



**HAL**  
open science

# Coupling crowd-sourced imagery and visibility modelling to identify landscape preferences at the panorama level

Jean-Christophe Foltête, Jens Ingensand, Nicolas Blanc

## ► To cite this version:

Jean-Christophe Foltête, Jens Ingensand, Nicolas Blanc. Coupling crowd-sourced imagery and visibility modelling to identify landscape preferences at the panorama level. *Landscape and Urban Planning*, 2020, 197, pp.103756. 10.1016/j.landurbplan.2020.103756 . hal-02462393

**HAL Id: hal-02462393**

**<https://hal.science/hal-02462393>**

Submitted on 5 Mar 2020

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# COUPLING CROWD-SOURCED IMAGERY AND VISIBILITY MODELLING TO IDENTIFY LANDSCAPE PREFERENCES AT THE PANORAMA LEVEL

Jean-Christophe Foltête<sup>1\*</sup>, Jens Ingensand<sup>2</sup>, Nicolas Blanc<sup>2</sup>

<sup>1</sup>ThéMA, UMR 6049 CNRS / University of Bourgogne Franche-Comté, 32, rue Mégevand F-25030 Besançon, France

<sup>2</sup>University of Applied Sciences Western Switzerland (HES-SO-HEIG-VD), Switzerland

\* corresponding author: FOLTETE Jean-Christophe - UMR ThéMA, 32, rue Mégevand, 25030 Besançon (France), Tel (33) 381 665 403, [jean-christophe.foltete@univ-fcomte.fr](mailto:jean-christophe.foltete@univ-fcomte.fr)

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

Foltête, J.-C., Ingensand, J., & Blanc, N. (2020). Coupling crowd-sourced imagery and visibility modelling to identify landscape preferences at the panorama level. *Landscape and Urban Planning*, 197, 103756. <https://doi.org/10.1016/j.landurbplan.2020.103756>

---

## Highlights

- Geotagged photos are analysed at panorama level
- Photos are associated with visibility metrics based on digital modelling
- Discrete choice modelling is applied to the set of photographed/antipodal view pairs
- Open and natural landscapes account in part for the choice of viewing direction

## Abstract

Geotagged photos posted on photo-sharing platforms have recently become a new source of information for analysing landscape preferences and investigating the aesthetic dimension of cultural ecosystem services. Most studies seek to explain photo density by landscape or spatial characteristics that might account for individual preferences and aesthetic criteria favoured by photographers. We focus instead on a “panorama level” of analysis, based on the assumption that photos represent preferential directions within a given panorama. The analysis consists in comparing the content of the photographed views with the content of the antipodal views (i.e. the view at 180°). We apply this method to a set of Flickr photos taken in the Lake Geneva region (Switzerland and France) characterised by landscape descriptors based on a visibility modelling approach. The results of discrete choice modelling at the global level are consistent with several key concepts of landscape preferences (e.g., openness, naturalness). The local analyses conducted at eight photo hotspots confirm the influence of open landscapes while revealing variations for certain other landscape characters depending on the geographical setting. We conclude that the panorama level approach combining geotagged photos and visibility modelling is suitable for identifying the landscape signature of the most appealing views. This signature could be used in further studies to detect the potential of visual amenities.

## Introduction

Over the last decade, crowd-sourced data shared on social media have emerged as a new source for rapidly gathering large datasets in numerous domains, and specifically for analysing people's behaviours and preferences (Agrawal, El Abbadi, Georgiou, & Yan, 2014). Geotagged photos posted on photo-sharing platforms such as Flickr or Instagram are a valuable resource for investigating recent land-use changes (Sitthi, Nagai, Dailey, & Ninsawat, 2016; Yan, Schultz, & Zipf, 2019), attractiveness for tourism (Sinclair, Ghermandi, & Sheela, 2018; Wood, Guerry, Silver, & Lacayo, 2013), place attachment and value of cultural landscapes (Tieskens, Van Zanten, Schulp, & Verburg, 2018), and more broadly the aesthetic dimension of cultural ecosystem services (Figueroa-Alfaro & Tang, 2017; Gliozzo, Pettorelli, & Hacklay, 2016; Lee, Seo, Koellner, & Lautenbach, 2019; Martínez Pastur, Peri, Lencinas, García-Llorente, & Martín-López, 2015; Oteros-Rozas, Martín-López, Fagerholm, Bieling, & Plieninger, 2018; Tenerelli, Demšar, & Luque, 2016; Yoshimura & Hiura, 2017). While a single photo may be insufficient for analysing aesthetic preferences (Palmer & Hoffman, 2001), the mass of data posted on photo-sharing platforms makes them relevant for capturing a wide diversity of views.

When using geotagged photos of outdoor views for identifying aesthetic services, each picture can be associated with three types of data: (1) the possible comment or key-words recorded by the depositor, (2) the geo-location of the photo, and (3) its image content. The first type of data can be used to classify the photos in terms of landscape characteristics (Figueroa-Alfaro & Tang, 2017) or landscape values such as cultural identity or community attachment (Chen, Parkins, & Sherren, 2018). However, the scarcity and heterogeneity of comments on photos means these data are rarely analysed. In contrast, the geo-location data by which each photo can be represented by a point entity in a GIS are frequently used for making spatial analyses, computing the local density of photos and identifying hotspots (e.g., Antoniou, Morley, & Haklay, 2010; Figueroa-Alfaro & Tang, 2017; Tenerelli et al., 2016; Tieskens et al., 2018).

The image content, i.e. the features visible in the photos, is essential for analysing landscape preferences. It conveys complex information identifiable by several methods. Some methods use the actual picture content, via manual coding (Angradi, Launspach, & Debbout, 2018; Martínez Pastur et al., 2015; Oteros-Rozas et al., 2018) or a tool based on artificial intelligence to automatically associate photos with tags (Lee et al., 2019). Other methods rely on coupling the pictures with landscape descriptors derived from geographical data such as land-cover maps and computed in the neighbourhood of the points of view. In recent studies, such computations have been based on the viewshed of each photo (Tenerelli, Püffel, & Luque, 2017; Yoshimura & Hiura, 2017). The viewshed analysis may be conducted either from the location of the photos all around the panorama as in Yoshimura and Hiura (2017) who mapped the "demand" for aesthetic services by overlapping all the viewsheds, or from the location of a virtual point (i.e. the centre of the cells in a grid) as in Langemeyer, Calcagni, & Baró (2018). However, an interesting approach is to use the azimuth and focal angle data recorded in photos taken with many recent smartphones and cameras to match the viewsheds with the space actually visible in the photos. Tenerelli et al. (2017) used this approach to characterise each photo by landscape metrics and so define a typology of aesthetic services. Basically, this method is helpful for analysing landscape preferences, because it provides more realistic results than the circular neighbourhood which represents an isotropic spatial environment only.

Whatever way landscape content is defined, most studies devised to identify landscape preferences focus on the local density and the presence of geotagged photo hotspots. Through this “geographical level” of analysis, the approach consists in comparing locations in terms of their landscape or the spatial characteristics likely to explain individual preferences or to make them attractive for tourists. The explanatory variables included in such investigations differ with the scale of analysis. For example, at country scale, Antoniou et al. (2010) correlate photo density with population density only. At a regional scale, Tieskens et al. (2018) explain the local density of photos by combining physical landscape attributes, population density, accessibility and infrastructure with place specific highlights. A similar approach is taken by Tenerelli et al. (2016) at a local scale, with the inclusion of precise spatial amenities such as the proximity to specific viewpoints, geological points of interest or points where refreshments are available.

In other research fields, eye-tracking focus maps have been applied to landscape views in an attempt to identify points of interest or landmarks. Recent developments in this area have shown that visual attention distribution can be well predicted by saliency maps (Dupont, Ooms, Antrop, & Van Eetvelde, 2016). These maps exhibit the salient features likely to attract attention, using specific characteristics of colour, orientation or intensity in contrast with the surroundings (Itti, Koch, & Niebur, 1998). The capacity of salience maps to predict potential landmarks in the case of landscape photos shows that the visual space of a given landscape cannot be considered as a uniform scene, but rather as a heterogeneous space in which certain features are striking while others go unnoticed.

Between the geographical level with its focus on photo density and the identification of landmarks using eye-tracking focus maps, we hypothesise there is an intermediate level that should be relevant for identifying landscape preferences. We refer to it here as the “panorama level”. We assume that when confronted with a panorama, some sets of landscape features may capture the attention in terms of aesthetics, leading viewers to look in specific directions from among the 360° of the potential view. This selection of preferential directions in a panorama should not result from the same process as the visual attention of an observer confronted with a fixed view, because human binocular vision is limited to a focal angle of around 45° (but varies with perception criteria) and looking at a panorama from a given point of view involves moving the viewing apparatus. In this case, we hypothesise that the choice of a specific direction when taking a photo of a scenic view may reveal landscape preferences. That being so, the geotagged photos posted on sharing platforms are likely to be informative as to landscape preferences if they are considered as a directional choice from among other possibilities in the panorama.

In this paper, we propose to test the relevance of the panorama level for identifying landscape preferences, when analysing a set of geotagged photos. Our research question is: “What is the specificity of the landscape features visible in the pictures of photo-sharing platforms as opposed to other features potentially visible from the same points?”. To investigate this, we extracted photographs taken in the south of the Canton of Vaud (Switzerland) from Flickr. These photos were associated with landscape attributes derived from a digital model of visibility.

## 2. Material and methods

### 2.1. The study area

The study was conducted in the Lake Geneva area, covering the south of the Canton of Vaud in the French-speaking part of Switzerland and the northern part of the department of Haute-Savoie, France. This area is mainly occupied by the western fringe of the Alps, where altitudes range from about 300 m to 3200 m. The centre of the area is occupied by Lake Geneva through which the River Rhône flows from East to West (Fig. 1). The north shore of the lake is composed of agricultural landscapes around the urban agglomeration of Lausanne (about 400,000 inhabitants). The limestone foothills of the Alps rise from the eastern and southern shores of the lake, which occupies a deep furrow dug by the glacial valley of the Rhône. These mountains are mainly covered by forest, grassland and rock, with small glaciers in the highest areas.

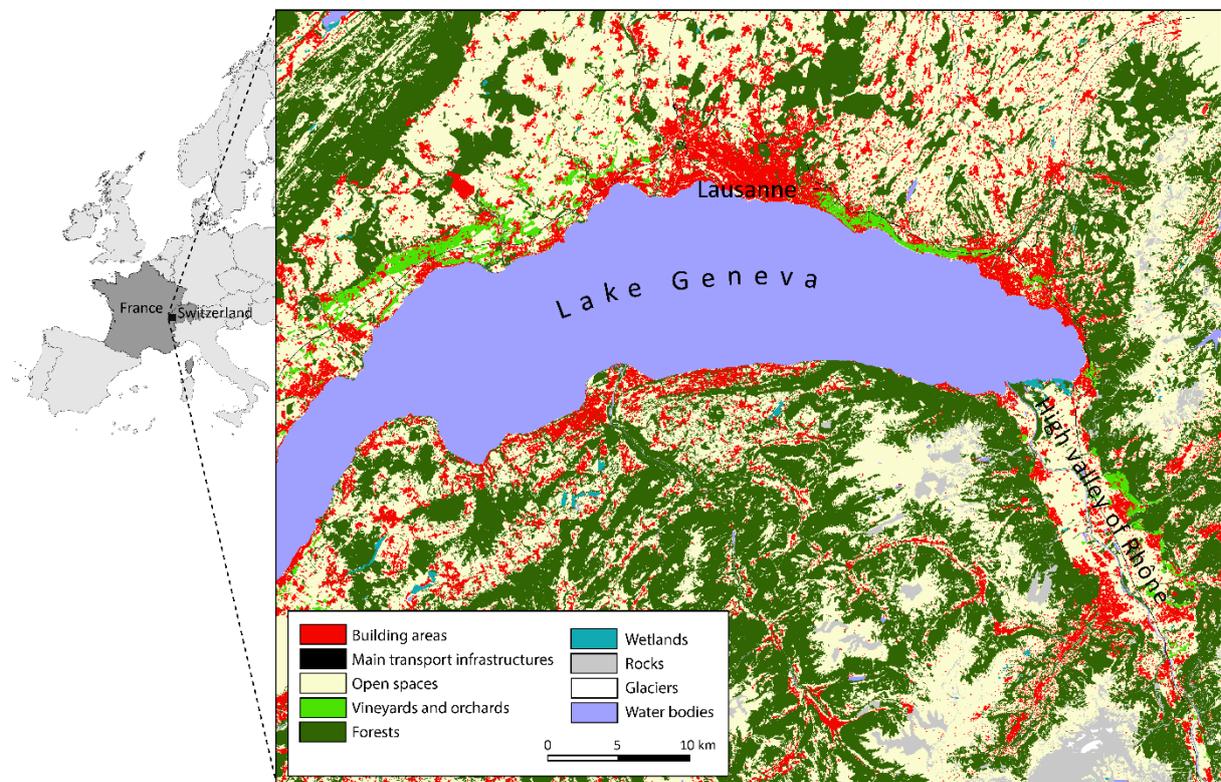


Figure 1. The study area.

### 2.2. Geotagged photos and geographic data

A set of geotagged photos was acquired from the API of the Flickr platform ([www.flickr.com](http://www.flickr.com)). As a first step, all photos posted in 2015 (to limit the volume of data for a first test), located in the Swiss part of the study area and with geolocation and azimuth data were downloaded. Each photo was considered as a point entity associated with the following attributes: geographical coordinates of the point of view, azimuth ( $^{\circ}$ ), focal angle ( $^{\circ}$ ). As the focal angle of the lens used depends on the size of the sensor, this attribute was harmonised to correspond to the focal angle of a 35 mm sensor (i.e. full format in photography).

Several selection criteria were then applied to define the dataset to be analysed. The outdoor views were selected by using a layer describing the building footprint ([www.openstreetmap.ch](http://www.openstreetmap.ch)) and by removing photos taken from indoors. This procedure may lead to exclude pictures taken through a window or from a balcony, but these photos are not interesting in our case since their viewing angle was not chosen within a potential panorama.

The investigation of azimuth values revealed an abnormal frequency of photos taken facing northwards (i.e. azimuth = 0°), leading to their removal from the sample. To limit edge effect in the visibility analysis, we also removed photos located within 500 m of the edge of the study area. The final step was to select the photos with a visual extent of at least 500 m (using the metric DISTmax, see section 2.3), to avoid very confined landscapes that could not readily be included in a digital modelling approach (see section 2.3). In addition, this last rule avoids the photos taken outside buildings but showing no landscape (e.g. picture inside a car). Starting from the initial set of 3065 photos, the selection procedure led us to retain 1313 photos (about 43%).

As the study area straddled the border between Switzerland and France, two maps were generated by combining data from both countries. A digital elevation model (DEM) was compiled using altitudinal data from the Swiss and French topographic agencies (Swisstopo and Institut Géographique National respectively) and resampled at the spatial resolution of 25 m. Similarly, a land-cover map was created by combining data from Swisstopo and BDTopo (Institut Géographique National) at the same spatial resolution. This map comprised nine classes: building areas, main transport infrastructures, open spaces (i.e. arable and grassland), vineyards and orchards, forests, wetlands, rocks, glaciers, and water bodies.

### *2.3. Characterisation of the photos by their landscape content*

We used a digital modelling approach to characterise the landscape content of each photo. For a given photo, this consisted in (1) positioning a virtual observer at the pixel corresponding to the point of view using the geographic coordinates recorded in the file, (2) applying the visibility rays method to identify the visible pixels from the point of view (Fisher, 1996) and (3) computing visibility metrics for characterising landscape features. We used the open access PixScape software (Sahraoui, Vuidel, Joly, & Foltête, 2018; <https://sourcesup.renater.fr/www/pixscape/fr.html>) to carry out these three steps and to benefit from specific functions. PixScape provides visibility metrics based on the tangential approach (i.e. assessment of visual weights in an angular surface unit) reproducing the view as it is perceived by a potential observer. This approach is more relevant than the planimetric approach (i.e. assessment of visual weights in number of visible pixels) commonly implemented in GIS software (Figure 2). Furthermore, the use of the tangential approach provides specific metrics of scene configuration that will be presented below.

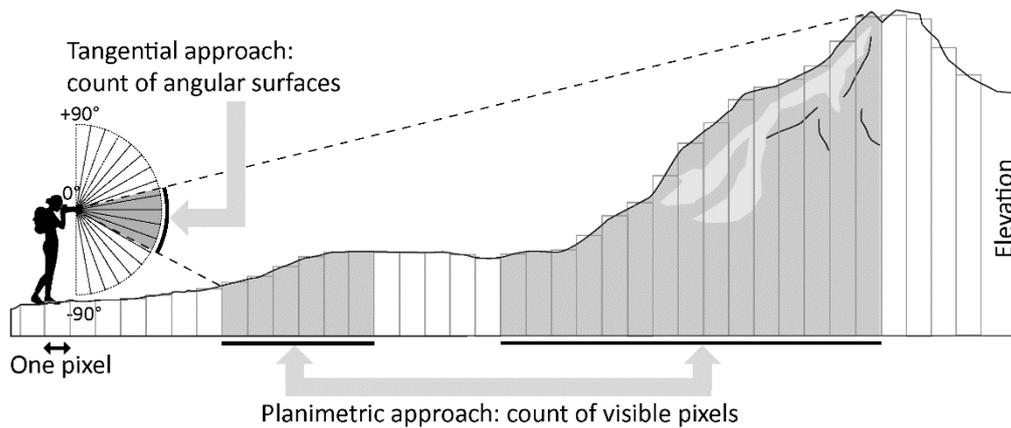


Figure 2. Tangential and planimetric approaches for modelling visibility from digital data

Given the relatively low spatial resolution, we ignored the potential presence of visual masks formed by buildings or woodland and requiring a digital elevation surface. Consequently, the visibility modelling was applied from the DEM only, the land-cover map being used to compute the visibility metrics defined at the land-cover class level.

Twenty-four visibility metrics were considered (Tab 1.). A first group (noted W) concerned landscape composition, including the visual weight of every land-cover class and the normalised Shannon diversity index for measuring diversity. The visual weight of a given class corresponds to the sum of the angular surface of each pixel of this class. The Shannon index was applied to the relative weights of the set of classes. A second group (noted P) also dealt with composition but expressed in terms of presence/absence by transforming the visual weights into binary variables. We assumed that the visual weight and the presence of a given class would provide complementary information, if for example the presence of a landscape element (e.g. set of buildings) increases the aesthetic value of a view, but decreases this value when the visual weight becomes too large. A third group was applied to the geometry of the view, including the degree of openness (average and maximum distances) and three metrics for describing the texture of the visual scene: the Shannon index applied to the distribution of distances of the visibility rays, expressing the statistical variation of the view depth, the “depthline” to characterise the spatial variation of the view depth, and the “skyline” to measure the more or less jagged aspect of the horizon (a low value meaning a flat horizon). For the computational details of all these metrics, see Sahraoui et al. (2018).

Type of metric	Code	Meaning
Composition (visual weight)	W-built	Visual weight of built areas
	W-infra	Visual weight of main transport infrastructures
	W-open	Visual weight of open spaces
	W-vineyards	Visual weight of vineyards
	W-forests	Visual weight of forests
	W-wetlands	Visual weight of wetlands
	W-rocks	Visual weight of rocks
	W-glaciers	Visual weight of glaciers
	W-water	Visual weight of water bodies
	Compo diversity	Normalised Shannon index of the landscape composition
Composition (presence/absence)	P-built	Presence/absence of built areas
	P-infra	Presence/absence of main transport infrastructures
	P-open	Presence/absence of open spaces
	P-vineyards	Presence/absence of vineyards
	P-forests	Presence/absence of forests
	P-wetlands	Presence/absence of wetlands
	P-rocks	Presence/absence of rocks
	P-glaciers	Presence/absence of glaciers
	P-water	Presence/absence of water bodies
Geometry	DISTavg	Average length of the visibility rays
	DISTmax	Maximum length of the visibility rays
	Skyline	Skyline, for measuring the shape of horizon
	Depth diversity	Shannon index applied to the distances (i.e. length of visibility rays)
	Depthline	Depthline, characterising the spatial variation of the view depth

Tab.1. Visibility metrics computed from each point of view

#### 2.4. Method for identifying preferences at the panorama level

As our aim was to test the distinctiveness of landscape features in each photo compared with features visible when focusing in another direction, the same set of visibility metrics was computed twice for each Flickr photo: once using the azimuth and the focal aperture recorded in the photo for representing “the photographed landscape”, and once using the same focal aperture but with the opposite azimuth, to represent the “antipodal landscape” (Fig. 3).

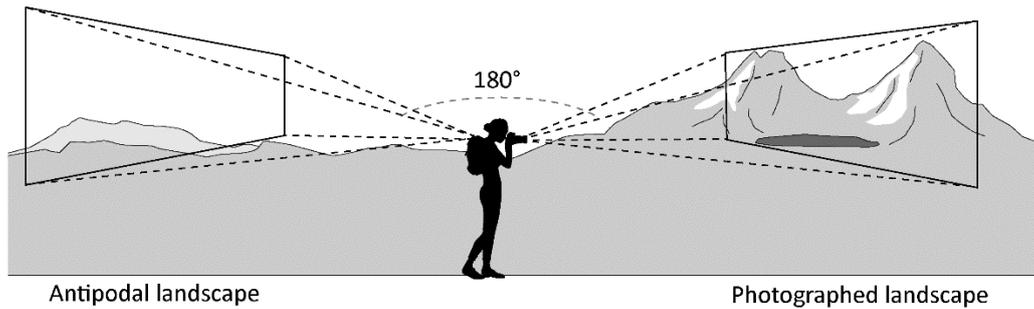


Figure 3. Principle of the panorama level of landscape preference analysis

A first approach for investigating the difference between these two sets of visual landscapes consisted in comparing the way they are transcribed in space. To do this, we aggregated all the viewsheds corresponding to the photos so as to ascertain the spatial signature of the photographed landscape. Then the same operation was applied to the viewsheds corresponding to the antipodal landscape. It is worth noting that the pixels comprising these viewsheds were weighted by their visual impact in the tangential view, i.e. by an angular surface rather than by a uniform weight. Finally, by subtracting the value obtained for the antipodal landscape from that of the photographed landscape, we drew up a map on which positive values indicate the recurrent preferential locations in contrast with the negative values.

A second approach aimed at the specific landscape features of the geotagged photos was based on a statistical analysis, in which each photo (i.e. the photographed landscape) was considered as a choice made by the photographer, as opposed to the antipodal landscape, which was considered as an alternative to that choice. This led us to implement discrete choice modelling, a statistical method similar to logistic regression and widely used in research on transportation (Ben-Akiva & Lerman, 1985; Ben-Akiva & Bierlaire, 1999). In this approach, the attributes of choice were the visibility metrics computed using the azimuth recorded in the photo, while the attributes of the alternative were the same metrics computed in the opposing direction. It is worth noting that in some cases, photos recorded in Flickr may cover several portions of the panorama visible from the same point of view, potentially providing statistical noise. However, we assumed that, given the large amount of data, statistical trends might emerge to distinguish the characteristics of photographed landscapes as opposed to those of the antipodal landscapes. Because we focused on the attributes of alternatives and not on the individual characteristics of photographers, we used a conditional logit model (CLM) (Ben-Akiva & Bierlaire, 1999; McFadden, 1973). Since our approach was to understand the choice criteria rather than to construct a predictive model, and given the moderate number of variables, they were selected in a stepwise process maximising the number of significant variables. This process was applied in reverse, by progressively pruning the model initially including all variables. It should be noted that we also tested the procedure of variable selection minimising the Akaike Information Criterion (Hosmer & Lemeshow, 2000), but this provided models with no significant variables. The CLMs were computed with CrimeStat IV (<http://www.nij.gov/CrimeStat>), a freeware application for analysing point datasets (Levine, 2015).

### *2.5. Extrapolation from the global statistical model to identify scenic views*

When considering the Flickr photos as a reliable signature of aesthetically valued landscapes, the outcome of the CLM explaining the choice of the photographed landscape versus the antipodal landscape was used to evaluate the potential of scenic views from the motorways in the study area, as if, for instance, we were seeking for implementing new rest areas with attractive views. To illustrate this application, we defined a set of points located every 2 km along the motorways, as if a scenic motorway service area were being planned. We first considered the mean of the focal angle calculated from the set of Flickr photos in the area. For each point, we used this focal angle to compute visibility metrics by moving the azimuth successively through 0, 30, 60, 90, 120, 150, 180, 210, 240, 270, 300 and 360°. The application of the CLM coefficients to the metrics calculated for the pairs of azimuths separated by 180° (i.e., including the direction of choice and that of its alternative) led us to assign a scenic score to each azimuth, and finally to represent those scores by geolocated vectors on a map. For a given point, large vectors contrasting with small vectors in the opposite direction indicate the direction for which a strong preference may occur. In the event of a small variation in the size of the vectors, there is no clear preference for any specific direction.

### *2.6. Local variations of landscape preferences*

The analysis of all the Flickr photos in the study area provides global results that may mask local variations due to specific landscape configurations. To investigate this effect, we applied the statistical approach based on CLM performed on subsets of photos relating to the same site. The identification of dense clusters of photos taken from specific sites led us to convert the set of points into a density map using the kernel density estimation method (Bailey & Gatrell, 1995; Gatrell, Bailey, Diggle, & Rowlingson, 1994). Since the choice of the bandwidth used in applying this method greatly impacts the results, we applied Ripley's K function to the set of points made up of the Flickr photos so as to determine the most relevant spatial scale (Ripley, 1977). To compare the observed pattern with a Poisson process (i.e. a random distribution), we considered the L-function derived from Ripley's K (Bailey & Gatrell, 1995), for which values above the higher confidence envelope indicate significant clustering patterns, and the difference between the observed and the expected functions. This method was applied for distances from 100 m to 10 km at 100 m increments. Once the bandwidth had been chosen, the density map was thresholded to identify the most characteristic hotspots of Flickr photos, resulting in the definition of subsets of photos. The CLM applied to the whole set of photos was conducted in a similar way for each subset.

In this local approach, we assumed that the relevance of the analyses depends in part on the more or less marked concentration in a specific direction. In a given city, for example, photographers may take numerous photos in all directions if many buildings are of architectural or historic interest (in this case, the local approach would be less relevant), while at another site they may concentrate on a particular monument (in this case, the local approach would be more relevant). To investigate this assumption, we calculated the angular standard deviation of the azimuths (Fisher, 1993) for the set of photos of each hotspot. This angular statistic quantifies the more or less concentration of the viewing angles around the average azimuth. It was expected to be lower when the explanatory power of the local model was higher.

### 3. Results

#### 3.1. Spatial analysis of landscape preferences

The values of the aggregated viewsheds corresponding to the photographed landscape and to the antipodal landscape were subtracted after being converted to logarithms because of the highly contrasted values. The resulting map (Fig. 4) shows positive and negative values mixing roughly, but a number of trends emerge from the details in the distribution. The most significant feature is the contrast along the northern shore of Lake Geneva, where positives values are mainly located along the shoreline, on the lake and on its southern shore, rather than on the slope overlooking the lake. In the east of the area, a corridor of visual preference takes shape, encompassing both the lake and its eastern edge. Elsewhere, the distribution is less readable but we can observe the directional preferences from several viewpoints.

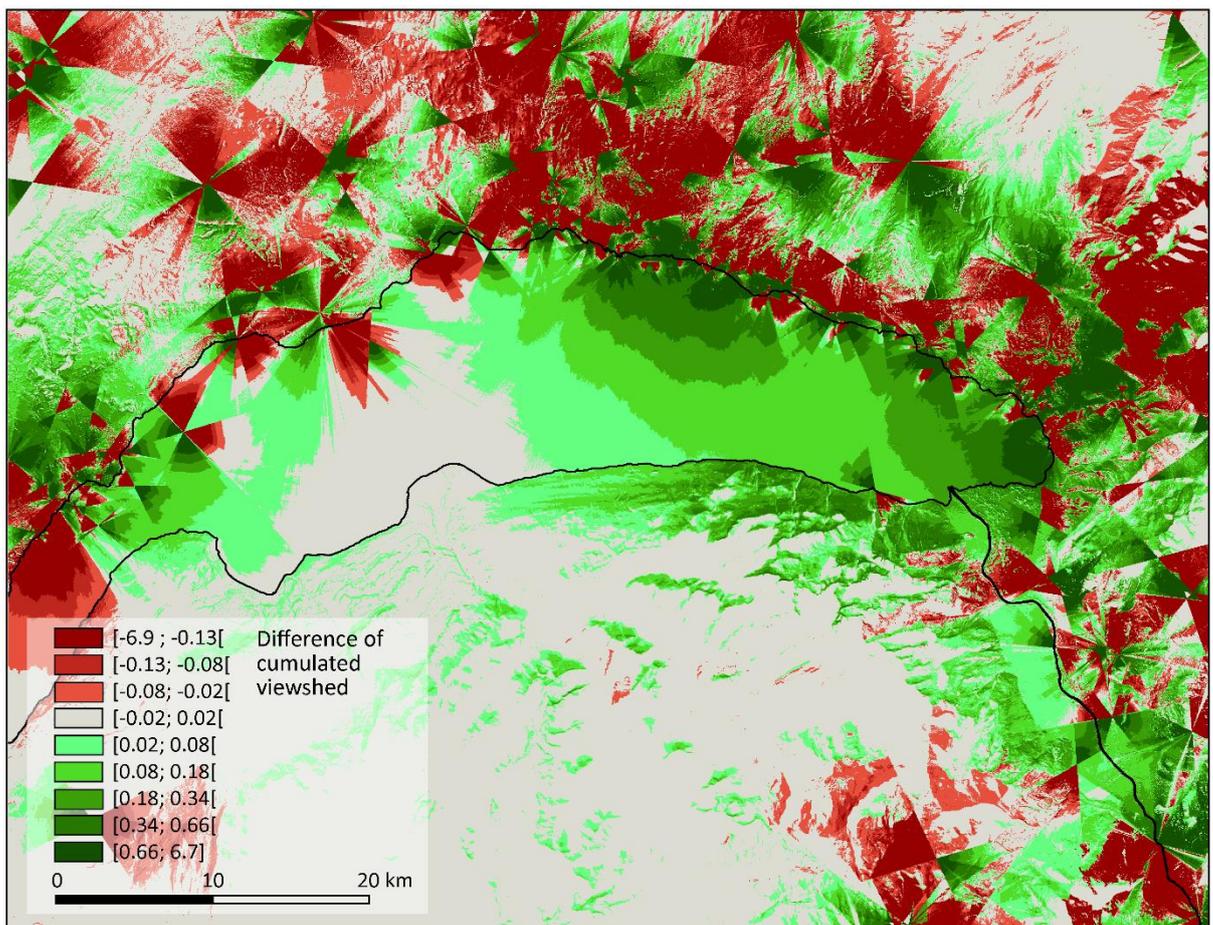


Figure 4. Spatial preferences in the Flickr photos

#### 3.2. Thematic analysis of landscape preferences

The 1313 photos were associated with two sets of visibility metrics, representing the photographed landscape and the antipodal landscape, resulting in a dataset of 2626 statistical individuals. Because of their decreasing and asymmetric distribution, the variables of visual weight

were transformed by a logarithm function. After this transformation, only W-built, W-open and W-forests had a suitable distribution, the other variables still had a highly asymmetric distribution.

The CLM applied to this dataset led to a model with an overall explanatory power (given by the adjusted pseudo McFadden R<sup>2</sup>) of 0.21. The CLM applied to this dataset led to the selection of six variables (Tab. 2), comprising one variable of visual weight (W-forests), two variables of geometry (DISTavg and Depthline) and three variables of presence (P-built, P-open and P-forests). Given the level of significance, the most important variables are DISTavg, P-forests and P-open. All variables have a positive influence, except for W-forests.

Variable	Coefficient	Standard error	t-value	p-value	Odds ratio
W-built W-open W-Compo	-0.301	0.107	-	0.01	2.617
P-built	0.962	0.343	2.809	0.01	2.617
P-open	1.533	0.379	4.048	0.001	4.636
P-forests	1.545	0.286	5.396	0.001	4.690
P-rocks P-glaciers P-water					
DISTavg Skyline Depth diversity	0.686	0.098	7.010	0.001	1.986
Depthline	0.542	0.241	- 2.255	0.05	1.719

Tab. 2. Results of the CLM

### 3.3. Extrapolation of the statistical model to the views from motorways

The coefficients of the logistic regression were applied to the metrics computed from the sample of points along the motorways in the 12 directions of the circular view. On the map showing the level of matching of the landscape with the photos from Flickr according to the direction (Fig. 5), the “cobwebs” (i.e. the 12 vectors drawn from a given point) take on different shapes in different locations. Along the shores of Lake Geneva between Nyon and Lausanne, the vectors tend to be larger towards the lake, although from certain spots attractive landscapes are to be found in other directions. Around the agglomeration of Lausanne, the views towards the lake prove to be more eye-catching, but here again, the preferred direction may vary locally. The attractiveness of the view in the direction of Lake Geneva becomes more pronounced where the motorway overlooks the eastern part of the lake. When the motorway enters the Rhône valley in the south-eastern part of the area, the cobwebs become more circular, meaning the attractive views do not lie in any specific direction.

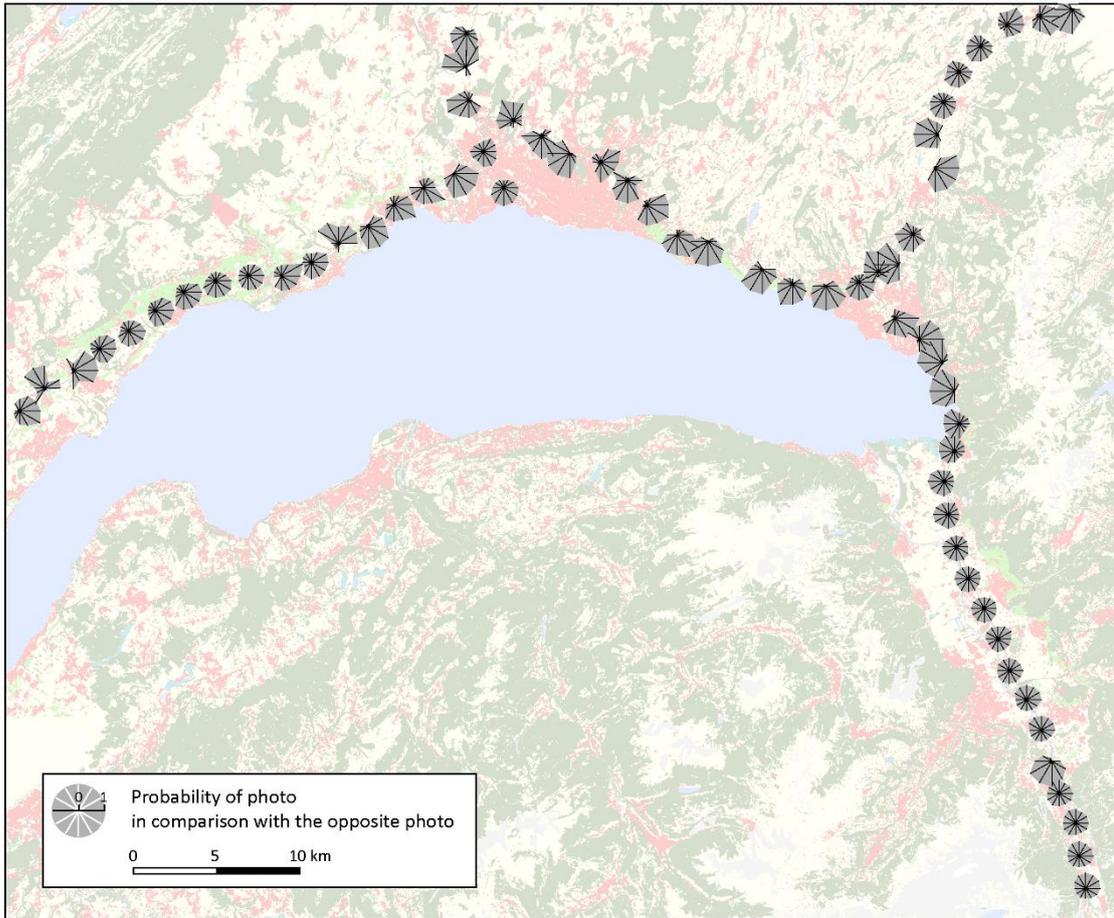


Figure 5. “Cobwebs” along motorways showing the preferred directions of view resulting from the analysis of Flickr photos.

### 3.4. Local analysis of landscape preferences

The application of Ripley’s K to the set of points shaped by the photos provided a curve of observed values lying well above the curve of expected values (Fig. 6a), indicating a clustering pattern at all spatial scales. Several peaks on the curve of the differences between observed and expected values (Fig. 6b) indicate the most characteristic scales of clustering. To focus on precise sites, we chose the first peak corresponding to the distance of 600 m to define the bandwidth which was then used in the local density calculation.

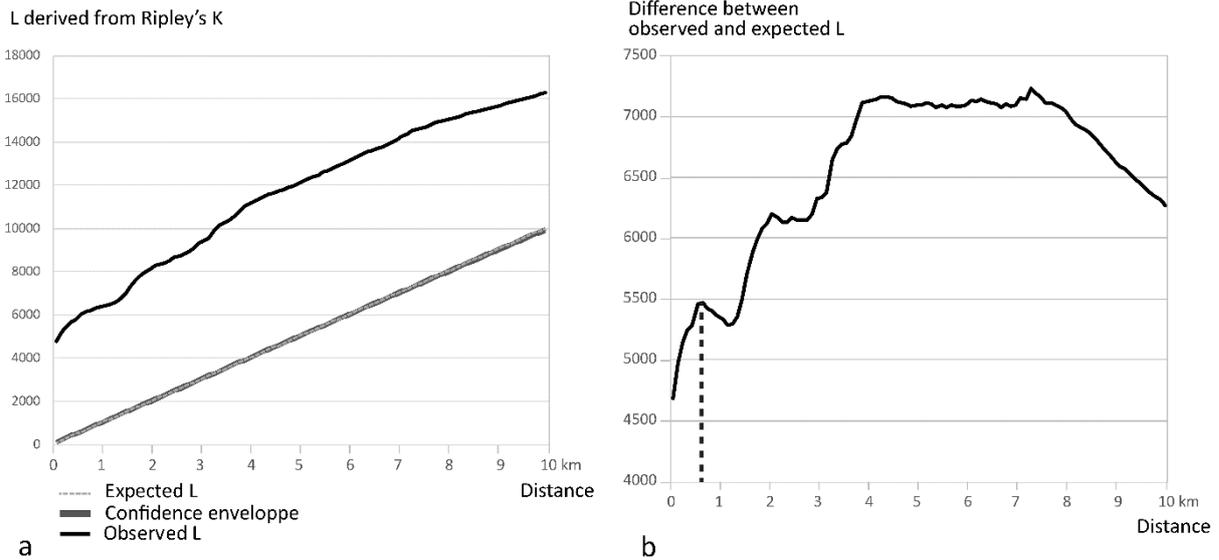


Figure 6. Curves of Ripley's K from 100 m to 10 km. (a) Observed and expected values with 95% confidence envelope. (b) Difference between observed and expected values. The dashed line indicates the shortest distance of clustering chosen for defining hotspots.

The computation of local density of photos yielded a hotspot map (Fig. 7). Among the few locations exhibiting a high density, we chose eight sites with at least 20 photos and sufficiently far from the boundary of the study area to avoid any edge effect: Nyon, Prangins, Buchillon and Ouchy on the shores of Lake Geneva; Lausanne centre and Lausanne Chilly in the main urban agglomeration; Bousens on the plateau overlooking the lake; Saint-Maurice in the upper Rhône valley.

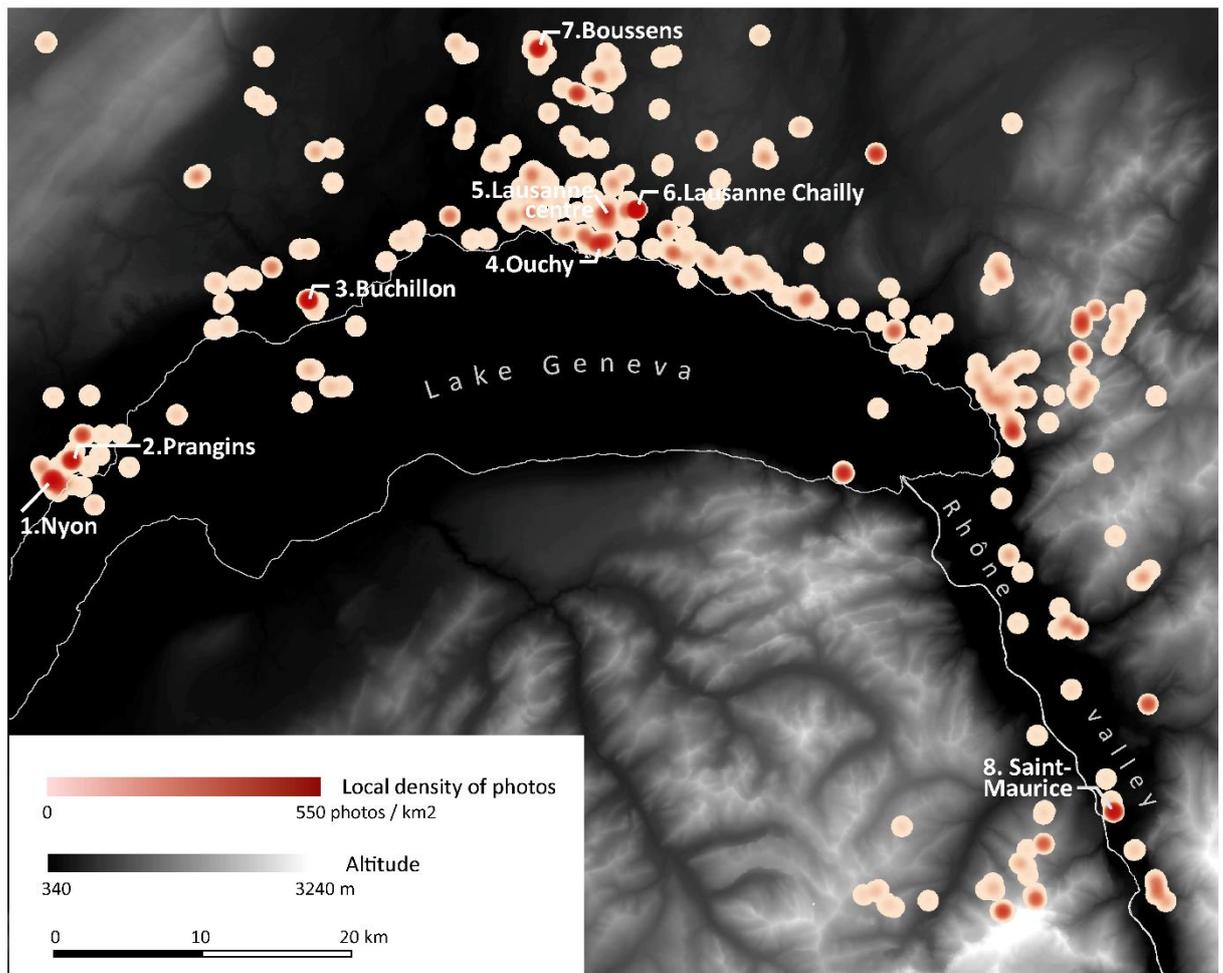


Figure 7. Selection of eight sites among the Flickr photo hotspots. The digital elevation model is visible where the density is zero. The white lines indicate the shores of Lake Geneva and the River Rhône.

The results of the CLM applied to the subsets of photos corresponding to the eight hotspots show great variability in the selected variables (Tab. 3). First, the CLM yields no significant result in the case of BousSENS and a very low pseudo R2 in the case of Buchillon and Lausanne centre. For the other five hotspots, DISTmax is always selected and has a positive influence, as does the variable DISTavg in the global model. The other visibility metrics exert a variable influence.

	Hotspots							
	Nyon	Prangins	Buchillon	Ouchy	Lausanne centre	Lausanne Chailly	Boussens	Saint-Maurice
Number of photos	108	47	134	38	20	182	49	65
Angular standard deviation (°)	70	72	80	68	70	65	74	69
Adjusted Mc Fadden pseudo $r^2$	0.36	0.34	0.01	0.32	0.09	0.16	0.0	0.28
W-built W-open W-forests Compo			-4.318*			-3.701* 0.758*		1.014* -0.277*
P-built P- P-open P-vineyards P-forests P-wetlands P-rocks P-glaciers P-water	2.783*	3.614* -2.739*				-0.816 1.667** 1.254*		
DISTavg DISTmax Skyline Depth diversity Depthline	1.642*** 1.944	7.806* -13.441*		1.111***	10.633*	1.431**		2.903* 1.872** 6.015**

Tab. 3. Angular characteristics and coefficients resulting from the CLM of the eight Flickr photo hotspots. Only the variables with a p value less than or equal to 0.1 are listed. The levels of significance are represented as follows:  $p < 0.001$  \*\*\*,  $p < 0.01$  \*\*,  $p < 0.05$  \*,  $p < 0.1$  no sign.

The angular standard deviation ranges around 70°. The linear correlation between this criterion and the pseudo R2 is negative (-0.56) but not significant given the small number of cases. However, it is noticeable that an angular variation of more than 72° leads to no significant models.

#### 4. Discussion

##### *Overview*

From a set of landscape photos posted on the Flickr platform, we have tested what we term a “panorama level” for analysing landscape preferences. This approach is original in that it considers that globally, the aesthetic value of landscape is not distributed in an isotropic manner around the locations of interest, but may vary in specific directions. Although some places offer attractive views around the entire panorama, many of what are considered aesthetic landscapes take in only limited portions of the total view. The difference between the aggregated viewsheds as well as the significant results obtained from CLM confirm that most of the time, the scenic views captured by photos result from a choice among all possible directions, and show that the panorama level of analysis is relevant.

Such an approach is complementary to the analysis explaining the presence of photo hotspots, which is referred to here as the geographical level. When investigating landscape preferences, the panorama level approach has the advantage of being independent of determinants of place (or touristic) attractiveness. By directly focusing on the views recorded from points of interest, the analysis deals with landscape features without involving criteria such as road access, population density, tourist facilities or other spatial amenities, as in Tenerelli et al. (2016). All these criteria are worth studying, but may be related to very different (and often unknown) spatial scales, whereas the panorama level approach is restricted to the single scale of the panorama.

By opposing the characteristics of the landscape photographed and those of the antipodal landscape (i.e. the view at 180°) by discrete choice modelling, the specificity of this study is that it considers the preference criteria in a relative manner, depending on the local panorama. In other words, the analysis looks to answer the question: “What are the landscape features explaining the preference for one view as opposed to another possible view from the same viewpoint?”. It is worth noting that, from the same dataset, the application of a standard logistic regression (i.e. opposing globally all captured landscapes and all antipodal landscapes) would lead to each view being considered an “isolated case” and would not answer our question.

It could be argued that the binary opposition between two views is simplistic because a 360° panorama offers several possible views, for example six views with a focal angle of 60°. The present study is an initial test of the approach, and the analysis could be extended to the whole panorama using multinomial discrete choice modelling. However, the focal angle varies from one photo to another (in our case between 12° and 64°) and the presence of wide-angle photos could limit the number of alternative views without any overlap. Another perspective would be to restrict the opposition between the photographed landscape and the other potential views to the nearby directions (e.g., at the left and at the right), to focus on landscape preferences without opposing very different topographical settings.

#### *4.2. What are the thematic findings resulting from the panorama approach applied to Flickr photos?*

Thematically, our results are consistent with previous findings as to landscape preferences. In the global model as well as in several local models applied to hotspots, the most significant metric (DISTavg or DISTmax) expresses the extent of the view. Its positive influence shows that the photographers posting their photos on Flickr train their lens preferentially on open landscapes. This brings us back to a character already recognised as a factor of visual appeal, in different contexts and using different methods (Coeterier, 1996; Hur, Nasar, & Chun, 2010; Rogge, Nevens, & Gulinck, 2007; Sahraoui, Clauzel, & Foltête, 2016, Sevenant & Antrop, 2009; Youssoufi & Foltête, 2013), the visual scale having been defined as one of the nine key characters of any landscape (Tveit, Ode, & Fry., 2006) according to Appleton’s prospect-refuge theory (Appleton, 1975). In the case of geotagged photos, our result can be likened to the study by Tenerelli et al. (2016) who find a correlation between the residuals of the model explaining the photo density and the extent of the panorama.

The presence of forests proves to be a positive criterion too. This is an expected outcome since many previous studies have reported the visual attractiveness of greenery in visual preference analyses based on photos (Sahraoui et al., 2016; Tieskens et al., 2018; Van Berkel & Verburg, 2014; Yoshimura & Hiura, 2017), residential satisfaction analysis (Ellis, Lee, & Kweon, 2006; Youssoufi &

Foltête, 2013) and landscape econometrics (Cavailhès et al., 2009). Furthermore, the view of forests can be related to the key criterion of natural landscapes (Tveit et al., 2006). However, in our global model (Tab. 2), the positive effect of the presence of forest combines with the negative influence of its visual weight. This means that the amount of forest cannot be used as an indicator of greenery invariably explaining the preferences in a positive manner. The implication is that the most attractive views are composed of a set of landscape features without any single one being prevalent as with a totally forested landscape. Such finding fits with previous studies applied to the Swiss Alps (Hunziker, 1995; Soliva, Bolliger, & Hunziker, 2010), in which forests were positively perceived when being included in patchworks rather than covering the major part of the view. We may establish a link with the preference for isolated and scattered trees outlined by Sherren et al. (2011) in a different geographical context as well. This is also consistent with the positive impact of spatial variation of the view depth, which is an indicator related to landscape complexity, another key character identified by Tveit et al. (2006) and already reported in previous studies (Dramstad, Sundli Tveit, Fjellstad, & Fry, 2006).

The impact of water bodies does not feature among our main thematic results, although it was expected to be positive in the choice of landscapes photographed. Indeed many studies report this positive effect (e.g. Saharoui et al., 2016; Tieskens et al., 2018). Furthermore, as a large expanse of water located on the border of the alpine massif, it was expected that Lake Geneva would be a very attractive feature especially as a study designed to value landscape amenities has outlined the role of views of lakes in Switzerland (Schläpfer, Waltert, Segura, & Kienast, 2015). Despite this local specificity, water bodies are absent from the global model; they have a positive role in the local model at one site only (Lausanne Chailly) and appear to have a negative influence for the sites of Nyon and Prangins. This can be explained by the appeal of vineyards in the area (Tab. 3). When investigating the spatial dimension of landscape preferences (Fig. 3), it can be seen that Lake Geneva does not feature uniformly but is specifically prevalent near Lausanne and at its eastern end near Montreux. This focus encompasses the mountains located on the French side and around the Rhône valley, suggesting a preference for the visual pattern associating lake and mountains rather than just the lake as an isolated feature. This could explain the absence of water bodies in the global model.

The local models based on hotspots in this study show that the influence of several landscape features may vary with location. This emphasises the importance of the local configuration of landscape and of “site effects” where some features work in a specific way. For example, while the visual weight of buildings often has a negative influence, its positive impact for the site of Lausanne Chailly could be explained by a preference for views of Lake Geneva over the town rather than views of the more rural hinterland. The local variability of the aesthetic values of landscape is nothing new (see for instance the negative appreciation of forests in Van Berkel et al., 2018) and can be associated with the outcomes of Tenerelli et al. (2016) who find spatial variations of the explanatory variables in their geographically weighted regressions. Although our local models have to be carefully considered because of the paucity of photos for some sites, the local variations show that only a few landscape features result in absolute preferences and that these preferences are usually related to their geographical context.

In three hotspots (Buchillon, Lausanne centre and Boussens) no significant results were found or they had very little explanatory power. In the cases of Buchillon and Boussens, this can be explained by the lack of any specific landmarks (the angular standard deviation of azimuths is maximum) and by

the fact that Lake Geneva cannot be seen from these places. In the case of Lausanne centre, this is probably due to the urban context where attractive views (e.g. architectural features) are to be found in very different directions.

#### *4.3. Limitations of the approach*

In spite of significant advantages provided by geotagged data from social networks compared with specific surveys, the analysis of geotagged photos has limitations that have been mentioned several times. The lack of information about the users of photo-sharing platforms remains a critical problem for investigating the connections between preferences and socio-demographic profiles (Tenerelli et al., 2016; Tieskens et al., 2018). This is all the more problematic because preference analysis becomes more significant when different judgement groups are considered, as in Dramstad et al. (2016), Hunziker, Felber, Gehring, & Buchecker (2008), Kalivoda, Vojar, Skřivanová, & Zahradník (2014) and Sahraoui et al. (2016). Furthermore, the use of social media could act as a filter by attributing greater importance to computer-savvy people and so skewing the analyses. While all these limitations are specific to photo-sharing platforms, our approach might be improved by considering all pictures taken by the same photographer from a given viewpoint: in this case, the analysis should be applied to combinations of photos instead of individual photos. Even so, such an improvement would lead to other problems in defining the antipodal landscape of non-adjacent views.

When combining the geotagged photos with indicators derived from GIS as in the present study, the accuracy of spatial data may be a real limitation. In the present case, we used land cover and altitudinal data with a low spatial resolution (25 m), that is why the visibility modelling was applied without taking potential obstacles into account. Using a higher spatial resolution and including visual obstacles would probably improve the relevance of the outcomes in a significant manner. Concerning the photos, the localisation of the viewpoint as well as the azimuth of the photo have to be precisely recorded if they are to serve as a relevant source of information, knowing that smartphones provide orientation data of very variable accuracy (Novakova & Pavlis, 2017). Here, to maintain the quality of the analysis, we removed all photos with aberrant values of elevation or with an azimuth recorded as 0°, meaning a significant proportion of the data was lost. This meant the density of photos was comparatively low, apart from in the vicinity of Lake Geneva. Conversely, the western part of the spatial preferences map (Fig. 3) shows a sharp distribution due to this low density. However, we can assume that technological advances will facilitate the recording of accurate data and that these problems will probably be overcome soon, especially because the development of augmented reality devices (e.g., Diao & Shih, 2018) involves progress in orientation accuracy.

#### *4.4. Prospects for the modelling approach to visibility*

The use of visibility metrics to create an analytical representation of views is facilitated by user-friendly tools such as Pixscape (Sahraoui et al., 2018). While most visibility modelling approaches work by counting visible pixels, the tangential approach provided by this tool yields more realistic metrics of composition and geometry for representing the content of a photo. Moreover, this approach directly integrates the role of distance into the visual weighting, unlike the planimetric approach which requires the view to be segregated among distance intervals, as in Tenerelli et al. (2016).

We certainly could add other metrics to enrich the analysis, for example by characterising the visual configuration (e.g. mean patch size in the visible space). A further challenge for making the digital modelling of visibility more relevant would be to consider how analytic metrics interact so as to have a more integrated description of pictures.

The data extracted from photo-sharing platforms could also be subject to selection or filtering to achieve specific analyses, for example to study the change in landscape preferences over time depending on the season or the weather. From this perspective, the use of machine-learning algorithms to automatically tag the photos would provide useful support.

## 5. Conclusion

In this paper, we have defined a panorama level for analysing landscape preferences, by comparing the spatial and thematic signatures of a set of landscape photos posted on a photo-sharing platform with those corresponding to the antipodal views from the same viewpoints. The application of this approach to a set of Flickr photos led to significant results validating our assumption about preferential directions within a panorama. Open landscapes and forests are the most recurrent features explaining these choices. Locally, the influence of some landscape attributes may vary with the geographical context. However, apart from this site effect, the overall findings of the statistical model obtained from the geotagged photos could lead to a better use of visibility modelling in other domains (e.g. characterising the potential of attractive landscapes, evaluating the visual quality of residential environments), by detecting the focal angles at which observers tend to view the landscape rather than scanning all directions and averaging the landscape descriptors.

## Acknowledgement

This research was supported by the “Communauté du savoir”, a network aiming at promoting French-Swiss collaborations in the Jura region.

## References

- Agrawal, D., Budak C., El Abbadi, A. Georgiou, T., & Yan, X. (2014). Big Data in Online Social Networks: User Interaction Analysis to Model User Behavior in Social Networks. *Databases in Networked Information Systems*. In Proceedings of the International Workshop on Databases in Networked Information Systems. Lecture Note in Computer Science, Springer, 1-16.
- Angradi, T. R., Launspach, J. J., & Debbout, R. (2018). Determining preferences for ecosystem benefits in Great Lakes Areas of Concern from photographs posted to social media. *Journal of Great Lakes Research*, 44(2), 340-351. doi - 10.1016/j.jglr.2017.12.007
- Antoniou, V., Morley, J., & Haklay, M. (2010). Web 2.0 geotagged photos: Assessing the spatial dimension of the phenomenon. *Geomatica*, 64(1), doi - 99-110. 10.5623/geomat-2010-0009
- Appleton, J. (1975). *The Experience of Landscapes*. Chichester - Wiley.
- Bailey, T. C., & Gatrell, A. C. (1995). *Interactive Spatial Data Analysis*. Harlow - Longman Scientific & Technical.
- Ben-Akiva, M. E., & Bierlaire, M. (1999). Discrete Choice Methods and their Applications to Short Term Travel Decisions. In R. W. Hall (Ed.), *Handbook of Transportation Science* (pp. 5-34). Norwell, MA: Kluwer.
- Ben-Akiva, M. E., & Lerman, S. R. (1985). *Discrete Choice Analysis: Theory and Application to Travel Demand*. Cambridge, MA: MIT Press.
- Cavailhès, J., Brossard, T., Foltête, J.-C., Hilal, M., Joly, D., Tourneux, F. P., Tritz, C., & Waversky P. (2009). GIS-based hedonic pricing of landscape. *Environmental Resource Economics*, 44(4), 571-590. doi - 10.1007/s10640-009-9302-8
- Chen, Y., Parkins, J. R., & Sherren, K. (2018). Using geo-tagged Instagram posts to reveal landscape values around current and proposed hydroelectric dams and their reservoirs. *Landscape and Urban Planning*, 170, 283-292. doi - 10.1016/j.landurbplan.2017.07.004
- Coeterier, J. F. (1996). Dominant attributes in the perception and evaluation of the Dutch landscape. *Landscape and Urban Planning*, 34(1), 27-44. doi -10.1016/0169-2046(95)00204-9
- Diao, P. H., & Shih, N. J. (2018). MARINS: A mobile smartphone AR system for pathfinding in a dark environment. *Sensors*, 18(10), 3442; doi - 10.3390/s18103442
- Dramstad, W. E., Sundli Tveit, M., Fjellstad, W. J., & Fry, G. L. A. (2006). Relationships between visual landscape preferences and map-based indicators of landscape structure. *Landscape and Urban Planning*, 78(4), 465-474. doi - 10.1016/j.landurbplan.2005.12.006
- Dupont, L., Ooms, K., Antrop, M., & Van Eetvelde, V. (2016). Comparing saliency maps and eye-tracking focus maps: The potential use in visual impact assessment based on landscape photographs. *Landscape and Urban Planning*, 148, 17-26. doi - 10.1016/j.landurbplan.2015.12.007
- Ellis, C. D., Lee, S.-W., & Kweon, B.-S. (2006). Retail land use, neighborhood satisfaction and the urban forest: an investigation into the moderating and mediating effects of trees and shrubs. *Landscape and Urban Planning*, 74(1), 70-78. doi - 10.1016/j.landurbplan.2004.10.004
- Figuroa-Alfaro, R. W., & Tang, Z. (2017). Evaluating the aesthetic value of cultural ecosystem services by mapping geo-tagged photographs from social media data on Panoramio and Flickr. *Journal of Environmental Planning and Management*, 60(2), 266-281. doi - 10.1080/09640568.2016.1151772
- Fisher, N. I. (1993). *Statistical analysis of circular data*. Cambridge - Cambridge University Press.
- Fisher, P. F. (1996). Extending the applicability of viewsheds in landscape planning. *Photogrammetric Engineering & Remote Sensing*, 62(11), 1297-1302.
- Gatrell, A. C., Bailey, T. C., Diggle, P. J., & Rowlingson B. S. (1994). Spatial Point Pattern Analysis and its Application in Geographical Epidemiology. *Transactions of the Institute of British Geographers*, 21(1), 256-274. doi -10.2307/622936

- Glozzo, G., Pettorelli, N., & Hacklay, M. (2016). Using crowdsourced imagery to detect cultural ecosystem services: a case study in South Wales, UK. *Ecology and Society*, 21(3), 6. doi -10.5751/ES-08436-210306
- Hosmer, D. W., & Lemeshow, S. (2000). *Applied Logistic Regression*. New York - Wiley.
- Hunziker, M. (1995). The spontaneous reforestation in abandoned agricultural lands: perception and aesthetic assessment by locals and tourists. *Landscape and Urban Planning*, 31, 399-410. doi - 10.1016/0169-2046(95)93251-J
- Hunziker, M., Felber, P., Gehring, K., & Buchecker, M. (2008). Evaluation of landscape change by different social groups: results of two empirical studies in Switzerland. *Mountain Research and Development*, 28(2), 140-147.
- Hur, M., Nasar, J. L., & Chun, B. (2010). Neighborhood satisfaction, physical and perceived naturalness and openness. *Journal of Environmental Psychology*, 30(1), 52-59. doi - 10.1016/j.jenvp.2009.05.005
- Itti, L., Koch, C., & Niebur, E. (1998). A model of saliency-based visual attention for rapid scene analysis. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 20(11), 1254-1259. doi - 10.1109/34.730558
- Kalivoda, O., Vojar, J., Skřivanová, Z., & Zahradník, D. (2014). Consensus in landscape preference judgments: the effects of landscape visual aesthetic quality and respondents' characteristics. *Journal of Environmental Management*, 137, 36-44. doi - 10.1016/j.jenvman.2014.02.009
- Langemeyer, J., Calcagni, F., & Baró, F. (2018). Mapping the intangible: Using geolocated social media data to examine landscape aesthetics. *Land Use Policy*, 77, 542-552. doi -10.1016/j.landusepol.2018.05.049
- Lee, H., Seo, B., Koellner, T., & Lautenbach, S. (2019). Mapping cultural ecosystem services 2.0 – Potential and shortcomings from unlabeled crowd sourced images. *Ecological Indicators*, 96, 505-515. doi - 10.1016/j.ecolind.2018.08.035
- Levine N. (2015). *CrimeStat: A Spatial Statistics Program for the Analysis of Crime Incident Locations (v 4.02)*. Ned Levine & Associates, Houston, Texas, and the National Institute of Justice, Washington, D.C. August.
- Martínez Pastur, G., Peri, P. L., Lencinas, M. V., García-Llorente, M., & Martín-López, B. (2015). Spatial patterns of cultural ecosystem services provision in Southern Patagonia. *Landscape Ecology*, 31(2), 383-399. doi - 10.1007/s10980-015-0254-9
- McFadden, D. (1973). Conditional Logit Analysis of Qualitative Choice Behavior. In P. Zarembka (Ed.), *Frontiers in Econometrics* (pp. 105-142). New York: Academic Press.
- Novakova, L., & Pavlis, T. L. (2017). Assessment of the precision of smart phones and tablets for measurement of planar orientations: A case study. *Journal of Structural Geology*, 97 93-103. doi - 10.1016/j.jsg.2017.02.015
- Oteros-Rozas, E., Martín-López, B., Fagerholm, N., Bieling, C., & Plieninger T. (2018). Using social media photos to explore the relation between cultural ecosystem services and landscape features across five European sites. *Ecological Indicators*, 94(2), 74-86. doi - 10.1016/j.ecolind.2017.02.009
- Palmer, J. F., & Hoffman, R. E. (2001). Rating reliability and representation validity in scenic landscape assessments. *Landscape and Urban Planning*, 54, 149-161. doi - 10.1016/S0169-2046(01)00133-5
- Ripley, B. D. (1977). Modelling spatial patterns. *Journal of the Royal Statistics Society Series B Stat. Methodology*, 39(2), 172-192.
- Rogge, E., Nevens, F., & Gulinck, H. (2007). Perception of rural landscapes in Flanders: looking beyond aesthetics. *Landscape and Urban Planning*, 82(4), 159-174. doi - 10.1016/j.landurbplan.2007.02.006
- Sahraoui, Y., Vuidel, G., Joly, D., & Foltête, J.-C. (2018). Integrated GIS software for computing landscape visibility metrics. *Transactions in GIS*, 22(5), 1310-1323. doi - 10.1111/tgis.12457
- Sahraoui, Y., Clauzel, C., Foltête, J.-C. (2016). Spatial modelling of landscape aesthetic potential in urban-rural fringes. *Journal of Environmental Management*, 181, 623-636. doi - 10.1016/j.jenvman.2016.06.031

- Schläpfer, F., Waltert, F., Segura, L., & Kienast, F. (2015). Valuation of landscape amenities: A hedonic pricing analysis of housing rents in urban, suburban and periurban Switzerland. *Landscape and Urban Planning*, 141, 24-40. doi - 10.1016/j.landurbplan.2015.04.007
- Sevenant, M., & Antrop, M. (2009). Cognitive attributes and aesthetic preferences in assessment and differentiation of landscapes. *Journal of Environmental Management*, 90(9), 2889-2899. doi - 10.1016/j.jenvman.2007.10.016
- Sherren, K., Fischer, J., Pink, J., Stott, J., Stein, J. & Yoon, H.-J. (2011). Australian Graziers Value Sparse Trees in Their Pastures: A Viewshed Analysis of Photo-Elicitation. *Society and Natural Resources*, 24(4), 412-422. doi - 10.1080/08941920.2010.488686
- Sinclair, M., Ghermandi, A., & Sheela, A. M. (2018). A crowdsourced valuation of recreational ecosystem services using social media data: An application to a tropical wetland in India. *Science of the Total Environment*, 642, 356-365. doi - 10.1016/j.scitotenv.2018.06.056
- Sitthi, A., Nagai, M., Dailey, M., & Ninsawat, S. (2016). Exploring land use and land cover of geotagged social-sensing images using naive Bayes classifier. *Sustainability*, 8, 921. doi - 10.3390/su8090921
- Soliva, R., Bolliger, J., & Hunziker, M. (2010). Differences in preferences towards potential future landscapes in the Swiss Alps. *Landscape Research* 35(6), 671-696, doi - 10.1080/01426397.2010.519436
- Tenerelli, P., Demšar, U., & Luque, S. (2016). Crowdsourcing indicators for cultural ecosystem services: A geographically weighted approach for mountain landscapes. *Ecological Indicators*, 64, 237-248. doi - 10.1016/j.ecolind.2015.12.042
- Tenerelli, P., Püffel, C., & Luque S. (2017). Spatial assessment of aesthetic services in a complex mountain region: combining visual landscape properties with crowdsourced geographic information. *Landscape Ecology*, 32(5), 1097-1115. doi - 10.1007/s10980-017-0498-7
- Tieskens, K. F., Van Zanten, B. T., Schulp, C. J. E., & Verburg, P. H. (2018). Aesthetic appreciation of the cultural landscape through social media: An analysis of revealed preference in the Dutch river landscape. *Landscape and Urban Planning*, 177, 128-137. doi - 10.1016/j.landurbplan.2018.05.002
- Tveit, M., Ode, A., & Fry, G. (2006). Key visual concepts in a framework for analyzing visual landscape character. *Landscape Research*, 31(3), 229-255. doi - 10.1080/01426390600783269
- Van Berkel, D. B., & Verburg, P.H. (2014). Spatial quantification and valuation of cultural ecosystem services in an agricultural landscape. *Ecological Indicators*, 37, 163-174. doi - 10.1016/j.ecolind.2012.06.025
- Van Berkel, D. B., Tabrizian, P., Dorning, M. A., Smart, L., Newcomb, D., Mehaffey, M., Neale, A., & Meentemeyer, R. K. (2018). Quantifying the visual-sensory landscape qualities that contribute to cultural ecosystem services using social media and LiDAR. *Ecosystem Services*, 31, 326-335. doi - 10.1016/j.ecoser.2018.03.022
- Wood, S. A., Guerry, A. D., Silver, J. M., & Lacayo, M. (2013). Using social media to quantify nature-based tourism and recreation. *Scientific Reports*, 3, 2976. doi - 10.1038/srep02976
- Yan, Y., Schultz, M., & Zipf, A. (2019). An exploratory analysis of usability of Flickr tags for land use/land cover attribution. *Geo-spatial Information Science*, 22(1), 12-22. doi -10.1080/10095020.2018.1560044
- Yoshimura, N., & Hiura, T. (2017). Demand and supply of cultural ecosystem services: Use of geotagged photos to map the aesthetic value of landscapes in Hokkaido. *Ecosystem Services*, 24, 68-78. doi - 10.1016/j.ecoser.2017.02.009
- Youssefi, S., & Foltête, J.-C. (2013). Determining appropriate neighborhood shapes and sizes for modeling landscape satisfaction. *Landscape and Urban Planning*, 110, 12-24. doi - 10.1016/j.landurbplan.2012.09.005