



The scale effects of landscape variables on landscape experiences: a multi-scale spatial analysis of social media data in an urban nature park context

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Abstract

Context The roles of landscape variables regarding the recreational services provided by nature parks have been widely studied. However, the potential scale effects of the relationships between landscape variables and categorized nature experiences have not been adequately studied from an experimental perspective.

Objectives This article demonstrates multiscale geographically weighted regression (MGWR) as a new method to quantify the relationship between experiences and landscape variables and aims to answer the following questions: (1) Which dimensions of landscape experiences can be interpreted from geocoded social media data, and how are these experiences associated with specific landscape variables? (2) At what spatial scale and relative magnitude can landscape variables mediate landscape experiences?

Methods Social media data (Flickr photos) from Amager Nature Park were categorized into different

dimensions of landscape experience. Estimated parameter surfaces resulted from the MGWR were generated to show the patterns of the relationship between the landscape variables and the categorized experiences.

Results All considered landscape variables were identified as relating to certain landscape experiences (nature, animals, scenery, engagement, and culture). Scale effects were observed in all relationships. This highlights the realities of context- and place-specific relationships as well as the limited applicability of simple approaches that are incapable of accounting for spatial heterogeneity and scale.

Conclusions The spatial effect of landscape variables on landscape experiences was clarified and demonstrated to be important for understanding the spatial patterns of landscape experiences. The demonstrated modelling method may be used to further the study of the value of natural landscapes to human wellbeing.

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Introduction

Nature provides numerous ecosystem services (ES) for human and ecological wellbeing (MA 2005; de

Groot et al. 2010; Brown et al. 2012). Four general categories of ecosystem services have been recognized in the ES framework; of these, cultural ecosystem services encapsulate the nonmaterial and intangible values people derive from human-ecosystem relations (Chan et al. 2012), such as “spiritual enrichment, cognitive development, reflection, recreation, and aesthetic experience” (MA 2005, p. 40). People interact with ecosystems in many indirect and direct ways (Russel et al. 2013), but in most cases, the benefits of cultural ecosystem services materialize through actual contact with or being present in ecosystems in the context of recreational activities (Hegetschweiler et al. 2017; O’Brien et al. 2017).

Interactions between humans and the natural environment arise from immersion in the environment that is experienced (Ittelson 1973) and thus are by nature closely associated with landscape features and attributes, i.e. landscape variables. Multiplicity in the scales of landscape patterns and biological processes in relation to landscape variables has grown in importance in landscape ecology since 1980s (e.g., Cushman and McGarigal 2002; Wu 2004; Graf et al. 2005; McGarigal et al. 2016; Huais 2018). It is increasingly recognized that spatial heterogeneity and scale multiplicity are universally exhibited in ecological (and social) spatial patterns and processes (e.g., Kolasa and Pickett 1991; Wu et al. 2002; Wu and Li 2006; McGarigal et al. 2016). However, such scale multiplicity has seldom been addressed in the field of the human experiential responses to landscape variables.

Many different individual, social and physical variables and processes contribute to perceived nature experiences. However, in this rather complicated interaction, in situ experiences are directly linked with landscape settings, where different landscape variables can mediate at varying levels of intensity and at multiple spatial scales. “Scale effects” addressed in this paper is thus conceptualized as the account for the variability of effects (including such as the levels of heterogeneity and magnitude of the influence) on experience of a given landscape variable with the spatial extent connected with it. This definition is different from other studies in landscape ecology, where “scale effects” refers to changes of analyses results due to scaling (varying scales by extent, resolution, grain size, etc.) in model/analysis designs or data sampling (e.g., Meentemeyer and Box 1987; Wu and Li 2006; Šímová and Gdulová 2012).

To illustrate, people can relate to a body of water from a long distance away, whereas people tend to experience certain landscape features, such as cultural relics, flowers, and insects at a close distance, and the intensity of such perception of relation may fluctuate over the space. Since landscape variables may work at different scales as medium in landscape experience, studying the scale effect provides a significant perspective to approach interactions between people and landscape as nuanced spatial processes. The insights obtained from accounting for scale effects can contribute to park management seeking to deliver nature benefits for the society in a more meticulous and effective manner.

There is a rich body of literature exploring interactions between humans and the natural environment and linking these interactions to natural recreational value. The adopted investigation methods include traditional surveys (Arnberger et al. 2010) and public participation GIS (Garcia-Martin, et al. 2017; Brown et al. 2020; Heikinheimo et al. 2020); recently, analyses of social media data have been used (Guerrero et al. 2016; Hausmann et al. 2017; Tenerelli et al. 2016; Heikinheimo et al. 2017; Hamstead et al. 2018; Ilieva and McPhearson 2018; Oteros-Rozas et al. 2018; Wartmann et al. 2018; Johnson et al. 2019; Wartmann et al. 2019; Foltête et al. 2020; Komossa et al. 2020; Pickering et al. 2020). Social media data analyses are based on crowd-sourced big data that are analysed as geocoded points in space expressing landscape experiences or perceived landscape values. In these studies, landscape variables, such as the index of landscape attributes and distance measures to landscape features, are used to identify the associations between the biophysical landscape and landscape experiences. A few recent studies have studied the scale effects of landscape features at the continental level (Gosal et al. 2021) and the national level (Chang Chien, et al. 2020). To our knowledge, no studies have explored such scale effects on in situ landscape experiences on a detailed level based on the types or categories of landscape experiences elicited from social media data. Therefore, little is known about the scale effects of individual landscape features in relation to the on-the-ground experience they stimulate.

In the present study, we aim to approach the relationship between landscape experiences and landscape variables with special attention to scale effects, which are then interpreted contextually with

the assistance of the on-site evidence. We do so by applying a spatial model that specifically deals with the scale effects to analyse the relationship between georeferenced social media data categorized by landscape experience dimensions and physical landscape variables sourced from geodata of the site, aimed at answering the following research questions:

- (1) Which dimensions of landscape experiences can be interpreted from geocoded social media data, and how are these experiences associated with specific landscape variables?
- (2) At what spatial scale and relative magnitude can landscape variables mediate landscape experiences?

Scale effects and landscape experience

The scale effects of landscape variables associated with in situ landscape experiences are complicated to study since landscape experiences are dynamic, elusive, and contextual in character. Landscape experiences are determined by social and individual perception, sensorial impressions, and cognitive processes, as well as the contextualized interplay of landscape patterns (Zube et al. 1982; Gobster et al. 2007). This contextualized human scale of experience has been called the perceivable realm (Gobster et al. 2007), and a detailed understanding of scale effects related to this realm has thus far been relatively neglected in studies associating landscape patterns with landscape experiences. In landscape preference studies, scale effects have been studied in terms of estimating the size of landscape rooms in landscape photos (Tveit 2009) or GIS calculations of the viewed size of landscape photos (Dramstad et al. 2006; Van Berkel et al. 2018; Foltête et al. 2020). Studies such as this take direct departure in a view distance to determine the scale effects of landscape patterns. Other studies building on PPGIS and social media data have included scale issues when deciding on the appropriate study resolution, such as the grid/cell size or radius search size used to calculate the spatial correlation of the share of landscape elements (% of area) and the number of experiences (mapped points or coded images within the same area) (e.g., Figueroa-Alfaro and Tang 2017; Garcia-Martin et al. 2017; Tieskens et al. 2018; Hale et al. 2019). In

such approaches, a small cell size would be able to capture the possible effects of detailed land-use categories, but fails to capture, e.g., land-based water views associated with distances longer than the cell size, and vice versa. Here the fixed size of the used cell is critical in determining the scale relationships between landscape patterns and landscape experiences. Furthermore, scale effects have been measured by proximity in terms of Euclidean distances between specific experience locations and the nearest specific landscape feature (e.g., Tenerelli et al. 2016; Tieskens et al. 2018; Komossa et al. 2020).

Recent studies using social media data have found that different landscape variables may have positive, negative, or mixed correlations with social media data distributions. The findings concluded that prominent experience locations tend to concentrate around landscape features, such as bodies of water, tourist attractions and roads, as well as areas with high levels of accessibility and openness; a mixed effect was reported in green spaces and areas with a high protection status and high land cover diversity (Table 1).

However, across all these studies on the drivers of landscape variables, scale effects were only touched upon to a limited extent, obtaining a coarse identification of the variable types using distance between the observer and the landscape features or indices of landscape attributes. None have tapped into the very aspects of the scale effects with regard to (i) the influential range of the specific landscape variables at multiple scales and (ii) the quantitative measurement of the varying intensity of such influence across the space. In this study, we build upon these findings and advance the analysis of scale effects by employing an up-to-date spatial regression method with its improvement in accuracy and robustness and capability to quantitatively describe the scale effects of landscape variables with a number of parameters describing and explaining the scale effects. The interdisciplinary applicability of this novel spatial regression model has the potential for future research dealing with various types of interactions of humans and the environment that could benefit from a more detailed focus on scale effects.

Social media data

Investigating various nature experiences and obtaining comprehensive information about human-nature

Table 1 Previous findings regarding positive and negative associations between landscape variables and the concentration of social media data activity

Landscape variable	Previous publications finding a positive correlation	Previous publications finding a negative correlation
Green space	Oteros-Rozas et al. (2018), Wang et al. (2018), Johnson et al. (2019), and Foltête et al. (2020)	Hausmann et al. (2017), Hamstead et al. (2018), and Foltête et al. (2020)
Water bodies	Hamstead et al. (2018), Oteros-Rozas et al. (2018), Tieskens et al (2018), Wang et al. (2018), and Wartmann et al (2019)	
Tourist attractions	Wang et al. (2018) and Heikinheimo et al. (2020)	
Roads	Hamstead et al. (2018), Wang et al. (2018), and Wartmann et al (2019)	
Accessibility	Guerrero et al. (2016), Tenerelli et al. (2016), and Heikinheimo et al. (2020)	
Protection status	Tenerelli et al. (2016)	Tenerelli et al. (2016)
Diversity of land use	Tenerelli et al. (2016), Hausmann et al. (2017), Oteros-Rozas et al. (2018), and Johnson et al. (2019)	Tenerelli et al. (2016)
Openness	Johnson et al. (2019) and Foltête et al. (2020)	

interactions can be challenging (Heikinheimo et al. 2020). Social media is a new, efficient and simultaneous source for investigating public perceptions and viewpoints (Toivonen et al. 2019), and it has great potential for obtaining knowledge about rather complex nature experiences on an unprecedented scale (Ruths and Pfeffer 2014). In this context, social media is defined as web-based services where the public can create and share user-generated content (McCay-Peet and Quan-Haase 2017).

The content of social media data can reveal an individual's in situ experience, reflect how people relate to the surrounding landscape, and enable researchers to tap into the context-dependency and holistic nature of experience (Calcagni et al. 2019). When aggregated, social media data become doubly relational, as what people express on social media has inevitably gone through a judgement process by individuals as to what is valued by society, adding a second layer of relationality to social media data (ibid).

However, social media data also come with limitations in terms of reduced socio-demographic information on the individual contributors, i.e., a lack of information on the individual and social context.

Among social media platforms, Flickr has been frequently used in nature-related research because of its orientation towards nature-based activities and nature experiences in content and its relatively minimal access restrictions (Toivonen et al. 2019). Moreover, as photos can be seen as representations

of various dimensions of experience (Garrod 2007), Flickr's image data together with associated tags provide a rich source of information for identifying natural experiences.

Methods

Case study area

Amager Nature Park is a vast green space (3500 ha) situated in the metropolitan area of Copenhagen at the fringe of the city core that provides opportunities for easily accessible natural experiences for citizens of Copenhagen (Fig. 1a). Historically, the majority of this area was underwater except Amager Fælled (the northeastern part), where the land uses (Fig. 1b) historically included military training fields, grazing land and landfill sites, and the southern and southwestern parts, which were dominated by afforestation and a system of old beach meadows (Kaae et al. 2019). During WWII, the rest of the land was reclaimed from the sea, and the construction of the drainage system resulted in more complex and diverse hydrological soil conditions. Military use has been an overarching theme in the area for a long time, leaving much cultural heritage on site. Extensive plantings were established after the military use phase, and due to the low intensity of human interference, nature has thrived over time. A diversity of flora and

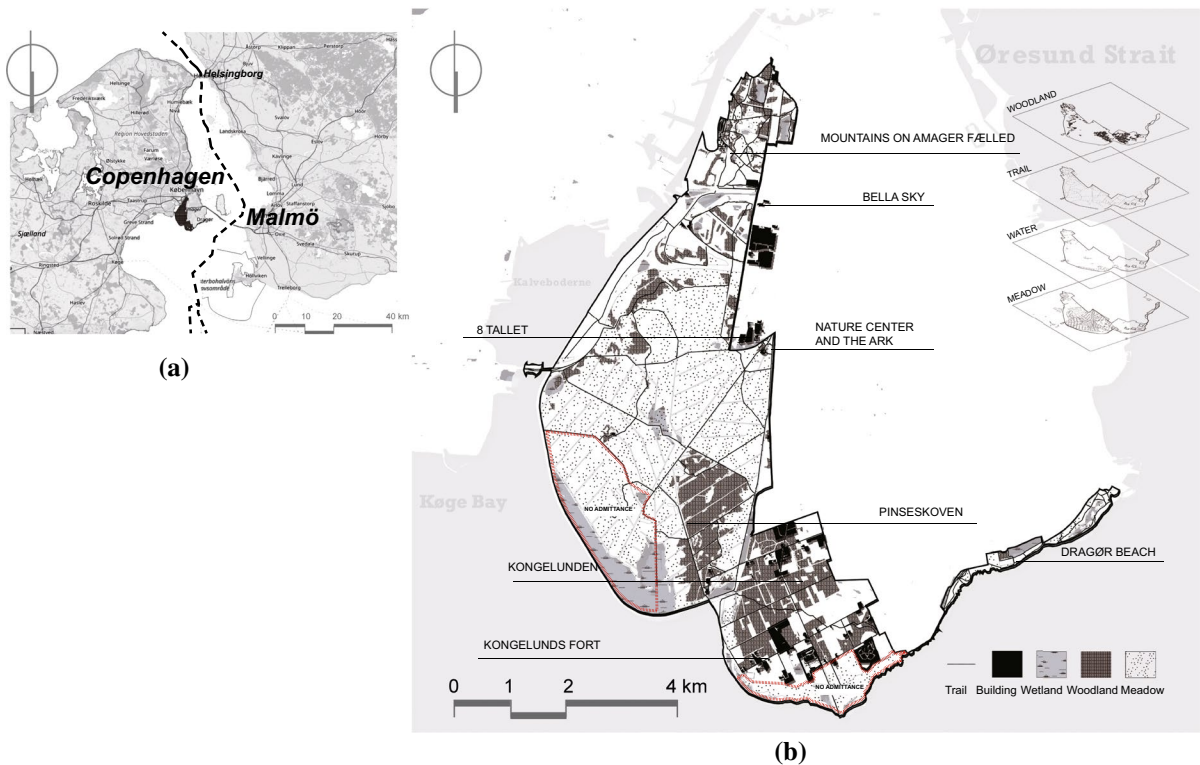


Fig. 1 **a** The location of Amager Nature Park is at the fringe of the city of Copenhagen and connected to Malmö with a bridge **b** land use in the study area (data source: Open Street

Map, Styrelsen for Dataforsyning og Effektivisering, Basemap of Denmark, 2018)

fauna, including abundant rare species, have colonized the area. Animals such as cattle, sheep and deer have been introduced since the establishment of plant communities. A series of protection plans have been published along with measures to enhance recreational opportunities. To date, 63% of the park area has been designated as an EU Natura 2000 area, meaning that habitats and threatened species are secured and monitored.

The land use and reclamation history as well as the current preservation prioritization efforts have resulted in a wide range of habitats and landscapes in the park, from meadows, wetlands, and forests to coastal land. Further, the landscape was diversified by an interplay of microclimate, microtopography, soil humidity, and water salinity variations. Recently (2015), it became one of the 14 "Danske Naturparker" (Danish Nature Parks) in Denmark, in which conservation and recreational values are emphasized equally. It is estimated that the park has

approximately 1 million visitors per year, and plans have been made for increasing visitation and large investments in recreational facilities (Naturparkplan 2015–2020). Overall, the park is suitable as a case study for exploring the relationship of landscape variables and landscape experience.

Database setup

Web scraping was performed with Flickr's public application programming interface (API) to extract data, including geotagged photos and descriptive text (image title, description, and tags). The JavaScript object notation (JSON) containing a key-value pair of user IDs and photo IDs for posts can be returned by calling the Flickr API request and specifying the geographic range and time span. The URL of Flickr post follows the structure "<https://www.flickr.com/photos/userID/photoID>". With the obtained URLs, the hypertext

markup language (HTML) of the webpage can be requested in a Python environment where different types of metadata can be compiled with regular expressions. The initial data acquisition resulted in 10,373 records within a coarse range of the site, of which 2089 were within the precise site boundary. Data cleaning was conducted to remove photo records with content that was too similar, irrelevant to the study topic or had incorrect location information. A maximum of five photos from each user per day was established to counteract bias from overactive users. The final database contained 980 records from 181 unique users over a time span of eight years (1/1/2012 to 12/31/2019). By comparing with the data size versus site area in other literature (e.g., Oteros-Rozas et al. 2018; Foltête et al. 2020; Komossa et al. 2020), we confirmed that the volume of the data gathered was aligned with other social media based landscape analyses.

Photo content analysis

To investigate the types of experiences in the park, the photos were manually categorized. A rather precise photo classification method was adopted initially. For a given photo with attached descriptive information (text such as tags), the examiners independently decided what theme(s) the photo referred to and then included the theme(s) on a list of experience dimensions. The categories of experience were finalized when no new themes emerged from the photos. The initial set of 9 experience dimensions were natural sight, animal, plant, outdoor recreation, scenery, man-made structure, architecture, and feeling expression. However, categorized datasets with an insufficient amount of data may produce an unreliable result for the subsequent spatial analysis—in the first round of categorization, only 24 photos were categorized as feeling expression, 43 were categorized as natural sight, and 71 were categorized as plants. Therefore, the initial dimensions were merged into five meta-dimensions to be used to establish dependent variables. Detailed descriptions and examples for each dimension are presented in Table 2. It should be noted that, in practice, some photos may suggest more than one type of landscape experience and therefore could be assigned to multiple categories.
















Nature experience dependent variables

Flickr data with geo-coordinates were imported into ArcGIS Pro for preprocessing. Given the location accuracy of Flickr data, a grid with a 250 m*250 m cell size covering the whole site area was created (Tenerelli et al. 2016; Heikinheimo et al. 2020). The grid cells within the bird sanctuary were manually removed so that only the accessible areas were considered in the study, resulting in 659 grid cells, which is the unit of analysis in the multiscale geographically weighted regression (MGWR) calibration. For each landscape experience, the photos were singled out to calculate the number of unique users within a cell (hereafter referred to as the user count), which was then assigned to the centroid of the corresponding cell as the dependent variable for MGWR modelling (the spatial distribution of the photos is available in Supplementary Material).

Potential landscape variables

The selection of explanatory variables was based on a literature review (Table 1), the characteristics of the site area, the availability of geodata, and the data type requirements. In landscape studies employing regression modelling methods, Pastur et al. (2016) performed logistic regressions with six explanatory variables: “water”, “vegetation”, “protected areas”, “urban settlements”, “accessibility” and “tourism offering”. Tenerelli et al. (2016) carried out GWR to study the association between landscape variables and peoples’ preferences and perceptions of cultural ecosystem services in mountain landscapes. In their study, 14 explanatory variables were used, which included 9 environmental variables (proximity to “sighting points”, “water”, and “geology interest points”; “average slope”, “average altitude”, “annual isolation”, “protection status”, “habitat class”, and “number of habitat types”) and 5 opportunity setting variables (proximity to “roads”, “ski resort”, “recreation points”, and “human settlement” and “population within 100 km”). Inspired by these studies, we used the nearest Euclidean distance between the landscape features and the centroid of every cell as the major type of variable because (1) the distance can be a straightforward numeric proxy of the effects of landscape features; (2) given the flat terrain of the park, topography-related variables such as slope, altitude,

Table 2 Categorization of photos into five experience dimensions

Criteria	Nature	Animal	Scenery	Engagement	Culture
Description	Plant close-up view, biophysical environment, natural phenomena, indication of wilderness	Animals living in the park, domesticated or wild animals, insects, mammals, amphibians, etc	Related to overlooks and configuration of landscape elements, and indicating space	Related to human activities, human emotions, etc	Obvious presence of man-made structures in the park and architecture
Indicators	Mist, snow, plant, light, flower, iconic tree, grass, sunset, deadwood, bog, meadow, forest, sea, lake, season, wilderness, natural landscape, etc	Bird, insect, cattle, fowl, sheep, fox, wild animals, toads, horses raised in the park, etc	Natural landscape, architectural landscape, mosaic of nature and architecture, skyline, vista over lake, sea, meadow, configuration of tree stands, etc	Cycling, sports, picnicking, walking a dog, horseback riding, boating, selfies, foraging, walking, running, motocross, kite surfing, bird watching, fishing, campfire, golfing, etc	Facility, board walk, shelter, cultural heritage, dike, urban texture, sculpture, graffiti, iconic architecture (8 Tallet, Bella Sky), railway, Øresund Bridge, etc
Flickr photo examples (under a CC-BY licence)	 By Frank Daugaard	 By Guillaume Baviere	 By Plougmann	 By Frank Daugaard	 By Faheem Hussain
	 By Mark Hougaard Jensen	 By Stig Nygaard	 By Nikolaj F. Rasmussen	 By Jacques Holst	 By Michael Scheinost
	 By Mark Hougaard Jensen	 By milroesen	 By karla Schuch Brunet	 By Gert Flørens	 By Guillaume Baviere

and annual isolation, which were often used in the studies of mountain areas, were considered to be less relevant here; and (3) the scale of the site area is relatively small; thus, the location of human settlements was not assumed to be a significant variable influencing peoples’ destination choices. In this way, a set of potential explanatory variables were established (Table 3).

Calculation of explanatory variables

For the first six variables in Table 3, the potential influence of landscape variables was indicated by the distance of landscape features to the central point of the grid cell where the photo was located, which was calculated with the Near tool in ArcGIS. The land use, including water, woodland, meadow and trail, was determined in ArcGIS for every grid cell. The

scores for protection conditions were in the range of 1–4, from poor to good, based on a habitat condition report (2010–2011) for the area. Spatial openness was indicated by the canopy density in a range of 1–5 with an increment of 20%, where 1 stands for 0–20% density, and 5 stands for 80–100%. All explanatory variable values were assigned to the centroid of the corresponding cell.

Measuring scale effects

We applied MGWR (<https://sgsup.asu.edu/sparc/multi-scale-gwr>) to evaluate the scale effects of landscape variables on the distribution of different categorized experiences. Its formal version, GWR, has been used as a familiar method in a wide array of applied domains (e.g., Arkema et al. 2015; Tenerelli et al. 2016; Ogneva-Himmelberger et al. 2009; Harris et al. 2010; Jaimes

et al. 2010), which allows to model spatial processes on a local level with an optimal bandwidth (Fotheringham et al. 2017), making up for the flaws lying in ordinary least squares (OLS), which assumes that spatial processes are constant across space and produces an “average” global estimate. Fotheringham et al. (2017) demonstrated the core principle of GWR; this method ties together the two distinguishing paradoxical features of the scale effects in space: (1) spatial dependence in data—at any location, data can be “borrowed” from the neighbourhood (indicated by the “bandwidth”) and weighted according to its distance, in line with Tobler’s (1970) first law of geography, and (2) spatial heterogeneity—relationships between dependent variables and explanatory variables are allowed to vary spatially.

However, MGWR allows for an even “more flexible and scalable framework in which to examine multi-scale processes” (Fotheringham et al. 2017), and with a relationship-specific bandwidth β_k in an ensemble of local spatial regressions, it may be described as (see for instance the functions in Fotheringham et al. (2017), Oshan et al. (2019, 2020), Yu et al. (2020)):

$$y_i = \beta_{i0} + \sum_k \beta_{ik} x_{ik} + \varepsilon_i, i = 1, \dots, n, \quad (1)$$

where y_i is the dependent variable observation at location i , x_{ik} is the k th explanatory variable observation at location i , β_{ik} is the regression coefficient for the k th explanatory variable at location i , β_{i0} is the intercept coefficient at location i , and ε_i is the random error term.

Incorporating the weighted least squares, MGWR computes a matrix of location-specific parameters for each

relationship. The estimator of the regression coefficient at spatial point i is described in matrix form as follows:

$$\hat{\beta}(i) = (X'W(i)X)^{-1}X'W(i)y, \quad (2)$$

$$W_i = \begin{bmatrix} w_{i1} & 0 & \dots & 0 \\ 0 & w_{i2} & \dots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ 0 & \dots & 0 & w_{in} \end{bmatrix}, \quad (3)$$

where $\hat{\beta}(i)$ is a column vector of k coefficients at location i , X is the an n by k matrix of the observations of explanatory variables, y is a column vector of n observations of the dependent variable, and W_i is the n by n spatial weighting matrix, of which the value of w_{in} for all observations follows a distance-weighting scheme given as Eq. (4). For the regression model at focal point i , we applied the bi-square kernel function, where the w -value is given by:

$$w_{ij} = \begin{cases} \left(1 - \left(\frac{d_{ij}}{b}\right)^2\right)^2 & \text{if } |d_{ij}| < b \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

where d_{ij} is the distance between calibration point i and observation point j , and b is the distance from i to the furthest neighbour point within the bandwidth. The kernel function applied to the spatial weighting matrix implies observations nearby are weighted heavier than those further away within the bandwidth, and the remaining observations are weighted to zero (Oshan et al. 2019).

Table 3 Potential landscape variables

Variable	Variable type	Data source
Distance to water	Continuous	Basemap03
Distance to woodland	Continuous	Basemap03
Distance to meadow	Continuous	Basemap03
Distance to trail	Continuous	Basemap03
Distance to tourist attraction	Continuous	Folder of Naturpark Amager (https://naturparkamager.dk/media/208681/naturparka_mag_er_m65_a3-godkendte-jan-2017.pdf)
Distance to city centre	Continuous	Basemap03
Diversity of land use	Count	Basemap03
Protection condition	Proxy	Natura 2000-væsentligheds- vurdering af “Naturpark Amager – Hovedindgange og blå støttepunkter”
Spatial openness	Proxy	EEA tree cover density geodata (https://land.copernicus.eu/pan-european/high-resolution-layers/forests/tree-cover-density/status-maps/tree-cover-density-2018)

Since we applied the adaptive bandwidth and bi-square kernel at each local regression, the value of bandwidth, which to some extent indicates the scale of the relationship of the variables, can be understood as the number of weighted observation points “borrowed” from the neighbourhood of the regression point. The weights of the surrounding points fade following Eq. (4). Therefore, bandwidth specification is crucial for spatial regression modelling. The optimized bandwidth for each independent variable is computed by MGWR. As a result, the value of the computed bandwidth essentially depends on the scale of spatial variation of the relationship between the variates—or rather, the sensitivity of the dependent variable to the change of a given covariable. Generally, a wider bandwidth implies that the model assumes that the explanatory variable has a relatively wider and yet averaged influence across the space, whereas a smaller bandwidth can suggest a stronger influence of the given variable in its neighbourhood.

While the matrix of coefficients β_k of the given dependent variable can directly reflect the heterogeneity of its influence intensity, Monte Carlo method was used to confirm whether there is spatial variability of these coefficients, where the variability is confirmed with a p -value < 0.05 . In other words, the scale effects of landscape variables on the experience of various dimensions was investigated in two aspects: (a) the influential range of a given variable, which can be indicated by bandwidths, and (b) the variability of coefficients for each independent variable, tested by the Monte Carlo test.

The mathematical meaning of the statistics above may be translated into the understanding of landscape experience. For instance, people generally perceive a body of water as a positive landscape feature and can relate to it from a far distance (indicated by bandwidth)—that is, a larger water feature may be regarded as a global variable with an influence at a relatively large perceived scale, of which the intensity can be rather stationary, as indicated by insignificant variability of the coefficients ($p > 0.05$ in Monte Carlo test), whereas for a “point” landscape feature with a relatively small volume, such as a pond, a statue, a bridge, a wooden hut, etc., people may tend to relate to them locally and feel a sudden rise in the intensity of the relation (indicated by a smaller bandwidth). Such a feeling may fluctuate being at different locations, resulting in a heterogeneous pattern of

influence in these landscape features, which is indicated by a smaller bandwidth and varying coefficients ($p < 0.05$ in the Monte Carlo test). However, while the measurement method demonstrated here seems to be rather indicative, it holds the potential to advance the current understanding of the drivers of the physical landscape on people’s natural experience. Computing a series of quantitative and informative statistics of scale effects may offer an important perspective to studies of human-nature interactions as an intricate process.

Model calibration and finalization of variables for each experience

At the beginning we did not test the multicollinearity among the explanatory variables in particular, since according to a simulation study reported by Fotheringham and Oshan (2016), (M)GWR has demonstrated its robustness to the effects of multicollinearity among explanatory variables. However, the local variation decomposition proportion (VDP) and the local condition number (CN) to detect the level of local multicollinearity (Oshan et al. 2019) are among the computed parameters in MGWR for a later reference.

The finalization of explanatory variables was performed for each experience model in order to reduce the chance that significant variables would be underrated due to inclusion of nonsignificant variables and to obtain the most parsimonious model. This was done by stepwise forward selection for the calibration of the MGWR model to achieve the best model fit, measured by the AICc. The final set of variables with the lowest AICc was considered the most relevant possible combination of independent variables from the set of potential variables. The adjusted R-square value of the final model represents the proportion of variance in the dependent variable that can be explained by the model with the selected independent variables.

Interpretation of the MGWR result

For each centroid of a cell assigned values of variables, MGWR was used to calculate the parameter estimates of the landscape variables as a function of the experience-related dependent variables (user count). The value of the parameter estimates

indicated the intensity of the influence of the dependent variates. The variability of the parameter estimates for the regression models was examined by Monte Carlo tests. If the p-value was lower than 0.05, then the variability of the influence of the dependent variable was confirmed, and that variable was identified as a local variable for the given type of experience; if not, then the parameter estimates indicated a relatively stationary pattern across the space, and accordingly the independent variable could be interpreted as a global variable. Bandwidth can also be seen as an indicator that reflects the spatial scale—a higher bandwidth value indicates a broader spatial scale of the influence.

In addition, to further collaborate the scale effects of the landscape variables, we compared the diagnostic statistics of MGWR with those of global regression to see whether the overall fit of the model improved after incorporating the multi-scale factor. This possible difference can be another sign of the scale effects of landscape variables (Tenerelli et al. 2016; Fotheringham et al. 2017; Chang Chien et al. 2020).

A number of parameters regarding the goodness of fit of the model and the spatial range, intensity and variability of the modelled relationships were obtained by performing the MGWR analysis (elaborated in Table 4). A csv file for each landscape experience was generated with the coordinates of every cell centroid and parameter estimates of the explanatory variables and their p-values at every centroid. This result file was then imported into GIS software for the visualization of the estimate parameters that reached statistical significance ($p < 0.05$) to illustrate the variability of scale effects of the landscape variables.

Results

Experience identified within the study area

The categorization of the Flickr photos by the five landscape experience dimensions is reported in Table 5. More than half of the photos were related to animals (64.1%); the rest of the categories were quantitatively similar, except culture (32.1%), which was the smallest. However, in regard to the

number of users, the statistics reflected a different pattern; culture became the most prominent experience across unique users (53.6%), followed by scenery (50.3%) and nature (49.7%), whereas the fewest users recorded animal experiences (24.9%). In comparing the counts of photo records vs. users, experiences related to nature (45.2% vs. 49.7%) and engagement (36.0% vs. 39.7%) were relatively consistent. However, a significant disparity between counts of photos and users was observed in animal (64.1% vs. 24.9%) and culture (32.1% vs. 53.6%) experiences.

Landscape variable scale effects on experience categories and parameter estimates

The parameter estimates for variables that reached statistical significance in relation to the five experience categories (95% confidence interval) are visualized in Fig. 2. To facilitate the understanding of the summary of parameter estimate surfaces, the following order of interpretation was applied.

1. Which pairs of landscape variables and experiences are found to be associated?
2. What is the range (coloured area) of the relationship of the pairs of identified variables?
3. How are the values of the parameter estimates (colour spectrum) distributed in the influenced area?

First, inspecting the pairs of landscape variables and the dimensions of experience (the surfaces not reaching significance level are not shown) shows that all ten explanatory variables exhibited an impact, to a certain extent. Water and tourist attractions were found to be landscape features that influenced all five experiences, while the rest influenced some of the experiences. In general, animal experience was the dimension influenced by the largest number of landscape variables (water, woodlands, trails, tourist attractions, city centre, protection condition and land use diversity), followed by engagement experience, which was influenced by six landscape variables (water, meadows, woodlands, trails, tourist attractions, and land use diversity). Both nature and culture experiences were found to be associated with four landscape variables (water, trail, tourist attraction and land use diversity; and water, tourist attraction,

Table 4 Description and function of key parameters returned by MGWR

Parameter	Description and function
Bandwidth	an index reflecting the scale of an explanatory variable's influence on an experience dimension. The highest value is 658 in this case, which is the total number (659) of grid cells subtracting the regression cell
Global variable	independent variables with relatively constant parameters that apply to the whole spatial range in a given relationship
Local variable	independent variables with significantly varying parameters that apply to local scopes in a given relationship
P-value in Monte Carlo test	used to confirm whether a variable is global or local in this case
Parameter estimate	indicates the intensity of the relationship between the explanatory variable and the dependent variable
Intercept	indicates the effects of the other covariables that together influence the dependent variable apart from the variables in the model, e.g., the characteristics of landscape features, management level, accessibility, context factors, etc
AICc	the criterion against which the combination of explanatory variables that best explains the experience value is identified via model calibration
Adj. R2	indicates the goodness-of-fit of the final regression model
VDP	diagnose the level of local multicollinearity at each regression point
CN	an aggregate measure of multicollinearity for all of the variables as a whole

Table 5 Number and proportion of Flickr photos and users corresponding to the five experiences (the total user and photo percentages can exceed 100%, as one photo may fall into multiple categories)

Count	Nature	Animal	Scenery	Engagement	Culture	Total
Photos	366 (45.2%)	519 (64.1%)	345 (42.6%)	292 (36.0%)	260 (32.1%)	980
Users	90 (49.7%)	45 (24.9%)	91 (50.3%)	72 (39.7%)	97 (53.6%)	181

city centre and land use diversity, respectively). The scenery experience was related to the smallest number of variables (water, tourist attraction and spatial openness).

Then, by ranges of coloured areas, it can generally be observed which part of the park is actually influenced by the landscape variables. Some of the relationships between the variables were significant across the entire park (the surfaces fully coloured). They included the relationship between water and nature, scenery, engagement, and culture experiences; trails and nature experiences; tourist attractions and animal experiences; and land use diversity and animal experiences. For the remaining relationships (partially coloured surfaces), the influence of the specific type of landscape variables (as a whole) was significant only at a small scale. Such variables were meadows, woodlands, distance to city centre, protection

condition and spatial openness. Note that the influential range of the landscape variable at a certain location in the area (as opposed to the landscape variable as a whole in the area) can be indicated by the bandwidth value.

Finally, the intensity of the colour reveals the intensity of the spatial relationships between variables and experience dimensions. Furthermore, the heterogeneity of the parameter estimates can be explicitly indicated by the p-value from the Monte Carlo test, which differentiates global variables and local variables (marked with asterisks in Fig. 2), verifying the variation of influence of a specific landscape variable across the space. It is clear from the results that the effect of the same landscape variable on a given experience changed across space and that the patterns of these effects were different for different types of experience.

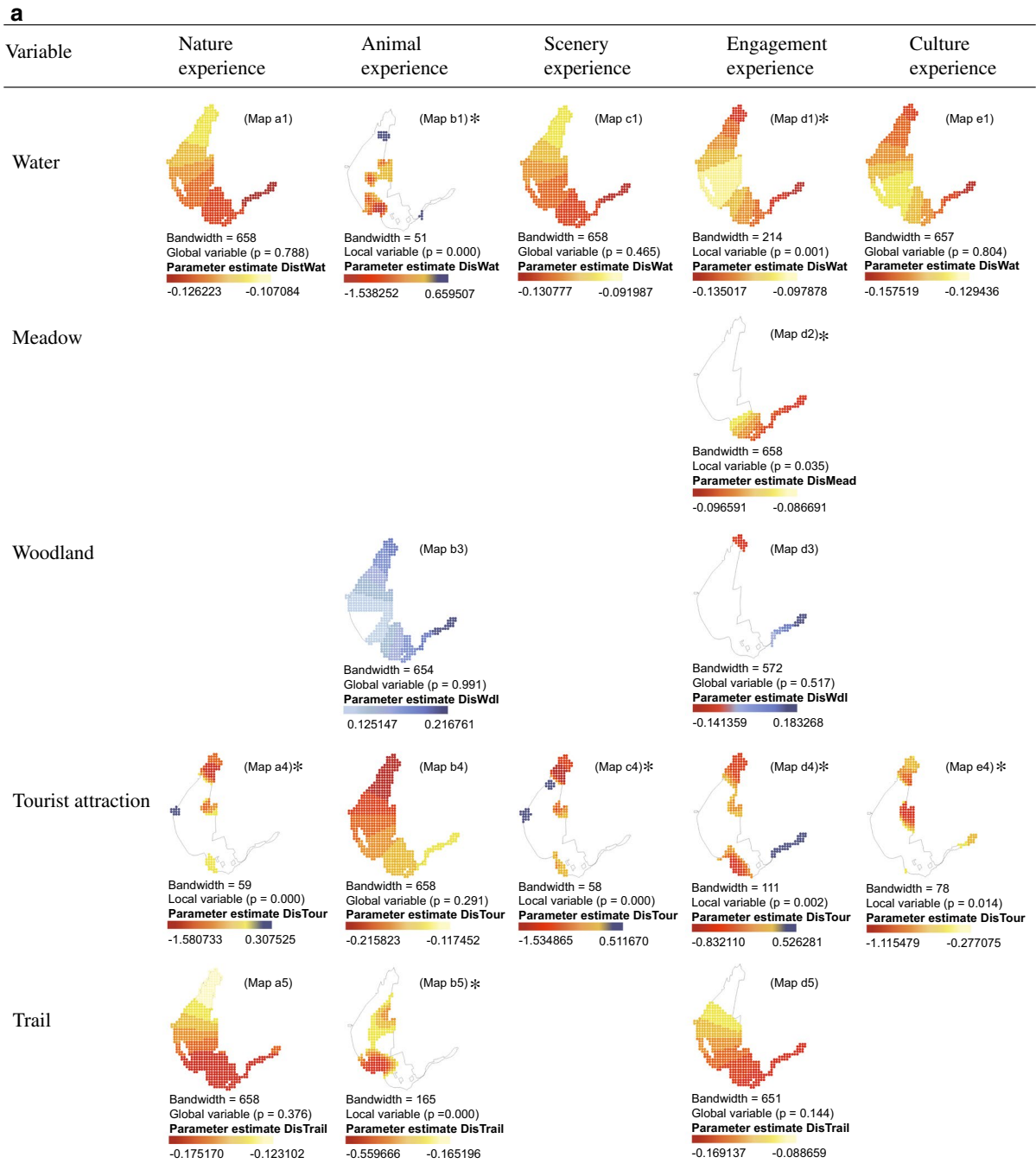


Fig. 2 Visualization of the parameter estimates of landscape variables in relation to five experiences (with a 95% confidence interval). The areas where the coefficient estimates are not significant were rendered white, which is assumed as not influenced by the given landscape variable, whereas the coloured areas are assumed to be the areas that are influenced by the given landscape variable. The parameter estimate surfaces where landscape variables act as local variables in the given

relationship are marked with asterisks (*); the rest are global variables. Areas in warm colours suggest that the landscape variable has a positive influence; cold colours indicate a negative influence. The colour shade corresponding to the values of the parameter estimates for a variable reflects the intensity of the relationship between the landscape experience and the explanatory variable

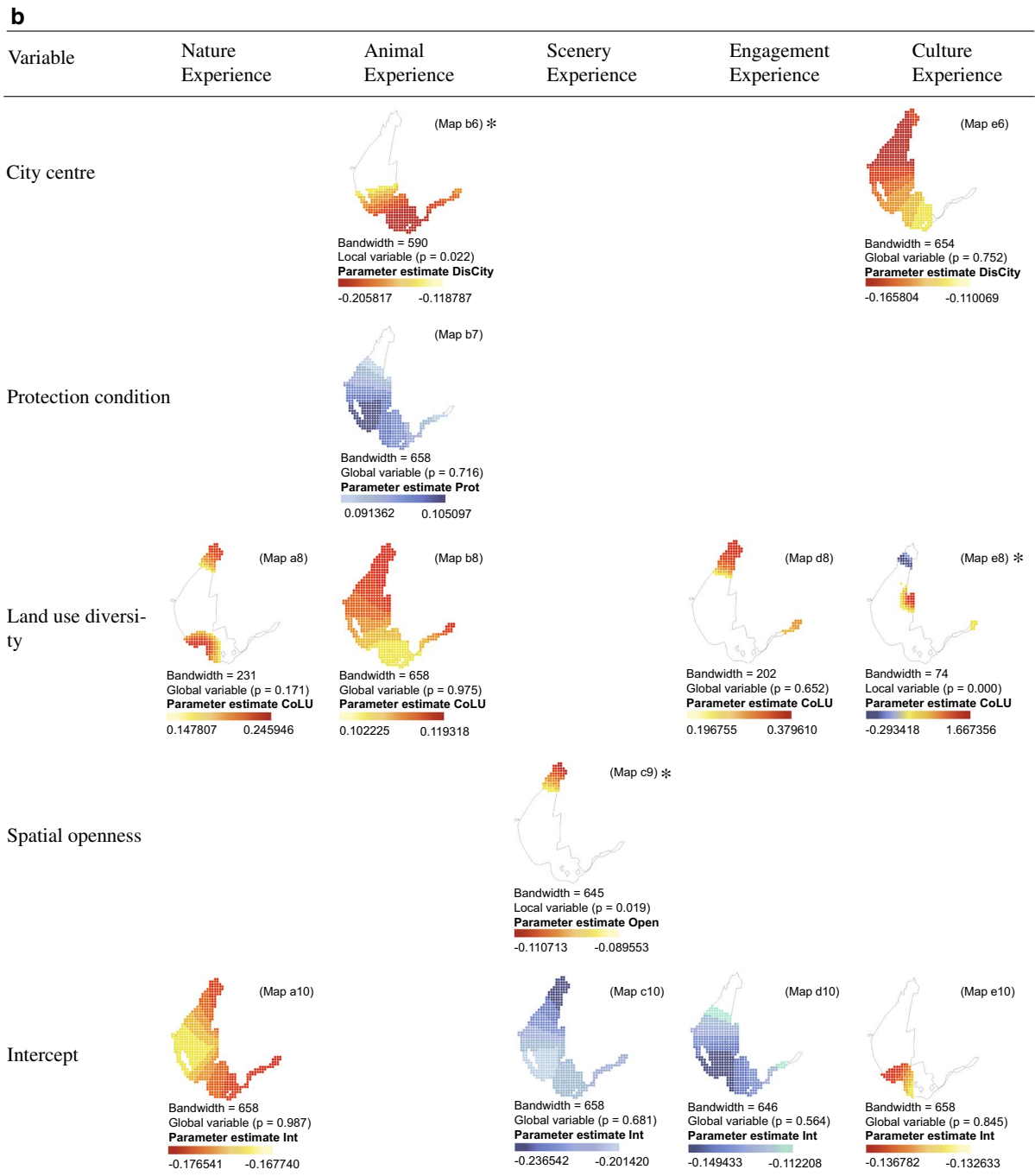


Fig. 2 (continued)

Statistical assessment of the resulting MGWR and the improvement in the model by considering the scale effects

VDPs at most locations are lower than 0.5, and none of the CNs are lower than 30, meaning that the multicollinearity among the explanatory variables was not an issue (Oshan et al. 2019). The goodness-of-fit

of the models suggested by the diagnostic statistics (adj. R-square and AICc) was measured along with the MGWR results. In this way, the global regression and MGWR were compared to verify the improvement of MGWR and thereby corroborate the presence of scale effects (Table 6). The AICc values of the MGWR models for all five experiences were lower than those of the global regression models, with a difference ranging from 61.578 (Engagement) to 103.777 (Animal); these results indicate the stronger explanatory power of MGWR. Additionally, the model fit was improved according to the adj. R-square values, with 27.8% of the variance in the dependent variable explained for animal experiences, 26.2% explained for nature, 25.1% explained for culture, 22.1% explained for engagement and 18.4% explained for scenery. This suggests that the landscape variables account better for animal, nature and culture experiences than for engagement and scenery experiences, partly because the variables related to engagement and scenery may be too intricate to be modelled with the variables selected in the present study. Generally, the MGWR models exhibited an improved fit compared with the global regression models, and the influence of the scale factor on the relationship between the landscape variables and the five experiences was confirmed and intuitively described by this multi-scale analytical approach.

Discussion

Identified experiences and the existence of scale effects on the associated landscape variables

This study used Flickr as a social media data source to assess cultural ecosystem services in a nature park.

Cultural ecosystem services are understood here as specific categories of landscape experiences as documented and shared by visitors in the park in line with other social media-based cultural ecosystem service studies (e.g., Tenerelli et al. 2016; Garcia-Martin et al. 2017; Oteros-Rozas et al. 2018; Johnson et al. 2019). Visitors' experiences in the park were inductively identified and categorized into five experience dimensions: animal, nature, scenery, engagement and culture. These categories are often used in photo content analysis across social media studies, with slight differences in the dimension names (Richards and Friess 2015; Tenerelli et al. 2016; Richards and Tunçer 2018; Callau et al. 2019; Hale et al. 2019; Retka et al. 2019; Zhang et al. 2020). For example, the animal dimension has been labelled as “wildlife” or “biodiversity”; nature has been labelled as “plants” or “natural landscape”; engagement has been labelled as “physical use of landscape”, “people”, “social recreation”, “artistic or cultural expressions and appreciation”, or “emotional reactions”; scenery has been labelled as “landscape” or “aesthetic”; and culture has been labelled as “cultural heritage”, “infrastructure appreciation” “history”, or “sense of place”. Hence, the five labels used to categorise experiences in this study are in accordance with similar types of labels in other social media categorisation studies of cultural ecosystem services.

In terms of the numbers of photos and users, we assume that the nonconformity can be attributed to two hypotheses. The first is related to social media posting behaviour; that is, people may tend to post several photos about animals at one time, whereas people may only share a few photos for a cultural experience. The second hypothesis, however, indicates the characteristics of different experiences per se; the disproportionately large number of animal

Table 6 Statistical diagnosis of MGWR, global regression and modelling improvement

Regression method	Diagnostic criterion	Experience dimension				
		Nature	Animal	Scenery	Engagement	Culture
MGWR	Adjusted R ²	0.262	0.278	0.184	0.221	0.251
	AICc	1711.149	1711.418	1770.734	1739.497	1731.121
Global regression	Adjusted R ²	0.122	0.095	0.046	0.113	0.077
	AICc	1792.867	1815.195	1846.100	1801.075	1825.171
Difference	Adjusted R ²	0.140	0.183	0.138	0.108	0.174
	AICc	−81.718	−103.777	−75.366	−61.578	−94.05

photos suggests that the animal experience may be more diverse, dynamic, and scattered to make a more spontaneous or incidental surprise interaction, as opposed to the cultural experience, which is often connected to static and fixed landmarks (Foltête et al. 2020), although the exact reason for the disparity in these values remains hypothetical.

The spatial distribution of cultural ecosystem services and landscape preferences have been found to be associated with landscape settings (Tenerelli et al. 2016; Foltête et al. 2020). Our results showed that each type of experience was particularly correlated with a certain group of landscape variables rather than with all landscape variables; moreover, instead of a constant pattern, varying patterns at multiple scales were explicitly discerned in the relationship between the landscape variables and different types of experiences. In the following we will discuss each of these relationships in relation to our selection of landscape variables.

First, the general positive relationship between water bodies and landscape experiences has long been articulated in studies relating to landscape aesthetics and preferences (e.g., Ode et al. 2008). Further, this positive relationship has also been articulated in studies based on social media activity (Hamstead et al. 2018; Tieskens et al. 2018; Wang et al. 2018; Heikinheimo et al. 2020). However, in contrast to these studies, we found that such an influence was not always positive but depended on the local geographical settings and type of experience. An inspection of the photo content and the spatial settings of these specific positive and negative geographic zones helps to explain why these patterns developed. The positive effect of water on certain experiences (nature, scenery, engagement and culture) may be ascribed to the common perception that water features can be natural and compositional elements, and are often a backdrop (featured by a long view distance) for nature, scenery and culture experiences (Hammitt et al. 1994; Richards 2001; Lin et al. 2018), which can also explain the large-scale influence of water features in these experiences, as suggested by the extensively coloured area in these coefficient surfaces and a higher bandwidth value (Map a1, c1, and e1). For the engagement experience that obtained a lower bandwidth value (Map d1), we assume that although water in general has a large-scale influence, an

individual water object tends to work over a short distance from the observer in recreational activities. With regard to animal experience, the results indicated that water bodies had mixed effects (Map b1). As indicated by the area in warm colour, in natural surroundings bodies of water acted as important animal habitats (mostly for wading birds), resulting in a high animal experience value; however, in highly managed environments (the area in cold colour), such as the golf course, the influence of water on animal experiences became negative. Additionally, water features act as a local variable in animal and engagement categories (with $p < 0.05$ in the Monte Carlo test), meaning that the influence intensity of water significantly changes with location. This point highlights the importance of the specific social-ecological context of landscape features, which is also noted in other studies of social media photos in mountainous landscapes (Tenerelli et al. 2016; Foltête et al. 2020), which is in contrast with the often reported universal positive effect of bodies of water on landscape experiences.

Second, as also documented by Foltête et al. (2020) and other studies coming to seemingly opposite conclusions (Table 1), green spaces, including woodlands and meadows, have a somewhat mixed relationship to landscape preferences. In our study, we were able to link this mixed relationship specifically to animal and engagement experiences. More specifically, meadow works as a positive local variable ($p < 0.05$) in engagement experience (Map d2), with the varying coefficients only significant along the coastal area. This together with the identified negative effect of woodlands on the engagement experience (Map d3) in areas around the seashore indicates that people prefer more open areas, such as coastal meadows. In fact, the activities documented in these areas are mostly connected with the sea and coast (such as coastal cycling, fishing, swimming, kayaking, kite surfing, sunbathing). Moreover, the results also revealed a negative effect of woodland features on animal experience, in contrast with studies identifying a positive relationship between wooded habitats and the species richness of animals (Helden et al. 2012). However, trees were found to be a positive feature at the northern entrance near the city centre (Map d3). Therefore, our findings show that the role of green space can be very contingent, which precisely supports the

fact that researchers studying green space can come to very divergent conclusions.

Third, the variable of tourist attraction was found to be a local variable for the four experiences (nature, scenery, engagement, and culture), with $p < 0.05$ and a small-scale bandwidth, being the variable that influences the most experiences at the local scale. This shows that tourist attractions have a positive influence in general, which is in line with other studies (Wang et al. 2018; Heikinheimo et al. 2020). However, we were able to identify the negative cases (marked in blue in Maps a4, c4 and d4) in the three experiences (nature, scenery, and engagement). A possible reason for this could be that, given the nature of the site, most of the tourist attractions selected are spots for animal interactions and artificial constructions in the park, which may also help explain the entirely positive pattern in animal and cultural experiences, whereas a somewhat mixed pattern may be found in other experiences.

Fourth, the positive influence of accessibility (in terms of roads and trails) on social media activity (Hamstead et al. 2018; Wang et al. 2018; Wartmann et al. 2019) was confirmed for only three of the experiences: nature, animal and engagement, suggesting that these types of experience might often occur simultaneously (during the visitors' activities) and thus tend to be clustered close to the trails. Specifically, trail features are found to be a local variable for animal experience, with a local-scale bandwidth and $p < 0.05$, highlighting the importance of small-scale design for trails to enhance the animal experience.

Fifth, social media data are often positively related to proximity to the city centre (Guerrero et al. 2016; Tenerelli et al. 2016; Heikinheimo et al. 2020). However, this relationship was found to be positive for animal and culture experiences only, indicating that the categorization of landscape experiences is noteworthy when studying the effect of proximity to the city centre. Meanwhile, the patterns of scale effects of the two experiences were different: in the animal experience (Map b6), the influence of this variable significantly changes with location (indicated by $p < 0.05$ and bandwidth=590), while in terms of culture experience, the influence is almost constant (indicated by $p > 0.05$ and bandwidth = 654).

Sixth, protection conditions and animal experience were found to be negatively correlated in our data. Similar results were obtained in the study of Tenerelli

et al. (2016), which reported a mixed effect of the protection condition variable on cultural ecosystem services. However, we assume that this purely negative pattern in our study may be primarily caused by the two restricted-access bird sanctuaries in our study area (the empty areas on the parameter estimate surface), and as the value of the bandwidth and p -value indicates, the influence of such variable does not significantly differ with the landscape attribute grade.

Seventh, land use diversity presented mixed patterns of influence on experiences, as suggested in Tenerelli et al.'s (2016) study. Land use diversity was found to be positively correlated with nature, animal, and engagement experiences, but in the northern part of the area with the highest diversity, the variable was negatively correlated with culture experiences and mediated as a local variable. This might relate to the design of the park, where cultural elements are concentrated in more homogenous parts of the park (e.g., the middle part of the area).

Finally, the positive influence of the openness variable found in other studies (Johnson et al. 2019; Foltête et al. 2020) was only significant for scenery experiences, with a limited influential range. This is indicated by the value of the bandwidth and the p -value that the openness degree has an influence at the local level, which has not been reported in other studies.

Novel application of MGWR approach

Most studies devoted to investigation of multi-scale ecological processes often consider scale hierarchies in their approaches (e.g., Allen and Starr 1982; Kolasa et al. 1991; Wu 1999; 2007; Cushman and McGarigal 2002; Wilson et al. 2020). Divergent from these studies, we treated the scale effects of variables as independent from each other, and as directly inferred by a series of parameters computed for each landscape variable with a multi-scale spatial model, thereby seeking to advance insights into the contextualised influence of landscape variables on categories of experiences at a certain site.

One of the most important insights was the nuances in the scale effects of landscape variables identified in the present study, which is seldom considered in previous studies concerning landscape experiences. And as demonstrated by the heterogeneous values of the bandwidths, it may cause problems

to assume a single averaged bandwidth (as is applied in GWR) for all the covariables in a regression model. MGWR allowed us to calibrate spatial models with separate bandwidths for centroid points of grid cells for the best-fit regression results, where the influential range of the landscape variable could be suggested by the bandwidth value. In addition, the parameter estimates were calculated for each centroid point of the grid cell, resulting in a surface that explicitly shows the intensity of the influence. Therefore, instead of an averaged measure of the influences, this article identified the spatial ranges and intensity of the positive or negative influences.

MGWR has been increasingly used in recent studies to better account for spatial heterogeneity and explicitly evaluate scale-related parameters in modelling spatial relationships. Chang Chien et al. (2020) assessed the robustness of OLS, GWR and MGWR in studying the relationship of experts' physical criteria of wilderness and public perception across the UK. Gosal et al. (2021) applied the MGWR approach to identifying stationary and nonstationary spatial variables in a natural area visitation study in Europe and North America.

However, these large-scale case studies did not pay much attention to linking statistical results with the actual interactions of people and the environment (i.e., experiences and spatial characteristics). In contrast, the present study was dedicated to precisely interpreting the detailed patterns revealed, which allowed us to analyse and explore the details of the multiple statistical relationships between landscape variables and landscape experiences. We believe this study has demonstrated the capabilities and possibilities of using MGWR to better understand the contextualized realities of landscape experiences within a specific case study area at the park level.

Limitations of the study

Although relationships between landscape variables and the distribution of social media data can be obtained from the results of analyses, locating the exact causes of these relationships is still challenging. It is unclear whether it is truly the geographic effect of a landscape variable or the effect of the non-landscape covariates (such as those that have been used to explain the results in this paper, e.g., the social media behaviour, intensity of maintenance, or activities that

are not directly stimulated by the landscape but prior expectations of visitors) that determine the relationship. This adds to the challenge of locating which landscape variables are relevant to the study. Moreover, questions about whether the pattern is real need to be assessed; there may be instances of “apophenia” where one tends to seek plausible connections to find patterns that may not actually exist (Boyd and Crawford 2011).

Additionally, limited information and potential representativeness issues of users remain a great challenge to leverage the potential of social media data (Guerrero et al. 2016; Wang et al. 2018; Foltête et al. 2020; Heikinheimo et al. 2020). It is worth noting that the nonconformity of the numbers of photos and users should be taken into consideration when analysing social media data. This article used user count as the dependent variable to counter the possible data size limitations and the impacts of overactive users who take multiple photos of the same object in the same spatial setting; in other analyses, the photo count may be more relevant (Antoniou et al. 2010; Guerrero et al. 2016; Tenerelli et al. 2016; Tieskens et al. 2018).

Furthermore, an analytical compromise took place during the spatial modelling and has to be acknowledged: the dependent variable for the categorized experiences was estimated as the value of the aggregated number of users in a grid cell, and the potential impacts of the landscape features were simplified into distance measures to each cell when the landscape features had differentiating characteristics, such as the size and shape of a water body, area of a woodland or meadow, density of trails, or spatial characteristics, such as the configuration of landscape features, depths of view, etc. Moreover, this study falls short in accounting for the mutual effect of landscape variables mediating in situ experiences.

Implications for future research and practical applicability

Despite the limitations above, the MGWR approach elicited a spatially explicit quantification of the effect of landscape variables regarding the categorized landscape experiences as an expansion of traditional assessments of a somewhat simple division between positive or negative landscape effects and indicator-based approaches (Ode et al. 2008, 2009; Paracchini

et al. 2014). Therefore, the demonstrated approach of using MGWR on the experience dimensions of social media activity might facilitate explaining the processes behind these experiences by linking collective trends with individual features. This may open up opportunities to broaden the current understanding of the associations of biophysical landscapes with the various types of experiences people can obtain from authentic in situ interactions within landscapes. Using this explorative approach, it is also possible to find evidence for the hypothetical associations that are often applied in design and planning processes, or to uncover new potential associations that had not been thought of before.

With the advantage of mappable parameters of scale effects, this method can possibly facilitate the pursuit of complex real-life problems related to spatial processes of human interaction with the environment in a rather quantitative and communicable manner. As opposed to arbitrarily transferring knowledge from other cases, the presented method offers a scientific and empirical base for decision-making in landscape monitoring and management, especially those related to subjective topics, such as people's perception, which is often deemed elusive.

Geolocated photos associated with informative text from social media enable a thorough categorization of in situ experiences. However, since treating experiences as points in space can result in the loss of the "density" of experiences, in future research, more sophisticated metrics need to be incorporated as landscape variables, such as the skyline, depth line, indexes of land use diversity, etc. (Foltête et al. 2020). In addition, there are numerous variables other than purely geographic variables that are involved in the process of experiencing nature and landscape, e.g., individual visitor motives, expectations, values, preferences, visitation history, and perceptions of site value and atmosphere (Atauri et al. 2000; Chiesura 2004; Zhang et al. 2013; Bertram and Rehdanz 2015; Brown et al. 2020). Thus, researchers may adopt combined methods that involve more qualitative approaches in the future (Hegetschweiler et al. 2017). Furthermore, we highlight the need for possible cross-case studies to be conducted in other contexts at different scales to test the validity of the patterns of relationships of landscape and experiences found in Amager Nature Park. With the popularization of social media and the development of technological

and analytical methods, the potential of the novel methods demonstrated in this article can be expected to be realized in a wider range of studies exploring the value of natural landscapes for human wellbeing.

Conclusion

This paper aimed to advance the study of the mediating effects of landscape on landscape experiences by tapping into the scale effects of landscape variables in relation to specific dimensions of experiences in an urban nature park. The results suggest that even a single landscape variable can exert an influence on different landscape experiences at multiple scales and that its effects can be both positive and negative according to the different geographical contexts. Among the other relationships identified, water and woodlands, which are frequently considered to positively influence the landscape experience in the literature, were found to have mixed effects on different experiences, and the scale range and intensity of these impacts were highly context-dependent. The identification of such nuances in these relationships can be attributed to the particular consideration given to the scale effects. We employed an approach that allowed us to calibrate the spatial models with separate bandwidths for every covariable to achieve the best-fit regression results. The range of influence of the landscape variables becomes measurable with the bandwidth value and parameter estimate surfaces.

Limitations such as data availability, reliability of the modelling method and the proper incorporation of explanatory variables were significant barriers to obtaining a more in-depth understanding of the experiential dimension of people's interactions with the landscape, and the interrelationships among different types of experiences that take place in the same spatial setting need to be further studied.

In the course of promoting ecosystem services in urban areas, enhancing landscape experience in urban nature park has been recognized as an essential part. Awareness of the fact that landscape variables are unlikely to have the same effects at different scales, either for landscape experiences or across an entire area, puts a more critical focus on the specific arrangements and selective augmentation of landscape variables linked to intended natural

experiences. Finally, the present study suggests a scientific means of effectively enhancing multiple experiences by prioritizing certain landscape variables in the targeted locations; such an approach can be used to optimize the overall outcomes concerning urban nature experiences and minimize costs and trade-offs.

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Data availability The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Code availability The Python scripts used to produce dataset in the study is available from the corresponding author on reasonable request.

Declarations

Conflict of interest Both authors have no financial or proprietary interests in any material discussed in this article.

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Consent for publication Both authors have consented to publication of this material.

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