	0.288	SUM	1.37E+07
Water	0.000	AVE	89.499
Artificial	0.000	SDIST	0.674
Resid. build	0.120	DEPTHLINE	22.351
Retail build	0.071	SKYLINE	1.103

Composition metrics		Configuration metrics	
Forest	8.746	SCOMP	0.239
Green	0.095	CONTAG	87.339
Cropland	48.206	IJI	63.598
Grassland	0.039	SUM	1.49E+07
Water	0.000	AVE	87.339
Artificial	0.269	SDIST	0.850
Resid. build	0.547	DEPTHLINE	17.884
Retail build	0.000	SKYLINE	2.081

Fig. 3. Example of landscape modelling for two photographs (a) by calculating angular surfaces (b). The point 0 corresponds to the eye of a potential observer and the rectangle ABCD the visible surface of a landscape element reconstructed from spatial data. The calculation of the angular surface of this object is obtained by computing the product $(AOB) \cdot (AOC)$, where AOB is the horizontal angle and AOC the vertical angle. This analysis allows to compute visibility metrics from the 2D images synthesis (c).

2.4. Statistical analysis

We first explored the differences in the individual judgments of landscape scenes. In order to synthesize individuals' responses, a principal component analysis (PCA) was performed on the table that brought together all individual judgments, i.e. eigenvectors assigned to each photograph derived from the pairwise comparison for each respondent.

From the factorial coordinates of individuals on the first factors, an ascendant hierarchical classification (AHC) based on the Ward method generated groups of individuals with similar judgments.

Then, we tested the capacity of the visibility metrics to explain landscape preferences of each group of individuals. As the preferences were dependent on the combination of several landscape characteristics, we used a multiple linear regression. For each group, the mean judgment of each photograph was the dependent variable and the visibility metrics were the explanatory variables. The best model was selected using a variable-selection procedure based on the minimization of the Akaïke Information Criterion (AIC) value for all possible combinations of variables. Collinearity among explanatory variables was evaluated using the variance inflation factor (VIF).

2.5. Mapping the aesthetic potential

The visibility metrics selected by the statistical models were calculated for the two entire study areas at a 5 m spatial resolution except for closed spaces (forests and buildings). The coefficients of the linear regressions were applied to these metrics to map the aesthetic potential of the landscape from each pixel considered as a viewpoint. The values of aesthetic potential quality resulting from this procedure were normalized by a linear transformation from 0 to 1 so that maps from each group could be easily compared.

3. Results

3.1. Analysis of individual judgments

Over two months 1889 individuals began the survey and 1420 completed it, i.e. a dropout rate of less than 25%. Descriptive statistics of the respondents (n = 1420) are listed in **Tab. 2**.

Table 2. Descriptive statistics of respondents socio-demographic characteristics

Professional background	%
Novice	84.9
Expert	15.1
Sex	
Female	65.4
Male	34.6
Age (years)	
16-25	38.4
26-35	28
36-45	15.2
46-59	13.9
Over 60	4.5
Residence	
Urban	58.9
Suburban	17.1
Rural	24

The PCA was performed on the table containing the aesthetic judgments of the 1420 respondents for the 30 photographs. Given the decline in the eigenvalues, only two factors were found to be significant for synthetizing individual judgments. The dendrogram of the HAC applied to these factors allowed us to define three groups of respondents (**Fig. 4**).

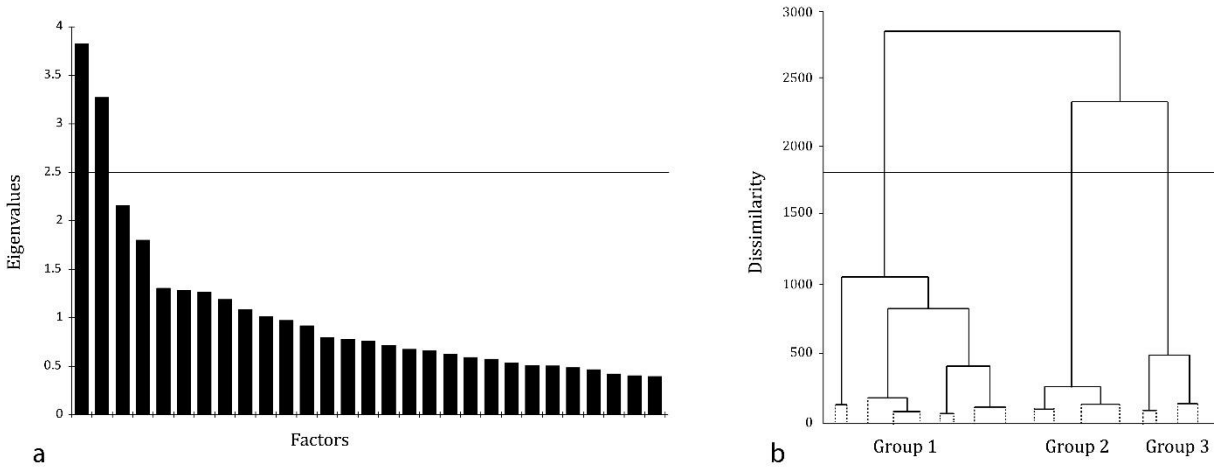


Fig. 4. Eigenvalues resulting from the principal component analysis (PCA) performed on the aesthetic judgments of the 1420 respondents for the 30 photographs (a). The first two factors are considered significant for synthetizing individual judgments. The dendrogram results from the hierarchical ascendant classification (HAC) based on the coordinates of the respondents on the first two factors of the PCA (b). Three main groups of respondents are identified.

We observed the socio-demographic composition of the groups from the proportion of individuals given their demographic characteristics in each case (**Tab. 3**). The rather rural novices are overrepresented in group 1. Group 2 is composed of more urban experts and older people. Group 3 includes more than half of the respondents and is more heterogeneous in composition.

Table 3. Trends in the socio-demographic composition of the three groups. Values correspond to the distribution (in %) of individuals by groups according to their socio-demographic characteristics.

	Group 1 (*n*=426)	Group 2 (*n*=267)	Group 3 (*n*=727)
Professional background			
Novice	90.8	67.8	87.8
Expert	9.2	32.2	12.2
Sexe			
Female	68.3	61.4	65.2

Male	31.7	38.6	34.8
Residence			
Urban	51.2	68.5	59.8
Suburban	17.6	15.0	17.6
Rural	31.2	16.5	22.6
Age (years)			
16-25	41.7	22.8	42.5
26-35	26.5	32.2	27.7
36-45	13.2	21.7	14.6
46-59	13.9	17.2	12.0
Over 60	4.7	6.0	3.3

Table 4. Results of the multiple linear regression analysis for the three groups.

Groups	Variable	Coefficient	Normalized Coefficient	Student t	VIF
Group 1	Constant	-0.0079			
$r^2 = 0.890$	SKYLINE	0.0030	0.5079	6.02***	1.355
$p<0.0001$	Water	0.3788	0.3810	5.00***	1.108
	Forest	0.0158	0.3027	3.60**	1.346
	CONTAG	0.0003	0.2773	2.75*	1.945
	AVE	0.0001	0.2332	2.65*	1.473
	Grassland	0.0159	0.2055	2.55*	1.240
	Residential build.	-0.0336	-0.2381	-2.57*	1.640
	Retail build.	-0.4159	-0.2582	-2.88**	1.527
Group 2	Constant	0.0171			
$r^2 = 0.672$	AVE	0.0001	0.4441	2.90**	1.718
$p<0.0001$	SKYLINE	0.0019	0.4345	3.22**	1.335
	Cropland	0.0121	0.3889	2.53**	1.731
	SDIST	0.0073	0.2652	2.07*	1.205
	Retail build.	-0.4958	-0.4258	-3.38**	1.163
Group 3	Constant	0.0184			

$r^2 = 0.700$	Forest	0.0201	0.5011	3.59**	1.364
$p<0.000$	SKYLINE	0.0019	0.4136	2.80*	1.521
	Grassland	0.0212	0.3569	2.62*	1.295
	AVE	0.0001	0.3541	2.33*	1.616
	Water	0.2294	0.3006	2.17*	1.347
	Green spaces	0.0106	0.2227	1.46	1.629
	Roads	0.0180	0.2505	1.68	1.563
	Retail build.	-0.3476	-0.2811	-2.06	1.304

** $p < 0.05$*

*** $p < 0.01$*

**** $p < 0.001$*

Of the 17 explanatory variables tested, three were excluded from the analysis because they were correlated with other variables (Pearson coefficient > 0.7). These were the proportion of artificial areas (correlated with the proportion of residential buildings), CONTAG (correlated with SCOMP) and SUM (correlated with AVE). **Tab. 4** presents the results of the multiple linear regression analysis. Globally, the selection procedure led to the definition of a significant model for each group. Of the 13 remaining variables, eight were selected in the Group 1 model ($r^2 = 0.890$), five in the Group 2 model ($r^2 = 0.672$) and seven in the Group 3 model ($r^2 = 0.700$). All VIF values are less than 2, confirming the absence of collinearity among variables.

The three models display certain similarities. The variables AVE (characterizing the degree of landscape openness) and SKYLINE are positively correlated with the aesthetic judgment values of all three groups. The presence of farmland also appears to be appreciated in each case, but with grassland for groups 1 and 3 and cropland for group 2. On the contrary, the visual presence of retail buildings has a negative effect for all groups. Some variables are selected by only two models, revealing differences in aesthetic judgments. The proportions of forest and water have a positive effect for groups 1 and 3. Finally, other variables are specific to one group. In group 1 the presence of residential buildings and landscape fragmentation (CONTAG) have a negative impact on aesthetic judgments. In group 2 the openness diversity (SDIST) has a positive impact. In group 3 the proportions of green spaces and roads are positively correlated with aesthetic judgments. The size of coefficients related to the visual presence of water (values always higher

than 0.28) and retail building (values always lower than -0.35) is noteworthy compared to the other coefficients, whose values never exceed 0.2.

3.2.Mapping landscape aesthetic potential

Maps of landscape aesthetic potential were made for each group (**Fig. 4** and **Fig. 5**). Globally, the resulting spatial pattern highlights an opposition between (1) urbanized areas that are the least appreciated and (2) open areas that are the most appreciated. However, several differences are visible between the groups of respondents. This is particularly the case of urban spaces, which overall are not appreciated by group 1 respondents, while only the areas surrounding industrial areas have a low aesthetic potential for groups 2 and 3.

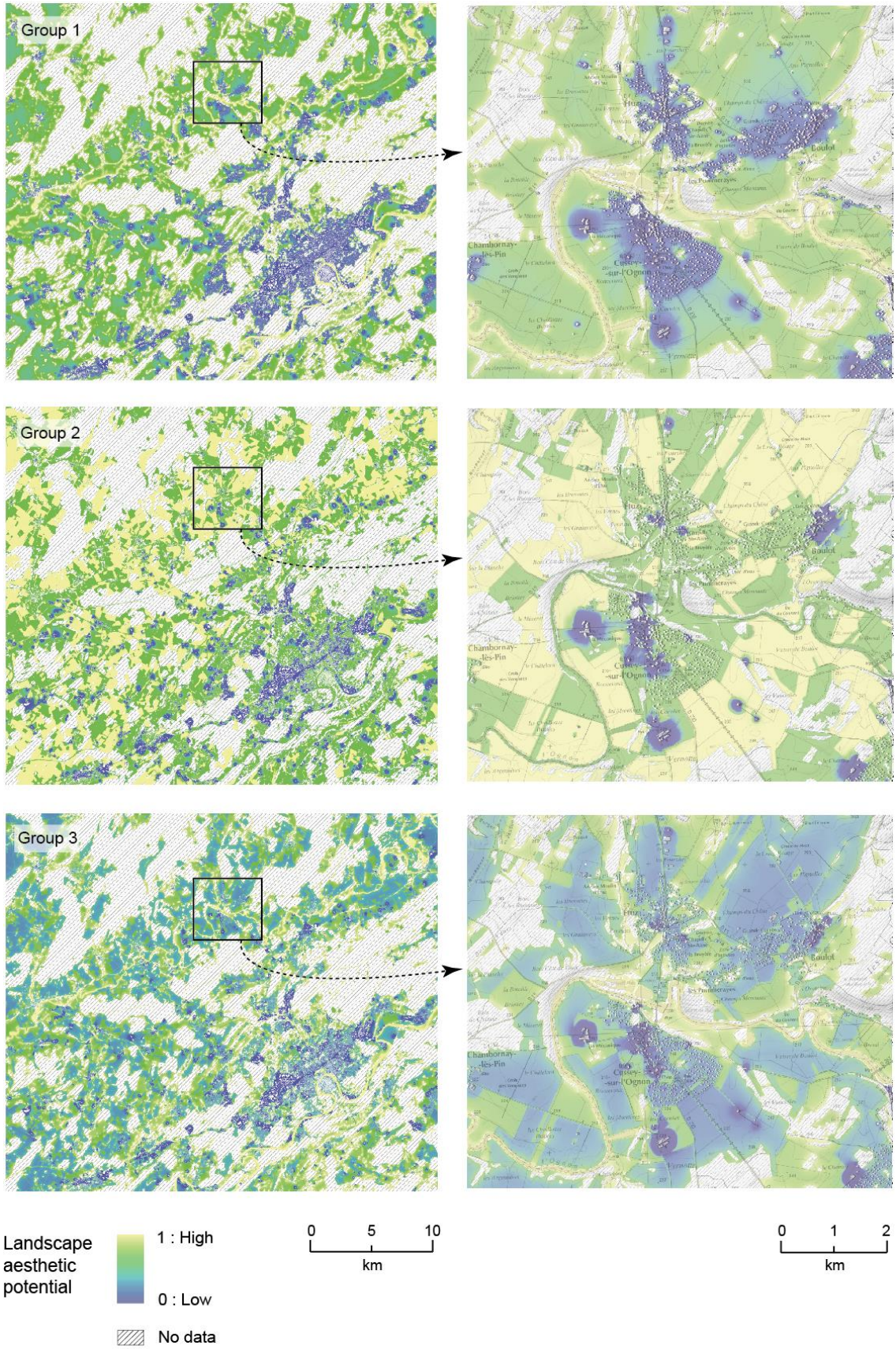


Fig. 5. Landscape aesthetic potential in the metropolitan area of Besançon

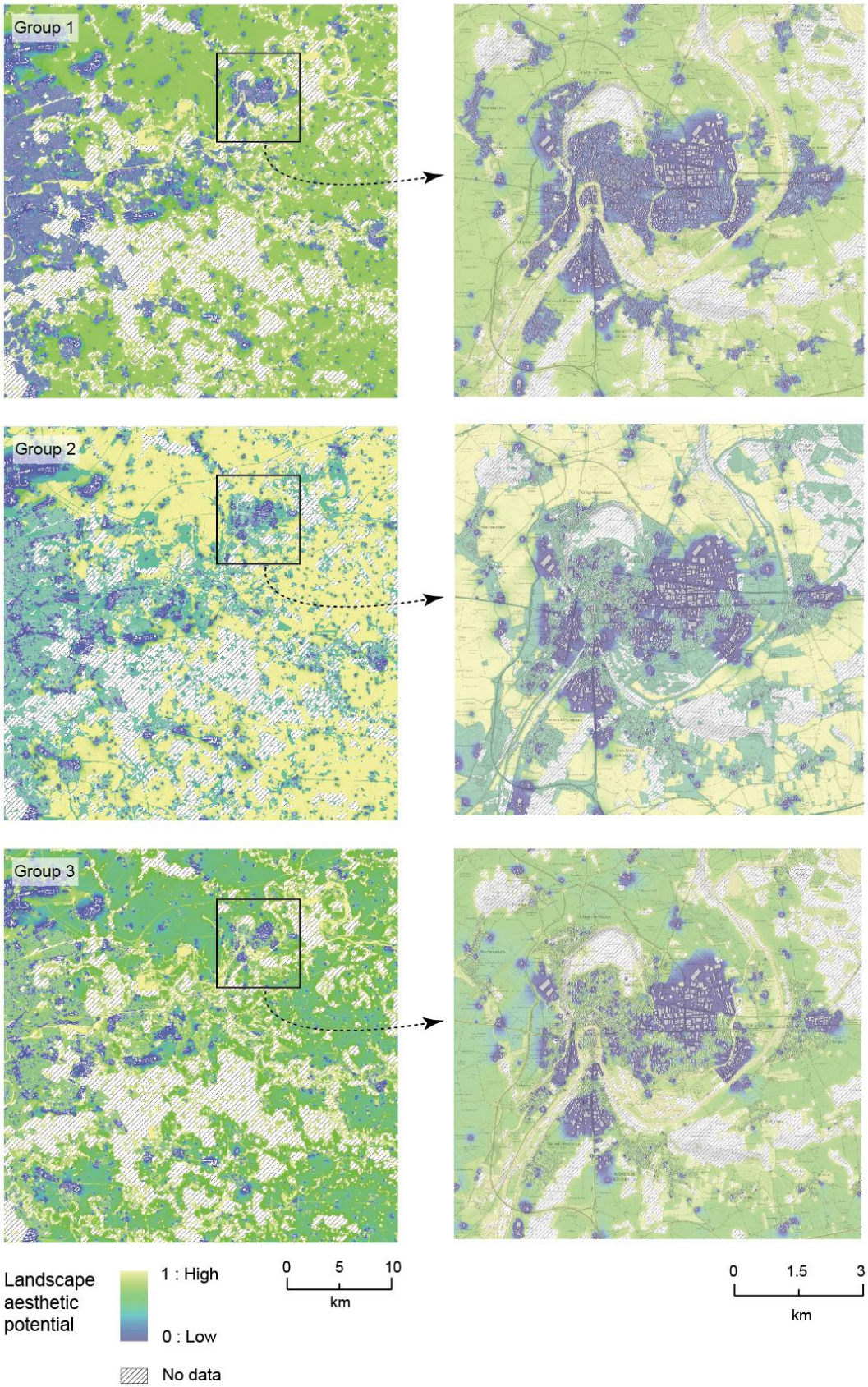


Fig. 6. Landscape aesthetic potential in the metropolitan area of Paris

The spatial relationships between the three landscape aesthetic potentials are analysed by combining them in an RGB image (**FIG. 6**) as in Vizzari (2011). The colour variations indicate how the three groups of judgments are spatially interrelated. The colour intensity indicates the global level of landscape aesthetic potential. The lighter areas exhibit high global potential and vice versa for the darker areas. The hue indicates the dominance level of the three groups according to the attribution of the colour bands. This mapping highlights (1) the areas commanding a global consensus, where the landscape is appreciated (white) or not (black), and (2) the areas over which groups disagree. A consensus can easily be identified between the three groups of respondents about the less appreciated areas around industrial and commercial buildings (in black). Other colours allow us to visualize areas of consensus between certain groups. For example, there is a consensus about the magenta hue areas between group 1 (red band) and group 3 (blue band). This concerns grassland and water areas especially.

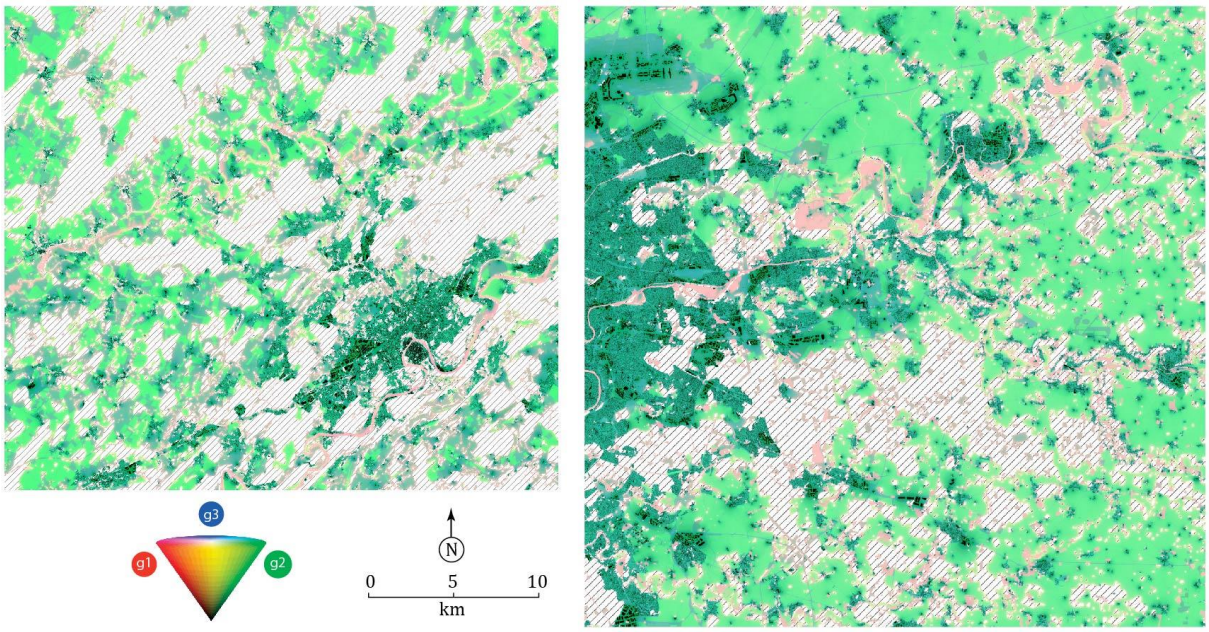


Fig. 7. RGB composite image of the three groups of aesthetic judgments

4. Discussion

The purpose of this article was to propose a spatial modelling of landscape aesthetic potential according to the differences between judgment groups. This modelling was conducted on the assumption that these judgments could be influenced by landscape characteristics.

Other researchers have studied consensus in landscape preference judgments (Hagerhall, 2001; Kalivoda et al., 2014) but without constructing homogeneous judgment groups. In this work, the proposed classification of the 1420 respondents led us to define a limited number of groups characterized by similar landscape aesthetic judgments. Thus there is a 'third way' between (1) expert approaches which assume that landscape quality depends directly on its visual attributes and (2) perceptive approaches focusing on individuals' socioeconomic, demographic or cultural characteristics. The intermediate approach used here allows us to synthesize individual landscape aesthetic judgments while highlighting the specificities of each aesthetic judgment group.

Statistically, the analysis provides results with good explanatory power. Regression models explain almost 90% of the variance at best and as much as 67% at worst. These results are similar to those in a similar analysis by (Schirpke et al., 2013). With regard to the metrics selected by the models, the analysis shows that artificial elements, whether residential buildings or retail buildings, have a negative effect on landscape aesthetic judgments. This finding is consistent with Arriaza et al. (2004) and with studies about restorative environments (Kaplan & Kaplan, 1989; Ulrich, 1979), which claim that exposure to urban environments (in contrast to natural environments) has a negative role on affective states or attention restoration. The one exception concerns the positive role played by the proportion of roads for group 3. However, we can relativize this positive role. Indeed, linear land cover elements occupy a very small proportion of the visible landscape unlike buildings, whose vertical development leads to significant visual salience.

For groups 1 and 3, we found a positive role played by natural elements such as water and forests, which is consistent with Arriaza et al. (2004), Bishop & Hulse (1994), Carvalho-Ribeiro & Lovett (2011), Ellis, Lee, & Kweon (2006) and Tahvanainen et al. (2001). Especially for water, many studies have shown that it is the most attractive element of a landscape (e.g. Faggi et al., 2011; Kaltenborn and Bjerke, 2002), producing beneficial psychophysiological effects (e.g. Hartig et al., 1991; Parsons, 1991) or influencing the amenity value of residential locations (Mahan et al., 2000; White and Leefers, 2007). Green spaces also influence aesthetic judgments positively for group 3, a phenomenon reported by several researchers (Matsuoka and Kaplan, 2008; Tyrväinen et al., 2007). These results also confirm research into restorative environments and especially the *biophilia* hypothesis of (Wilson, 1984). However, several empirical studies showed that aesthetic judgments may also be influenced by water movement or healthiness (Brown and Daniel, 1991; Cottet et al., 2013), and by the management of forests (Carvalho-

Ribeiro and Lovett, 2011; Tyrväinen et al., 2003), features that were not included in this work. Moreover, agricultural areas, whether grassland or cropland, also appear to have a positive role on landscape aesthetic judgments. However, many studies have highlighted that croplands (unlike grasslands) have a negative effect on aesthetic judgments (e.g. Hietala-Koivu, 1999; Howley et al., 2012; Lindemann-Matthies et al., 2010). As for landscape openness, the metric corresponding to average openness has a positive effect in all three models, confirming what is generally reported in the literature (e.g. Coeterier, 1996; Rogge et al., 2007), especially the prospect-refuge theory of Appleton (1975). Contrary to our expectations with regard to the literature on landscape preferences (Dramstad et al., 2006; Kaplan and Kaplan, 1989; Schirpke et al., 2013), the influence of landscape configuration seems to be relatively absent, except for group 1 for which the contagion index plays a positive role, expressing a preference for the least fragmented landscapes. Finally, the computation of these metrics on the whole areas at 5 m spatial resolution provides a fine-scale map of the landscape aesthetic potential of viewpoints. Schirpke et al. (2013) have also produced such maps in a mountain context, but for much smaller areas and at a lower resolution.

The reproducibility of the statistical and cartographic results may also be questioned. We can assume that our results are strictly valid in a spatial context of urban fringes. However, the two areas are (1) the fringes of a medium-sized city and (2) the fringes of a large metropolitan area. Therefore, the results can be extrapolated for identical spatial contexts, regardless of the size of urban agglomerations.

A sensitive issue of this research is the level of information details captured by the data. It is therefore important to question the grain of the spatial information upon which the visibility analysis rests. The land cover information precludes the mapping of some landscape characters that may affect individuals' aesthetic appreciation, for example high voltage pylons (Devine-Wright and Batel, 2013) or isolated trees (Ives and Kendal, 2013). Using very high spatial resolution data could improve the landscape description based on visibility metrics. However, working on large areas, we must find a trade-off between precision of analysis and computation time. We should also emphasize the need for closer consideration of land use rather than mere land cover. Landscape cannot be reduced to its material characteristics alone. It is also interpreted and meaningful in terms of the use of the objects that compose it. Those uses may well influence aesthetic judgments. This is particularly true for farmland. In this work, we distinguish only grassland and cropland. However, some research emphasizes the influence of the traditional or intensive character of farmland on aesthetic preferences (Howley et al., 2012)

or the role played by the diversity of plant species (Lindemann-Matthies et al., 2010). Similarly, we ignore here the architectural characteristics of residential areas. However, some buildings are likely to engender positive aesthetic judgments (e.g. historical heritage monuments), a factor that is not captured by spatial data.

We can also discuss the use of an online survey based on landscape photographs to explain landscape aesthetic judgments. In our study, it was not possible to precisely test the influence of the people's residential settings on their level of appreciation of the landscape. However, residential satisfaction surveys constitute another commonly used approach for landscape quality assessment (Youssoufi and Foltête, 2013), with the advantage to know the residential location of people and to take into account landscapes that are their living environment.

Specifically for photographs, several studies highlight problems related to the technical aspects that determine their quality and thus their validity. Coeterier (1983) noted for example that photographs fail to capture all information on a large-scale landscape with some of the subtleties of relief. Sevenant & Antrop (2011) report that many factors affect the validity of a representation such as the angle of view, the preference variable measured, or the landscape represented. The question of the view angle is certainly the most problematic. A 60° horizontal angle was used in this study, corresponding to human vision. However, head and eye movements enable landscapes to be observed through much wider angles. Concerning the survey construction, respondents were only invited to choose their favourite photo, in order to limit the response time at each step. This method precludes respondents from stating in addition a level of preference. Recommendations for further analysis could be to ask at each step for a weighting reflecting the degree of importance attributed to each photograph, as proposed by (Yager, 1977) in a pairwise comparison method.In this work, we demonstrated that landscape configuration has a direct effect on aesthetic judgments. In the perspective of this research, it would be interesting to focus more closely on the influence of the landscape configuration on the visual perception of photographs. Research based on eye-tracking experiments has already enabled analysis of the attention of individuals observing landscape photographs (Berto et al., 2008), or the influence of landscape characteristics and properties of photographs on eye-movement patterns (Dupont et al., 2014). In this perspective, it seems interesting to examine whether the viewing patterns play a part in people's aesthetic judgments. As for the maps resulting from the models, we think that the consideration of the quality of soundscapes might be one way to improve the spatial modelling of landscape quality potential. In the same way as visible landscape preferences, the soundscape approach considers the sound perceived as a

resource and focuses on sounds that people prefer or want (Brown, 2012). (Carles et al., 1999) have already studied interactions between visual and acoustic stimuli on landscape perception. The comparative analysis of landscape and soundscape appreciation requires, however, further *in situ* observations, or the mobilization of acoustic tools for representing sound environments (Oldoni et al., 2015).

5. Conclusion

The present study based on a landscape photograph survey shows that individuals' landscape aesthetic judgments can be compiled into a limited number of groups. Landscape visibility metrics were constructed from spatial data and studied as variables influencing aesthetic judgments. The results of the regression analysis confirm several landscape aesthetic theories, especially the positive influence of natural elements, as opposed to built elements. They also seem to suggest the positive influence of landscape openness, farmland and hilly skylines. Landscape visibility metrics provide a spatial representation of the landscape aesthetic potential for each judgment group. This mapping could provide leads for an operational application in urban and regional planning in such areas. In a prospective approach for example, this modelling could guide urban planners when it comes to minimizing the impact of new building projects or infrastructures on landscapes.

Appendix 1. Details of metrics computation

For a landscape category i, P_i is the proportion of angular surface given by:

$$P_i = \frac{a_i}{\sum_{j=1}^{n} a_j}$$

where a_i is the number of pixels corresponding to the category i and n is the number of landscape categories.

Based on the notion of entropy, the normalized Shannon diversity index (Shannon and Weaver, 1971) measures the diversity of the visible landscape, such that:

$$SCOMP = -\frac{1}{log(n)} \sum_{i=1}^{n} P_{ji} \log(P_{ji})$$

Two metrics adapted from landscape ecology were used to measure the degree of aggregation or fragmentation of the visible landscape, the contagion index and the interspersion and juxtaposition index.

The contagion index (O 'neill et al., 1988) is initially based on pixel adjacencies of the image. It corresponds to the probability of finding a pixel of the landscape category *i* next to a pixel of the landscape category *j*, such that:

$$CONTAG = \left[1 + \frac{\sum_{i=1}^{m}\sum_{j=1}^{m}\left[p_i \frac{g_{ij}}{\sum_{k=1}^{m} g_{ik}}\right]\left[ln\left(p_i \frac{g_{ij}}{\sum_{k=1}^{m} g_{ik}}\right)\right]}{2\ln(m)}\right]100$$

with P_i the proportion of angular surface of the landscape category i, g_{ik} the number of adjacencies between pixels of landscape categories i and j, and n the number of landscape categories in the image. Higher values indicate that pixels of a same landscape category are grouped together, whereas lower values characterize images in which all such pixels are dispersed.

The interspersion and juxtaposition index (McGarigal and Marks, 1995) is based on patch adjacencies of the landscape. Each category is evaluated according to its adjacency with all other categories, such that:

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

with e_{ik} the total length of edges between the landscape categories i and k, E the total length of edges, and m the number of landscape categories. Values are close to 0 if landscape categories are arranged in a very structured manner and close to 100 if no regularity is observed.

The degree of openness of the visible landscape was quantified by two metrics based on the length of sight lines. As each view was modelled by a series of *k* sight lines of length *s*, statistical indicators of sum (SUM) and average (AVE) were computed as follows:

$$SUM = \sum_{i=1}^{k} s_i$$

$$AVE = \frac{1}{k}\sum_{i=1}^{k} s_i$$

These indicators are expected to be higher when there is a wide field of view.

The texture of the visible landscape, i.e. the smaller or larger variation of sight lengths, was also evaluated from the lengths of sight lines with two other metrics (SDIST and DEPTHLINE). By defining *m* length classes noted *lc*, the ratio of sight lines in each length class was used to compute a normalized Shannon index as follows:

$$SDIST = \frac{1}{log(m)} - \sum_{i=1}^{m} lc_i \cdot log(lc_i)$$

This metric provides values close to 0 when only a few variations of length are present, and close to 1 when many variations occur. This metric was applied with five length classes: less than 10 m, from 11 to 100 m, from 101 to 1000 m, from 1001 to 10 000 m, and more than 10 000 m.

As *SDIST* ignores the spatial structure between sight lines, sight lengths were used to evaluate the spatial variation of the view depth, by the metric DEPTHLINE such that:

$$DEPTHLINE = \frac{vl}{cl}$$

where *vl* is the length of the viewshed contour and *cl* is the perimeter of the circle corresponding to the same area. This metric gives a minimal value of 1 in the case of a circular viewshed, and high values (not bounded) in the case of strong variations of view depth.

A final metric was devoted to the shape of the skyline, which can be more or less rough according to the relief or the presence of elevated elements. The metric SKYLINE was obtained by dividing the total length of the horizon *hl* by a straight line whose length *sl* corresponds to the width of the view:

$$SKYLINE = \frac{hl}{sl}$$

Values are close to 1 when the horizon is planar and highest (without bound) in the case of a very rough skyline.

Appendix 2. Descriptive statistics of variables.

Metrics	Min.	Max.	Mean	Stand. Dev. (n-1)
IJI	0.000	78.554	37.400	23.133
CONTAG	67.282	98.559	83.376	8.539
SCOMP	0.023	0.609	0.317	0.165
AVE (in meters)	5.403	173.286	54.723	34.201
SKYLINE	1.000	5.593	2.933	1.714
SDIST	0.018	0.966	0.599	0.267
DEPTHLINE	4.712	65.089	18.190	12.837
Forest (in % of angular surfaces)	0.000	0.980	0.119	0.196
Green (in % of angular surfaces)	0.000	0.575	0.075	0.165
Cropland (in % of angular surfaces)	0.000	0.527	0.208	0.238
Grassland (in % of angular surfaces)	0.000	0.462	0.045	0.132
Water (in % of angular surfaces)	0.000	0.056	0.002	0.010
Resid. build. (in % of angular surfaces)	0.000	0.305	0.040	0.072
Retail build. (in % of angular surfaces)	0.000	0.026	0.003	0.006
Roads (in % of angular surfaces)	0.000	0.334	0.073	0.109

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