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RESEARCH ARTICLE

Favourite places for outdoor recreation: Weak correlations between perceived qualities and structural landscape characteristics in Swedish PPGIS study

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Abstract

1. Connections between outdoor recreation and various health and well-being benefits are well established. However, questions remain regarding which landscape characteristics that best predict places in the landscape that correspond to people's needs and preferences. The perceived sensory dimensions (PSDs) model proposes eight basic perceived qualities that people commonly seek in outdoor environments to support complementary needs: a *Natural*, a *Cultural*, a *Cohesive*, a *Diverse*, a *Sheltered*, an *Open*, a *Serene* and a *Social* quality respectively.
2. These PSDs have increasingly been suggested as a tool for green space assessment and planning. How strongly they correlate with objective landscape characteristics is, however, still an open question. We surveyed recreationists in Sweden, tasking them with noting their favourite places on a map ($n=275$), and to report the degree to which the PSDs were present. The qualities typically reported as most prominent at these places were *Open*, *Serene* and *Sheltered*, while the least prominent were *Social* and *Cultural*.
3. A cluster analysis further revealed that favourite places could be classified into two main groups regarding perceived qualities. One associated with presumably more restorative qualities, emphasising *Natural* and *Serene* settings, the other instead suggesting a more outward-directed experience, strong in the perceived *Social* and *Cultural* dimensions.
4. Machine learning models, however, revealed weak links between objective landscape characteristics and perceived qualities, with stronger correlations found with attributes connected to personal characteristics, such as the degrees to which a person identifies as nature or urban oriented.
5. Although largely confirming the basic relations between the PSDs suggested by earlier studies, our results cast some doubt on the way they often have been understood and used, as describing an 'objective' truth of places, rather than representing qualities that largely emanate from the individual experience. Our

results instead confirm previous reports of weak general links between objective landscape measures and perceived qualities.

KEYWORDS
cultural ecosystem services, landscape preferences, outdoor recreation, perceived sensory dimensions

1 | INTRODUCTION

Urbanisation continues to increase (UN, 2019) while noncommunicable, lifestyle-dependent and often stress-related, illness dominate globally (WHO, 2021). Meanwhile, outdoor recreation and experiences of nature and greenery are recognised as important contributors to human health and well-being (e.g. Aerts et al., 2018; Bratman et al., 2019; Egorov et al., 2016; Hartig et al., 2014; McMahan & Estes, 2015). However, people's needs vary over time and between individuals, highlighting the potential need for diverse landscape features and biodiversity to accommodate different recreational styles (e.g. Marselle et al., 2021). This presents a challenge for landscape and urban planners, necessitating practical guidelines and models that can be used to predict how well the surrounding landscape supports general recreational needs. One such model is the perceived sensory dimensions framework (Adevi & Grahn, Grahn & Stigsdotter, 2010; Stoltz & Grahn, 2021) which attempts to define a set of basic perceived qualities, or perceived sensory dimensions (PSDs), that people commonly seek in recreational outdoor spaces. More than 60 studies employing this framework in various ways have been conducted in different parts of the world, including examples from the Nordic Countries (Lindholst et al., 2015), Estonia (Maikov, 2013), Serbia (Vujcic & Tomicevic-Dubljevic, 2017), Canada (Lockwood, 2017), Iran (Memari et al., 2017), Malaysia (Mansor et al., 2017) and China (Gao et al., 2019).

In a review and synthesis of several previous studies, Stoltz and Grahn (2021) proposes a model summarising the PSDs as eight basic perceived qualities: *Natural*, *Cultural*, *Cohesive*, *Diverse*, *Sheltered*, *Open*, *Serene* and *Social*, interrelated as in Figure 1a (ibid.). They suggest these qualities to support complementary recreational needs, relevant to both activity and rest. Stoltz (2022; fig. 1b) furthermore proposes an evolutionary model, linking the PSDs to different habitat conditions during the evolution and development of the human species, to explain how they support different stages of restoration and rehabilitation from high stress levels and cognitive fatigue. This model proposes a unified restorative pathway based on the PSDs, synthesising the two main theoretical approaches explaining nature-based restoration from an evolutionary perspective, the *attention restoration theory* (ART; Kaplan, 1995; Kaplan & Berman, 2010) and the *stress reduction theory* (SRT; Ulrich et al., 1991) respectively. It suggests *Serene*, *Sheltered*, *Natural* and *Cohesive* environments of primary importance to support early stages of such restoration, when stress levels are high and/or attentional capacities low, whereas *Diverse*, *Open*, *Cultural* and *Social* settings increase in importance at subsequent stages, as fundamental attentional capacities have been restored and stress levels lowered. This model is supported by empirical evidence presented by,

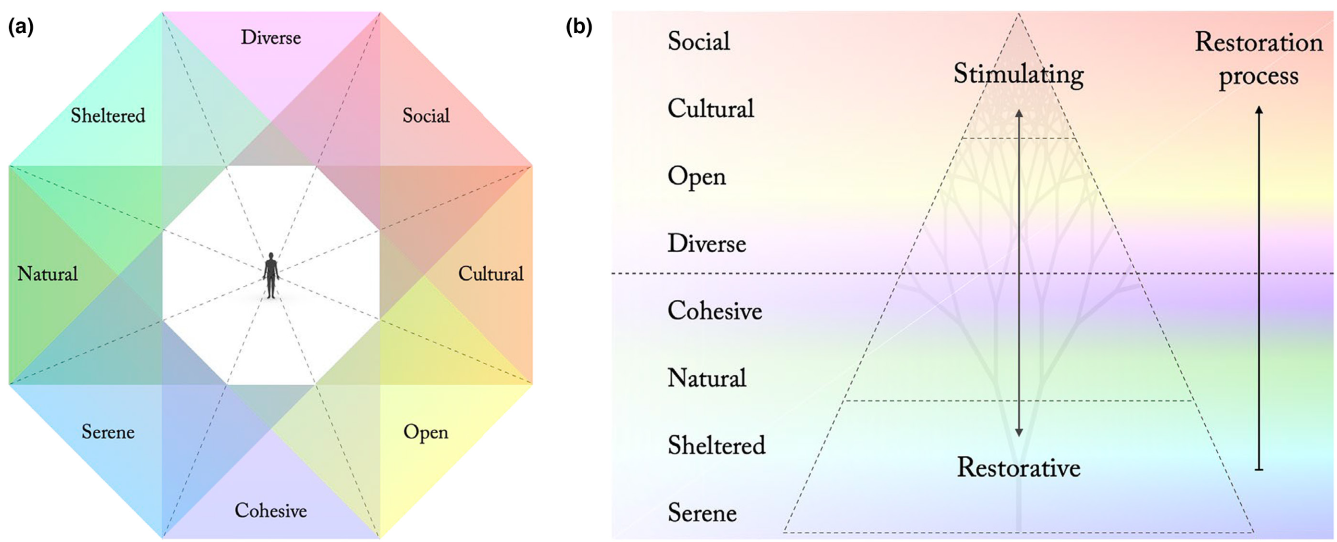

FIGURE 1 Schematic relations between the eight perceived sensory dimensions, where (a) correlations between perceived qualities are stronger the closer they are in the model (Stoltz & Grahn, 2021), and (b) in relation to supportive influence on restoration from high stress levels and cognitive fatigue, according to an evolutionary model (Stoltz, 2022).

among others, Grahn et al. (2010), Memari et al. (2017), Stigsdotter et al. (2017) and Pálsdóttir et al. (2018).

If certain landscape characteristics adequately could predict such perceived qualities of recreational areas, this could be useful for planning purposes when health and well-being outcomes and general recreational needs are considered. However, Stoltz and Grahn (2021) emphasise the necessity of an ecological approach to perception (Chemero, 2009; Gibson, 1979) when analysing the PSDs, viewing them as classes of *affordances* (ibid.); perceivable and utilisable behavioural possibilities offered in the environment, equally influenced by the physical world and the specific needs and abilities of the individual. To the extent people are similar, similar environmental attributes could be expected to reinforce each PSD. However, since humans also exhibit great individual variation, the PSDs cannot be seen as solely definable in terms of specific landscape features as individual characteristics most likely also will shape perceived affordances for the PSDs. The question is then to what extent the PSDs can be understood as universally shaped by certain landscape characteristics, and to what extent they are shaped by individual characteristics that vary in the population. Previous research by, for example, Leslie et al. (2010) has indicated a general lack of agreement between perceived qualities and objective landscape measures, which might be due to the influence of such individual characteristics in how environments are perceived. One example is provided by Gunnarsson et al. (2017) who reported that individuals considering themselves as mainly 'nature-oriented' rated areas with high objectively estimated biodiversity more in line with actual biodiversities than people who considered themselves as mainly 'urban-oriented'. Thus, attitudes and knowledge influence how people perceive the same objective landscape features.

Direct general connections between the PSDs and various structural landscape characteristics have been studied, if in a limited fashion, in urban (e.g. Skärbäck et al., 2014; Stoltz & Schaffer, 2018), rural (Adevi & Grahn, 2012; de Jong et al., 2012) and forest settings (Stigsdotter et al., 2017; Stoltz et al., 2016). In a Swedish survey study ($n=121$) of urban green spaces, Qiu and Nielsen (2015) concluded that experiences of the PSDs were related to the diversity of biotopes offered by an urban green space and that larger green spaces containing more biotopes supported the experience of more PSDs. This appears in line with the suggestion by Stoltz (2022) that the PSDs can be connected to different habitat conditions during our evolution and development as a species. They also found experiences of the PSDs to be consistent across gender, age and frequency and type of recreational use, granting some legitimacy to the framework in assessment and mapping of recreational experiences (Qiu and Nielsen, 2015).

Björk et al. (2008) operationalised PSDs using a mix of objective landscape variables (land cover, noise, other map data), following the parameters used in a Swedish report by Skärbäck et al. (2009). Based on these models, they suggest that the presence of mapped PSDs within 300 m of residence correlates positively with well-being and propensity to exercise. The same GIS model was used by Annerstedt van den Bosch et al. (2015), who present a follow-up of the survey participants who have moved since the last study and compare the landscape conditions they moved from to what they moved to, as well as how they felt before and after. Based on their result, they suggest that moving to *Serene* environments might decrease the risk of mental illness. However, neither of these studies empirically validate their predictive PSD models, that is, show that the selected landscape variables cause people in general to perceive a particular PSD as stronger. de Jong et al. (2011, 2012) chose a different strategy and instead of structural landscape data constructed area-aggregated measures, derived from large public health surveys in which participants were asked about their perceptions of the PSDs in their close-by living environment. These results indicate that people tend to perceive their neighbourhood in a similar way as other people living within the same 1-km^2, which could suggest an underlying structural basis in the landscape for these perceptions. However, it also seems possible that such similarities, at least in part, could be attributed to some individual factors uniting people living in similar areas.

The main motivation for our study here was to investigate experiences of the PSDs at people's favourite places for outdoor recreation, and whether these could be predicted by a comprehensive set of landscape variables. As the PSDs have become more and more widely used both practically and in various research studies around the world, often with the assumption that they, more or less, directly reflect underlying objective landscape features, we wanted to test this assumption against a comprehensive set of landscape data together with a smaller set of individual characteristics. We also wanted to characterise people's favourite places in terms of general landscape types. To accomplish this, we gathered survey data on people's experiences at their favourite places during outdoor recreation. We employed a novel methodology, where we calculated what landscape was visible from the favourite places, using LiDAR data, to capture a closer approximation of the actual recreation experience. We utilised a large amount of map data as covariates, which was made possible by employing a flexible machine learning algorithm in the form of boosted regression trees (BRT) for modelling. Our main research questions were:

1. Which are the general landscape types at people's favourite places for outdoor recreation?
2. Which perceived qualities, PSDs, do people report at these places, and in which combinations?
3. Can the strength of these perceived qualities be accurately predicted by objective landscape characteristics at the site independent of individual characteristics, such as gender, age, educational background or nature/urban orientation?

2 | MATERIALS AND METHODS

To address our research questions, a digital survey was employed to residents of a large Swedish city. The collected data were then analysed by training a machine learning model on the characteristics of favourite places in the landscape.

2.1 | Survey

2.1.1 | Study area

The study area (Figure 2) consisted of Umeå Municipality, in Västerbotten County, Sweden. It covers an area of approximately 2300 km^2 and has an estimated population of 130,000, with a population density of 56.21/km^2 (2020). Its seat, the city of Umeå, is known for its university and many birch trees, giving it the nickname the 'Town of Birches' ('Björkarnas stad'). It is located near the coast of the Gulf of Bothnia, at the 63rd parallel. Climate is cold continental, with freezing winters and mild summers. Between the end of April and mid-August, the sun sets, but it does not get completely dark even at midnight. The Ume River that passes through the city widens into a fjord before flowing into the sea. The surrounding landscape is a mix of forests (mainly coniferous), arable land, some wetlands and lakes.

2.1.2 | Survey design

An invitation to participate in the survey was sent out to 3000 residents over the age of 18 in the city of Umeå via mail in September 2021. The list of recipients was acquired from the Swedish state person address registry, which provided a stratified sample designed to be proportional to the population of Umeå with regard to gender and age. A reminder to answer the survey was sent out 3 weeks later. The survey invitation contained a link to the digital survey, which was implemented using the GIS-based survey tool Maptionnaire (Mapita). In the survey, the respondents were asked to provide some basic demographic data (age, gender and level of education). They were also asked two separate questions to assess to what degree they would consider themselves as being 'nature-oriented' and 'urban-oriented' respectively. These terms were not further defined for the respondents and the questions were included as they have been shown to reflect factors with potential effect on greenspace use (Gunnarsson et al., 2017). Both questions had a slider with a range between 0 and 100, where 0 represented 'Not at all' and 100 'Fully'.

The main part of the survey was divided into two parts. The first part tasked the respondents with summarising their outdoor recreation within Umeå municipality by drawing typical routes they take, and providing details (e.g. type of activity, frequency and duration of visits etc.) of each route. These data were collected for a separate study and will not be further discussed here. The second part of the survey tasked the respondents with marking the location of their favourite places when performing recreation. A favourite place was defined as a place 'holding any specific importance, such as a place of beauty or somewhere you often stop and spend time in'. For each place, they were also asked to assess eight statements, each corresponding to one PSD (Table 1). These were based on the definitions of the PSDs described by Stoltz and Grahn (2021) and were phrased as simple one sentence statements, intended to capture the essence of each PSD. As such, they were very similar to the statements used by, for example, Björk et al. (2008), de Jong et al. (2011, 2012) and Stoltz et al. (2016).

For each statement, the respondents were presented with a slider that ranged from 0 to 100, where 0 corresponded to 'Not at all' and 100 to 'Fully'. The slider's starting position was in the middle (Stoltz et al., 2016). The participants were also asked to mark their home location on the map. Prior to deployment, the survey was tested on a convenience sample of 45 friends and colleagues, after which minor changes in wording of questions were made.

Since the survey did not handle sensitive information, we assessed it as not falling under any of the criteria listed in the Swedish Ethical review act (2003:460), and thus did not need authorisation from the Swedish Ethical Review Authority. The collected data were handled in accordance with GDPR, and the respondents were provided information on how the collected data would be handled at the start and the end of the survey, where consent was asked.

2.1.3 | Summary of responses

Of the 3000 invited participants, 658 opened the link to the digital survey, and 285 finished the entire survey. One hundred and ninety-five individuals placed one or more favourite places, yielding a total sample of 318. Favourite places outside Umeå municipality were removed ($n = 26$). Favourite places where the respondent had not interacted with any of the eight PSD sliders were also removed ($n = 17$). For respondents that had interacted with at least one of the sliders, untouched sliders were interpreted as having been left in the middle deliberately and counted as 50. Final sample consisted of 275 favourite places, originating from 181 individuals. The gender distribution of the respondents was 47% male and 53% female. Median age was 45, with a standard deviation of 17, which is similar to the Umeå average (49 ± 18, Umeå kommuns demografidatabas 2023). The respondents were more educated than the Umeå average, with 69% having attended higher education in some capacity, compared to the Umeå average of 38% (Statistics Sweden, 2021).

2.2 | Correlations between PSDs and cluster analyses

To see how reported PSDs at favourite places were correlated to each other, a correlation matrix was produced. To investigate if favourite places could be sorted into different clusters regarding PSDs, *K*-means clustering was performed. *K*-means clustering is a commonly used unsupervised machine learning algorithm that partitions a data set into a given number (K) of different clusters, where each observation belongs to the cluster with the nearest mean (Hartigan, 1975). The algorithm iteratively updates the cluster centroids and assigns

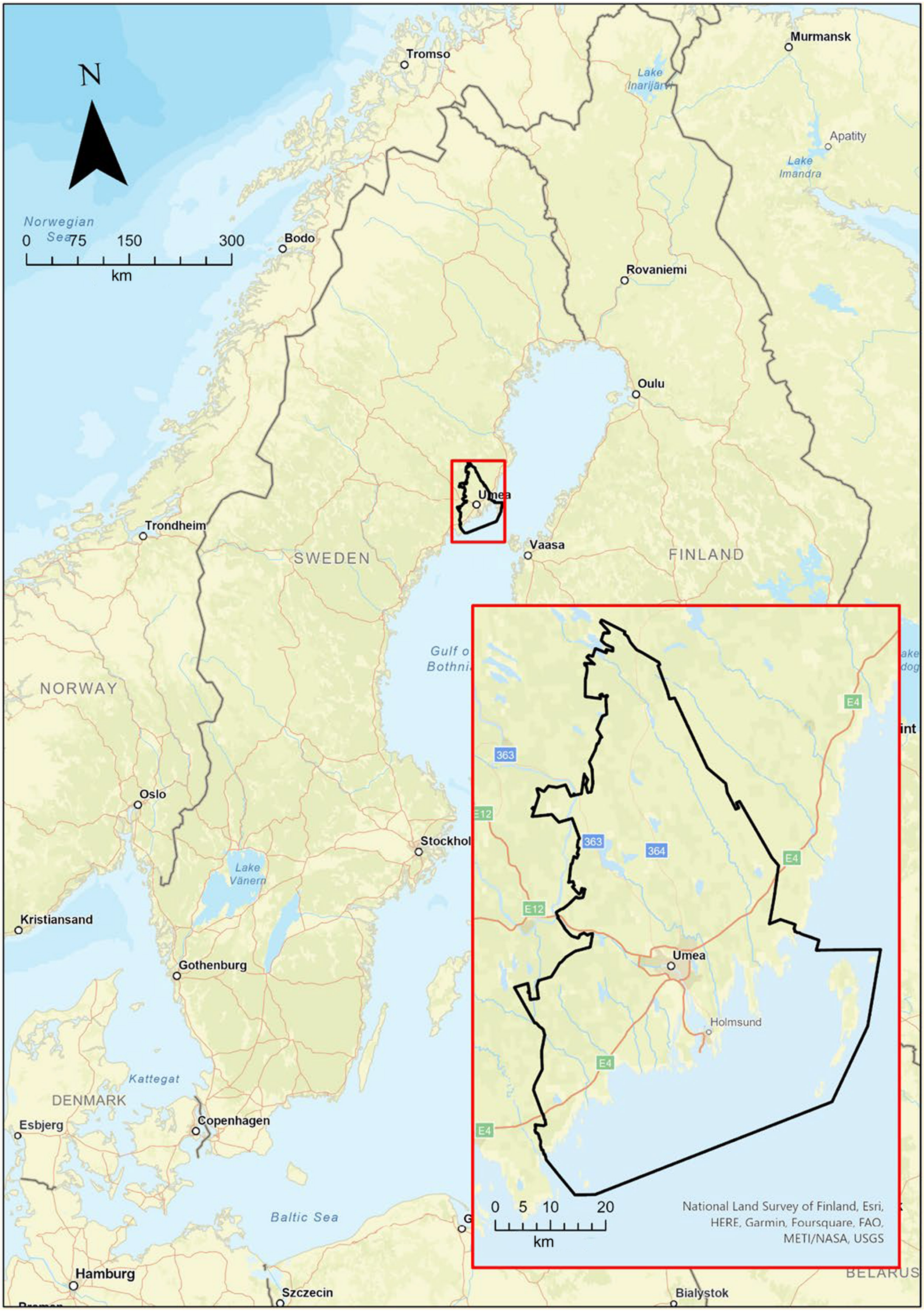

FIGURE 2 The study area of Umeå municipality, located in northern Sweden.

each observation to the nearest centroid until convergence. The resulting clusters can be used for exploratory data analysis, pattern recognition and other data mining applications. A prerequisite to employ the method is to choose the number of clusters (*K*), and as we did not have any prior hypotheses on the number of groups, we employed two methods to estimate how many clusters existed in the data set: the Caliński-Harabasz index (Caliński & Harabasz, 1974) and the silhouette method (Rousseeuw, 1987), which both are algorithms that estimate how well a given data set clusters.

2.3 | Predictive PSD modelling using landscape characteristics

To evaluate whether PSDs could be predicted by landscape or individual characteristics, eight machine learning models were created, one for each PSD.

TABLE 1 Statements for each PSD in the survey, answered using sliders from 0 ('Not at all') to 100 ('Fully').

PSD	The place evokes a sense of...
Natural	... wild and untouched nature
Cultural	... being shaped by humans
Open	... openness, with opportunities for vistas
Social	... a social space, with opportunities to interact with other people
Cohesive	... a cohesive whole, of being a world in itself
Diversity	... diversity and variation
Sheltered	... shelter
Serene	... serenity

Abbreviation: PSD, perceived sensory dimension.

2.3.1 | Converting points to experienced landscape

To define the extent of each place a combination of two approaches was employed. First, a circular buffer with a radius of 50 m was created around each point which represented the immediate surroundings the respondent experienced. Second, using a high-resolution digital surface model (DSM), a viewshed was calculated that represented the area that was visible from a height of 1.5 m when standing at the point using ArcGIS Pro 3.0.0. The viewshed was calculated with a maximum sight distance of 1 km for computational reasons. Trees and vegetation were assumed to be total sight blockers, except for within the 50 m buffer. Figure 3 shows two examples of the sampled landscape around two favourite places in our study.

2.3.2 | Model predictors

Several different landscape characteristics were sampled using different map sources (Table 2). Some landscape predictors were sampled in both the viewshed and the buffer, while others were exclusive to the buffer. Land cover was extracted from the CadasterENV Sweden map (Swedish Environmental Protection Agency, 2018) and reclassified from 25 original classes into 13 for easier model interpretation (Supplementary Materials S1). Each land cover type's cover in % of the buffer and the viewshed was used as a predictor, but they were also used to estimate landscape heterogeneity. This was done by calculating the Shannon–Wiener diversity index (Shannon, 1948). The SLU forest map (SLU, 2015) added nuance to the land cover maps in forested areas by supplying estimates of tree height and volumes of different tree species, as well as total biomass volume.

Biodiversity was included in the model by combining several sources of map data: the extent of all formally protected areas

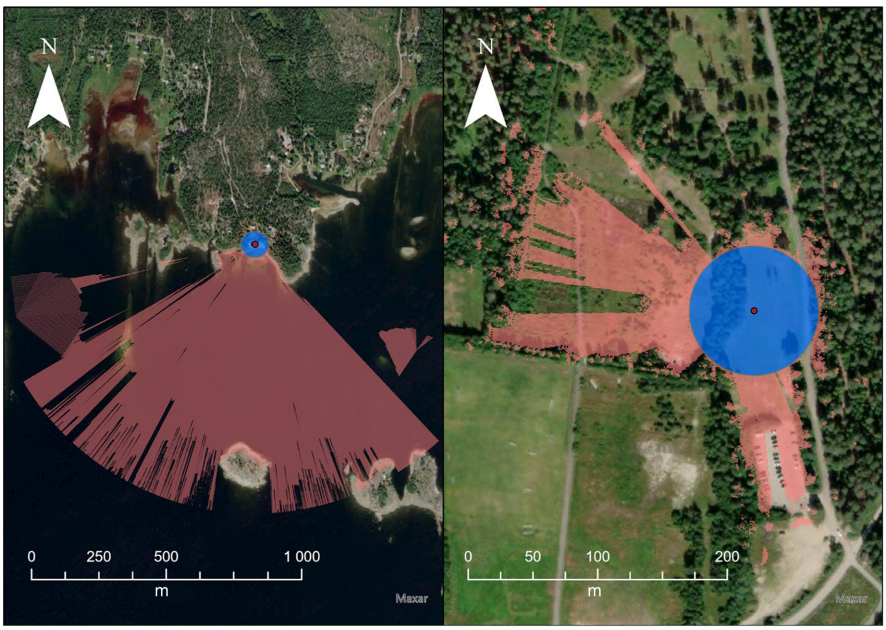

FIGURE 3 Examples of the sampled landscape around two favourite places. Centre point is the favourite place provided by the survey respondent. The blue circle is the 50 m buffer around this point, and red areas the calculated visible landscape, viewshed (360 degrees), when standing at the point.

(national parks, nature reserves, protected biotopes) was merged with maps of woodland key habitats (forests with high biodiversity values, see e.g. Timonen et al., 2010). Maps provided by the municipal government on areas with high biodiversity values were also included, with the predictor used in the model being the percentage overlap between the buffer and any of these maps. The municipal government provided three maps of estimated average noise levels due to road traffic, railroad traffic and industry respectively. These were combined by taking the highest estimated noise level at each point of the three maps, and then calculating the average across the buffer. Paths and roads were extracted from OpenStreetMap (Openstreetmap Foundation, n.d.), and lengths of each were calculated within the buffer. Data on recreational infrastructure (shelters, toilets and fireplaces) was also supplied by the municipal government and used as a predictor by calculating the distance from the point to the nearest recreational infrastructure. Topography was considered by calculating the median, standard deviation and the range (largest difference) of elevation above sea level within the buffer and the viewshed. Table 2 shows a summary of the landscape predictors used in the machine learning models. In addition to these landscape predictors, demographic data were included as predictors (Table 3). Age was excluded from the demographic variables due to 63 missing responses.

2.3.3 | Boosted regression trees

Modelling was performed using BRT. BRT is a machine learning approach where a predictive model is created by iteratively building an ensemble of many decision trees (Friedman, 2001). The method has several advantages: It does not assume linear relationships between predictor variables and response variables; it can handle a large number of predictors regardless of multicollinearity; and it avoids

TABLE 2 Summary of landscape predictors used in the machine learning models.

Predictor	Description
Land cover (13 predictors)[a,b]	Composition of land cover types. Data source CadasterENV
Shannon-Wiener diversity[a,b]	Landscape heterogeneity, calculated using the land cover classes
Tree height[a,b]	Average height of trees (m). Data source SLU Forest map
Spruce volume[a,b]	Average volume of Norway spruce (m^3/ha). Data source SLU Forest map
Pine volume[a,b]	Average volume of Scots pine (m^3/ha). Data source SLU Forest map
Birch volume[a,b]	Average volume of birch (m^3/ha). Data source SLU Forest map
Deciduous tree volume[a,b]	Volume of deciduous trees except birch (m^3/ha). Data source SLU Forest map
Biomass volume[a,b]	Total volume of all vegetation (m^3/ha). Data source SLU Forest map
Elevation (3 predictors)[a,b]	Median, standard deviation and range of elevation. Data source LIDAR DSM Lantmäteriet
Noise[a]	Average noise(db) over 24 h. Data source Umeå municipality noise estimates based on models of road and railroad traffic and industry
High biodiversity area[a]	Overlap of buffer with areas of high biodiversity (%). Areas included national parks, nature reserves, woodland key habitats and areas of high conservation value in the municipal inventory
Path/road length[a]	Length of paths/roads within buffer (m). Data source OpenStreetMap
Amenity distance	Distance (m) from point to the closest recreational amenity (shelter, toilet, fireplace). Data source Umeå municipality

[a]Predictor was sampled within the 50 m buffer.
[b]Predictor was sampled within the viewshed.

TABLE 3 Individual characteristics used as predictors in the machine learning models.

Variable	Description	Values
Gender	The gender of the respondent	Man, woman, other
Education	Highest level of finished education	Elementary school Secondary school Folk high school Folk high school University > 2 years
Urban oriented	To what extent the person identifies as urban-oriented in terms of general environmental preference	Discrete [0,100]
Nature oriented	To what extent the person identifies as - nature-oriented in terms of general environmental preference	Discrete [0,100]

the need for model selection or pre-specifying interaction effects in advance. The main disadvantage of BRT is the lower interpretability of the final models, having more aspects of being a 'black box' than traditional regression models such as GAMs or GLMs. However, with recent methodological advances, such as the Interpretable Machine Learning package for R (Molnar, 2018), these shortcomings can be mitigated to a larger extent.

All analyses and visualisations were carried out using the *gbm* package (Greenwell et al., 2020) in R version 4.0.3 (R Core Team, 2020). Boosted regression trees were constructed following the recommendations outlined by Elith et al. (2008), using a Gaussian distribution with each PSD as the response variable. When fitting BRT, three hyperparameters that affect model fitting are set: (1) tree complexity (how many splits are allowed in each tree); (2) learning rate (how quickly the algorithm converges, with lower values leading to better models at the cost of computing time); and (3) bag fraction (how large a fraction of the data set to use in each iteration). We created models with combinations of five different tree complexities (Adevi & Grahn, 2012; Aerts et al., 2018; Annerstedt van den Bosch et al., 2015; Beery et al., 2015; Bratman et al., 2019) and two bag fractions (0.5 and 0.75) and lowered the learning rate until a model of at least 1000 trees was fitted (ibid.). Model performance was evaluated using cross-validated R^2-values. Feature importance, interaction effects and partial dependence plots were evaluated using the *iml* package (Molnar, 2018).

3 | RESULTS

3.1 | General landscape types at favourite places

Our first research question related to which general landscape types that are found at people's favourite places. Figure 4 shows the coverage (%) for general land cover classes within the 50 m circular buffer at people's favourite places. The four forest classes (spruce, deciduous, pine and mixed) were grouped together. Forest and water dominated at favourite places, with forest being the most common land cover type (Figure 4). This seems quite in line with the supply in the study area as whole, which consists of a mix of forests (mainly coniferous), arable land, some wetlands and lakes. Figure 5 shows the locations of people's favourite places within the study area.

3.2 | Distribution and combinations of PSDs at favourite places

Our second research question related to the distribution and combinations of PSDs at people's favourite places.

3.2.1 | Distribution of PSDs

Figure 6 shows the distribution of ratings (0–100) for the presence of each PSD at the favourite places. The *Natural*, *Cultural*, and *Social* PSDs showed a larger variation in response than the other PSDs, which mainly elicited responses at or above 50. *Serene*, *Open* and *Sheltered* were the most pronounced qualities at favourite places (mean 74, 71 and 69 respectively), while *Cultural* and *Social* were the weakest (mean 50 and 46 respectively).

3.2.2 | Correlations between PSDs at favourite places

Table 4 shows correlations between PSDs at favourite places in our study. Green highlights positive and red negative correlations between perceived qualities. More saturated colour indicates stronger correlation. Correlations weaker than ±0.1 are not highlighted with any colour.

3.2.3 | Cluster analysis of PSDs at favourite places

The Calinski–Harabasz index and the silhouette analysis both suggested that the data set contained two clusters. Using k-means

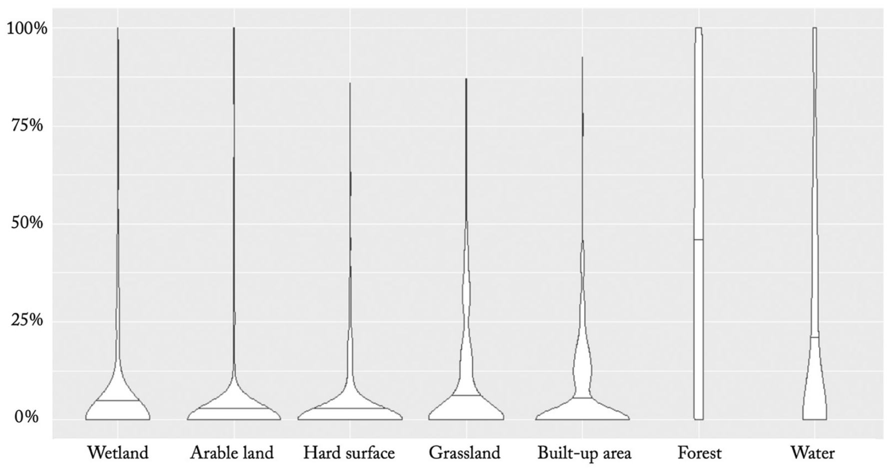

FIGURE 4 Violin diagrams showing the distributions of land cover percentages (0–100) of the 50 m circular buffers around favourite places in the study area. The width of each violin is a smoothed density plot, corresponding to the amount of data for each value along the *y*-axis. The median value is represented by the horizontal line within each diagram.

clustering with two clusters yielded groupings whose main differences were between the *Natural–Cultural* and *Serene–Social* axes of the PSD model: Group 1 is characterised by a stronger influence of the *Social* and *Cultural* PSDs, while Group 2 emphasises *Natural* and *Serene*. The remaining qualities (*Sheltered-Open*, *Diverse-Cohesive*) all clustered weakly with *Social* and *Cultural* in Group 1 (Figure 7).

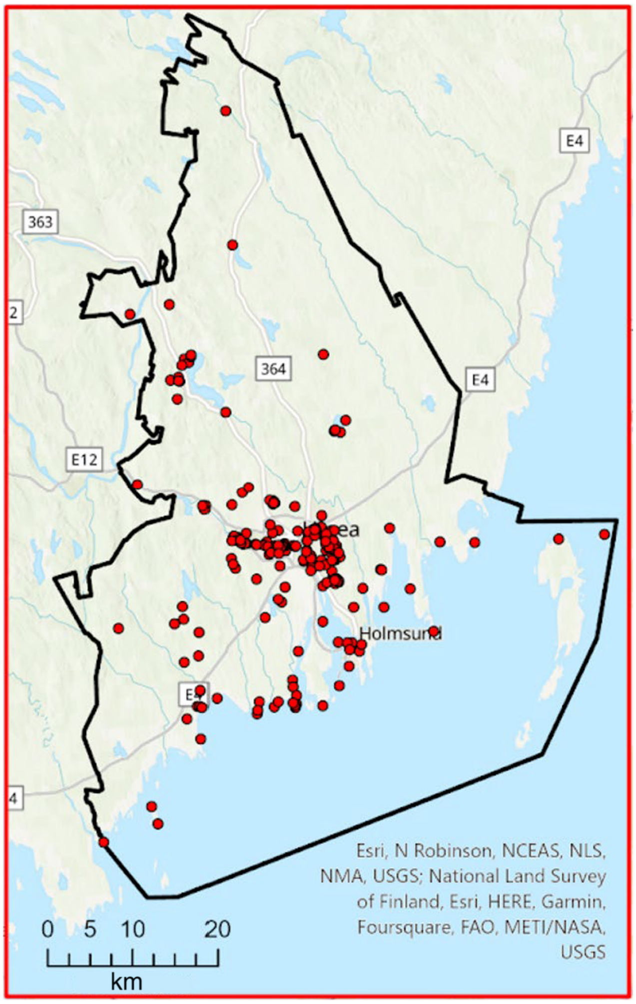

FIGURE 5 Locations of people's favourite places in the study, all within the borders of Umeå municipality, Sweden (see Section 2.1.1).

3.3 | Predicting PSDs using landscape characteristics

Our third research question regarded whether the reported strength of the PSDs could be accurately predicted by objective landscape characteristics at the site independent of individual characteristics. Overall, the eight models predicting PSDs achieved low predictive power. The strongest model was for the *Natural* PSD ($R^2 = 0.27$), followed by *Social* ($R^2 = 0.19$) and *Cultural* ($R^2 = 0.14$). The *Open*, *Cohesive*, *Diverse*, *Sheltered* and *Serene* models had little explanatory power ($R^2 < 0.1$) and were deemed too weak to draw any meaningful conclusions from. Which predictors had the largest effect on the outcome of the models were evaluated by calculating the relative influence of each predictor, a measure of how important each predictor is for model performance. When interpreting BRT models, a rule of thumb is that predictors with a relative influence higher than the inverse of the number of predictors (in our models 1/53 ≈ 1.9%) are worth looking at. However, with weak models and many predictors as in our study, this rule is less applicable.

To investigate the specific effects of each predictor, partial dependence plots are created. These evaluate how model outcomes change when the predictor of interest varies, while keeping all other predictors at their median value. Our models had one to two predictors that were responsible for most of each respective model's performance, followed by many predictors with low relative influence. Figures 8–10 show partial dependence plots of the six most influential predictors for our three models with explanatory power, R^2, greater than 0.1. Above the *x*-axis of each predictor is a rug plot, showing the distribution of values within the data set, with each notch representing 1% of the data set. The graphs show the entire range of values for each predictor within the data set, but as the machine learning algorithm fits few trees where there are little data. Interpretation should thus be focused on sections with higher data densities, approximately highlighted with rectangles in

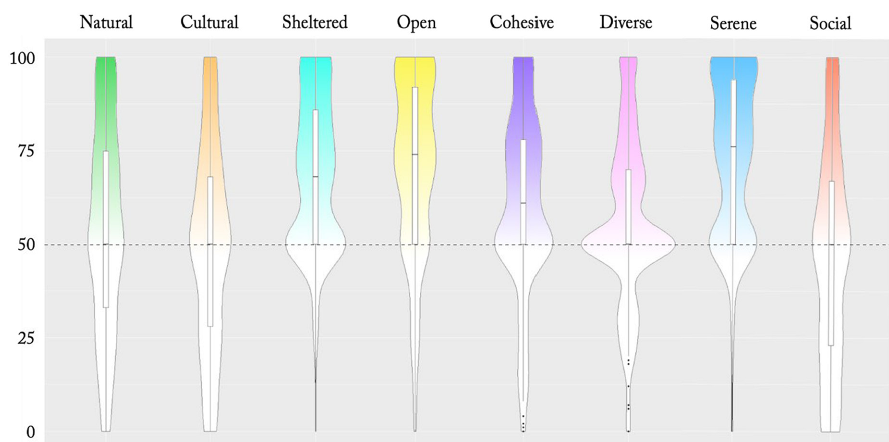

FIGURE 6 Violin diagrams showing distribution of ratings (0–100) for the strength of each perceived sensory dimension at people's favourite places. The width of each violin is a smoothed density plot, corresponding to the amount of data for each value along the *y*-axis. Within each violin is a box plot showing quantiles, with the median value as a line. Outliers are marked by dots.

TABLE 4 Correlation coefficients between PSDs at favourite places ($n = 275$).

	Cohesive	Serene	Natural	Sheltered	Diverse	Social	Cultural
Open	0.17	0.10	0.16	0.10	0.03	0.24	0.14
Cultural	0.00	−0.17	−0.28	0.09	0.17	0.43	
Social	0.02	−0.11	−0.07	0.14	0.29		
Diverse	0.42	0.15	0.27	0.44			
Sheltered	0.42	0.48	0.20				
Natural	0.48	0.35					
Serene	0.38						

Note: More saturated colour indicates stronger correlation.
Abbreviation: PSD, perceived sensory dimension.

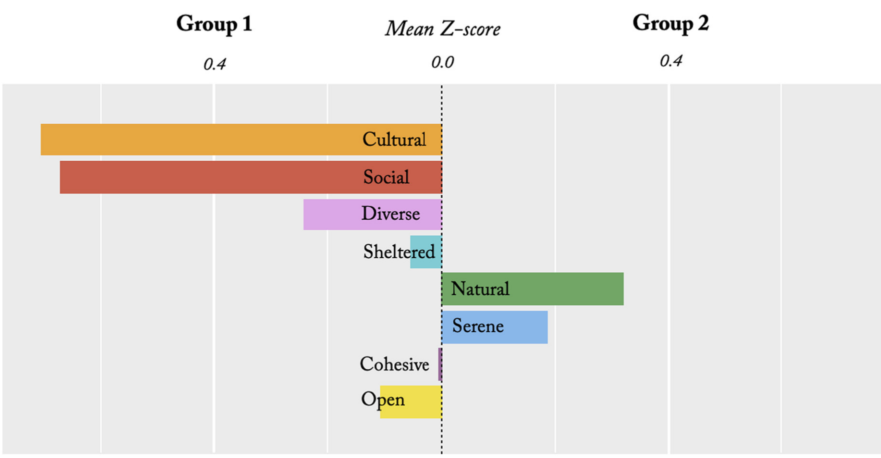

FIGURE 7 Differences between perceived sensory dimensions (PSDs) in the two groups of favourite places suggested by the performed cluster analyses. The higher the score, the greater the difference for this PSD between the two groups.

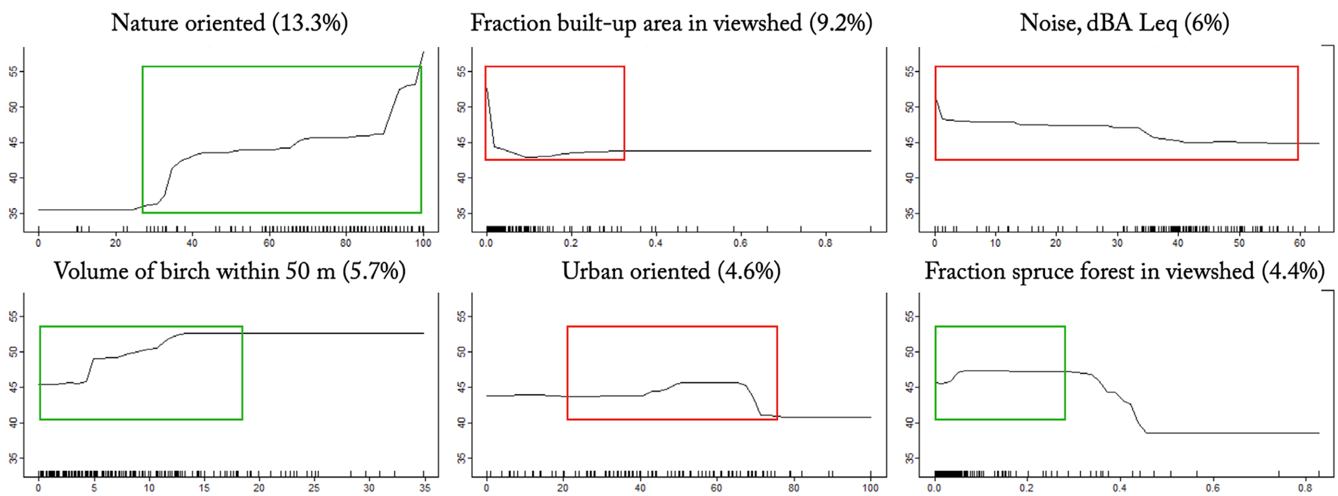

FIGURE 8 The natural perceived sensory dimension (PSD) model. Partial dependence plots for the six most influential predictors show how the PSD value (*Y*-axis) was predicted to change with each predictor. Relative influence of each predictor within parentheses (%).

green (positive), red (negative) or blue (U-shaped) colour, depending on the observed trend for the variable in relation to PSD strength. The full list of influential predictors for each model can be found in Supplementary Material S2.

In the model for the *Natural* PSD (Figure 8), higher ratings were positively correlated with identifying as a nature-oriented person, the volume of birch within 50 m and the fraction of spruce forest in the viewshed. The fraction of built-up areas in the viewshed, the amount of noise and identifying as an urban-oriented person were all negatively correlated. In the *Cultural* PSD model (Figure 9), the fraction of built-up area, the Shannon diversity index and identifying as an urban-oriented person were all positively correlated with perceiving the quality at favourite places. Distance to recreational infrastructure and identifying as a nature-oriented person were

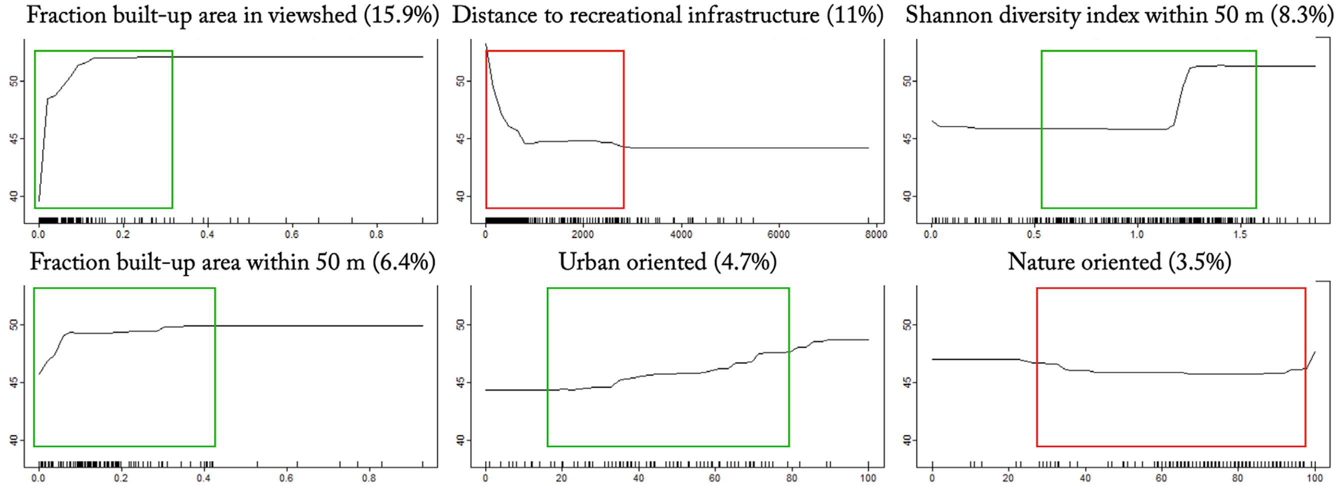

FIGURE 9 The cultural perceived sensory dimension (PSD) model. Partial dependence plots for the six most influential predictors show how the PSD value (*Y*-axis) was predicted to change with each predictor. Relative influence of each predictor within parentheses (%).

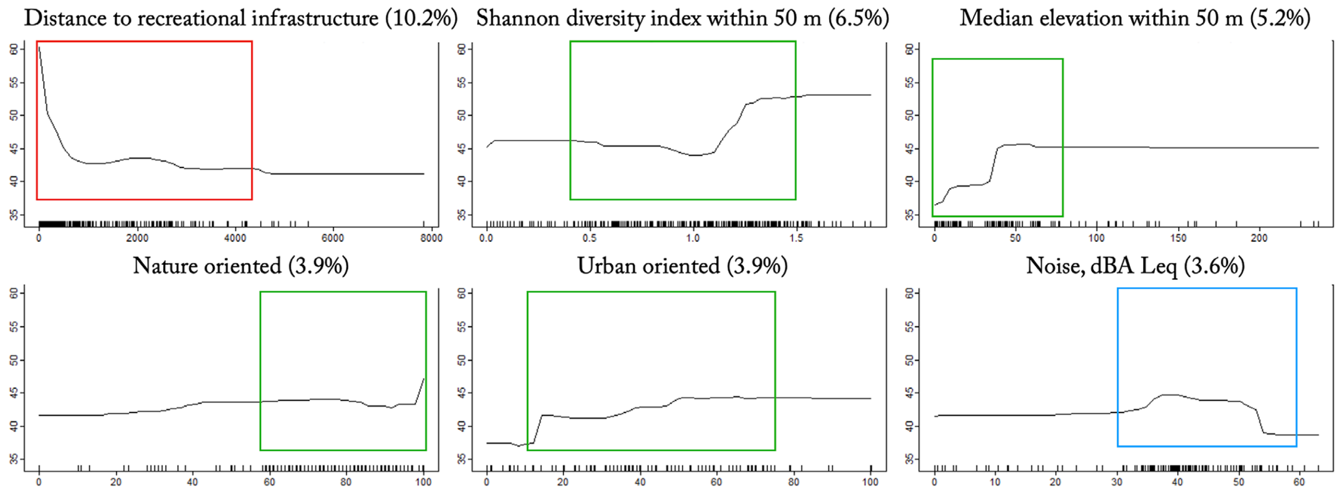

FIGURE 10 The social perceived sensory dimension (PSD) model. Partial dependence plots for the six most influential predictors show how the PSD value (*Y*-axis) was predicted to change with each predictor. Relative influence of each predictor within parentheses (%).

negatively correlated. Finally, in the *Social* PSD model (Figure 10), the Shannon diversity index, the median elevation and the degree of identifying as urban-oriented were positively correlated with perceiving the quality, while increased distance to recreational infrastructure was negatively correlated. Noise interestingly seems to indicate a *U*-shaped relation to this quality, suggesting perhaps that a certain amount of noise is a tolerable or maybe even a positive attribute of *Social* environments, whereas there are limits above which the quality diminishes.

4 | DISCUSSION

The main goals with our study were to (1) determine which general landscape types describe people's favourite places for outdoor recreation; (2) which PSDs that people experience at these places, and in which combinations; and (3) to determine the degree to which biophysical landscape characteristics could predict these PSDs and whether individual characteristics could be an important factor for such models to consider as well. We approached these questions by training machine learning models on a large set of landscape data surrounding favourite places against survey data with locations of favourite places for outdoor recreation and basic individual characteristics, including gender, age, educational background and the degrees to which a person identifies as nature and urban oriented respectively.

4.1 | General landscape types at favourite places

Regarding our first research question, forest and water were the dominating land cover types at people's favourite places in our study, with forest by far being the most common (Figure 4). It thus does not seem like favourite places in our study differ dramatically from what is provided by the landscape in large, at least not at this rather coarse level of analysis. Future studies might want to explore direct links between landscape features and favourite places for recreation in more detail, using higher resolution landscape data for the predictive models.

4.2 | Distribution and combinations of PSDs at favourite places

Our second research question was related to which perceived qualities, PSDs, that people experience at their favourite places and in which combinations.

4.2.1 | Distribution of PSDs

The most pronounced PSDs at favourite places in our study ($n=275$) were *Serene*, *Open* and *Sheltered*. *Cohesive* and *Diverse* showed a similar trend, with values mainly above 50. *Natural*, *Cultural* and *Social* showed a larger variation in response than the other PSDs with both high and low values being represented at favourite places. That *Open* stands out as the most pronounced perceived quality at favourite places in our material could indicate that this quality is (a) overall common in the available landscape or (b) particularly important to people and thus actively sought out, or both. Since we do not have comparable direct assessments for PSDs at places that are not considered favourite places for recreation, we are not able to assess the degrees to which (a) or (b) might be the case here. The *Open* PSD is associated with long, unbroken sightlines and plenty of space to roam freely without physical obstacles (Grahn & Stigsdotter, 2010; Grahn & Stigsdotter, 2003; Stoltz & Grahn, 2021). Other studies have revealed similar importance to 'view', 'openness' and 'open landscapes with a view' (Hedblom et al., 2019; Knez & Eliasson, 2017; Schirpke et al., 2013), although all in mountain landscapes. However, Pouwels et al. (2020) revealed that distance to roads and openness were the two most important factors predicting visitor densities in parks.

Serene was the second most pronounced PSD at favourite places in our study, followed by *Sheltered*. Both these qualities have been strongly associated with restoration of high stress levels and cognitive fatigue (see e.g. Grahn et al., 2010; Stigsdotter et al., 2017; Pálsdóttir et al., 2018; Figure 1b). Hence, this could indicate a bias in our survey sample towards seeking restorative support in the recreational landscape. There was a tendency for *Natural* to be a more pronounced perceived quality at favourite places than *Cultural*. However, neither dimension was generally perceived as particularly articulated (mean values around 50), suggesting that isolation of either quality along this axis might be less important than perhaps expected (a *Natural* quality is generally considered as the more restorative; ibid.).

Similarly, the *Diverse* PSD, associated with perceived biodiversity and structural variations, also appears as a less important factor at favourite places in the study than initially hypothesised (following, e.g. Marselle et al., 2021). Again however, this might reflect a low support for such a quality in the environment rather than a low general demand, something this study is not able to determine. The opposite, *Cohesive* PSD, appears as generally slightly stronger at favourite places than *Diverse*. This might again indicate a bias in our sample towards selecting restorative settings for recreation, since the *Cohesive* PSD generally is considered the more restorative of the two, although the importance of *Diversity* for restoration seems to increase as stress levels and mental fatigue diminish (see e.g. Grahn et al., 2010; Memari et al., 2017; Figure 1b).

Overall, our results here can be compared to another survey study from the south of Sweden, reporting *Open* ('prospect'), *Serene* and *Cohesive* ('space') as the most commonly perceived PSDs, and *Cultural* and *Social* the least (Qiu & Nielsen, 2015). A result much in line with our findings here, although the latter study did not focus specifically on favourite places but rather on perceived availability of the PSDs in a limited number of preselected urban green spaces.

4.2.2 | Correlations between PSDs at favourite places

The oblique rotation factor analysis that is the basis for the PSD model allows for some correlation between qualities (Stoltz & Grahn, 2021; Figure 1a). At the same time, it is important for the relevance of each factor that they are not too closely related but indeed point towards and assess distinct aspects of the perceived environment. That no correlation coefficient exceeds 0.5 in our study here (Table 4) indicates that this is indeed the case; the PSD model seems to assess eight distinct dimensions of the perceived environment, however with some PSDs being more strongly related than others. The model suggests that correlations between qualities are stronger the closer to each other they appear, with the perceived tension between qualities being at its maximum at the opposite quality. Largely, this is confirmed here by the observed correlations between PSDs reported at favourite places (Table 4); correlations tend to decrease when moving away from a quality in the PSD model and to be the lowest around three to five qualities away, as suggested by the model (ibid; Figure 1).

Both the *Social–Serene* and the *Cultural–Natural* axes follow this pattern. *Serene* and *Social* were negatively correlated ($R^2=-0.11$), as predicted by the model. The same was true for the *Natural* and the *Cultural* qualities ($R^2=-0.28$). *Cultural* and *Serene* also appear far apart in the PSD model and are thus predicted to not be strongly correlated, which was also confirmed by our results here ($R^2=-0.17$). The same was true for the *Social* and *Natural* PSDs ($R^2=-0.28$). The relatively strong correlation between *Cultural* and *Social* ($R^2=0.43$) is also in line with what the model would suggest, where these qualities are adjacent. In addition, *Serene* is strongly associated with *Sheltered* ($R^2=0.48$; Table 4). These two qualities are commonly mentioned as the most restorative in empirical studies (e.g. Grahn et al., 2010; Stigsdotter et al., 2017; Pálsdóttir et al., 2018; Figure 1b). The fact that they often occur together at favourite places in our study could thus suggest a preference for restorative sites in our survey sample. This is further supported by an overall negative association with the *Social* PSD and favourite places in our material, a quality usually considered as the least restorative of the PSDs (ibid.; Figure 1b).

There are, however, also some exceptions to this general pattern that are interesting to highlight. One of these is the weak correlation in our study between perceptions of a *Natural* and a *Sheltered* quality (R^2=0.2). They are suggested as closely related by the PSD model and might thus be expected to often occur more together. In part, this might be due to a slight mistranslation of the English word '*sheltered*' into Swedish '*trygg*', that associates with a more general sense of safety rather than the more immediate physical protection emphasised by the English word. The PSD *Sheltered* is associated with both these aspects, however, usually emphasises possibilities for physical protection and possibilities to 'see without being seen' (Stoltz & Grahn, 2021). Furthermore, PSDs *Cohesive* and *Diverse*, which are suggested as opposing qualities in the PSD model, are quite strongly associated here (R^2=0.42). According to an evolutionary model (Stoltz, 2022; Figure 1b), these two PSDs can be seen as evolutionary closely related, which might explain why the distinction between them often is perceived as less sharp compared to that between, for example, a *Natural* and *Cultural*, or a *Social* and *Serene* quality, which appear further away from each other evolutionary, according to this model. Perhaps is this a reason why people often seek environments where both of these qualities can be perceived simultaneously.

The *Open* PSD seems relatively unaffected by the other qualities in our study, although a weak trend can be seen supporting the general rule of thumb of diminished correlation for qualities more distant in the PSD model. However, the specific correlation between PSDs in this study of course also depends on the overall distribution and supply of the different PSDs in the landscape, which was not controlled for. There is a relatively weak positive correlation between a *Sheltered* and an *Open* quality (R^2=0.1), even though these qualities appear as opposites in the PSD model (Stoltz & Grahn, 2021; Figure 1a) suggesting that attributes in the environment supporting a sense of *Shelter* in general decrease perceptions of *Openness*, and vice versa. Our results, however, might indicate that people actively seek out places where these two qualities can be perceived in close proximity, in a similar way as with the *Diverse* and *Cohesive* qualities discussed above. This could be taken as support for the *prospect-refuge theory* suggested by Appleton (1975), the idea that humans share an affinity for settings providing physical protection combined with a broad overview of the landscape, due to evolutionary causes. Finally, the PSD model (Stoltz & Grahn, 2021; Figure 1a) suggests that the *Open* quality is closely related to the *Cohesive* PSD, a sense of spatial and structural unity. In our study here, these two qualities appear as moderately associated (R^2=0.2).

4.2.3 | Cluster analysis of PSDs at favourite places

To further investigate the existence of typical landscape types, defined as combinations of certain PSDs, a cluster analysis was performed. This suggested two clusters in our material. Group 1 is defined by the relative strength of *Cultural*, *Social*, *Diverse*, *Open*, as well as to some degree *Sheltered*. Group 2 is distinguished by a relative strength of *Natural* and *Serene* compared to Group 1. In many ways, these results seem to be in line with what is suggested by the PSD model, where *Social* and *Serene* are suggested as opposites, and also appear in opposite clusters here, the same for *Natural* and *Cultural*. It is thus clear that the separation between the two groups occurs around the *Natural*–*Cultural* and the *Social*–*Serene* axes of the PSD model. *Cohesive* and *Sheltered* both grouped with *Social* and *Cultural* (Group 1), rather than with *Natural* and *Serene* (Group 2), in our sample. Considering the suggested relative restorativeness of the PSDs (Stoltz, 2022; Figure 1b), it nevertheless appears as if Group 1 expresses a more outward-directed or activity-oriented recreational experience, whereas Group 2 seems to emphasise a more rest-oriented recreational style, highlighting qualities from the bottom of this gradient.

As mentioned, neighbours in the PSD model are suggested to share associations and supporting attributes, and thus often correlate in the perceived landscape, while opposing qualities in the model might weaken each other and more rarely be strong together (Stoltz & Grahn, 2021; Figure 1a). To a large extent, this seems to be reflected also in how people perceived the PSDs in our study here, as there is a clear gradient for the cluster associations (Figure 7) when moving stepwise in the PSD model (Figure 1a). The *Cohesive* PSD shows barely any difference between the two groups and thus seems to be of equal importance at both main types of favourite places. It thus poses as a potentially more universally relevant PSD, independent of whether the place is perceived as more *Natural* or *Cultural*, *Serene* or *Social*. The *Cohesive* PSD is a quality associated with the capacity to provide the visitor a sense of a united, cohesive whole, a 'world in itself', possible to enter and explore without immediately perceiving its boundaries (ibid.). It thus directly depends on a certain size of the area, that will need to be large enough to support such an experience. However, the overall size of the area indicated as a favourite place was not something this study took into consideration, as each such place was indicated as a point in the map within a 50-m circular buffer. The opposing quality in the PSD model, *Diverse*, is often perceived as more stimulating while the *Cohesive* PSD is emphasised as important for earlier stages of restoration (see e.g. Grahn et al., 2010; Stigsdotter et al., 2017; Memari et al., 2017; Pálsdóttir et al., 2018; Figure 1b). This is also reflected in our results here, where *Diverse* clusters more strongly with the presumably more stimulating, and less restorative, *Social* and *Cultural* qualities (ibid.; Figure 1b).

4.3 | Predicting PSDs with structural landscape characteristics

Our third research question was whether the PSDs can be accurately predicted by objective landscape characteristics independent of individual characteristics. Our PSD machine learning models generally had low explanatory power, showing that the included landscape variables and individual characteristics were largely insufficient to efficiently predict the PSDs. The three strongest models, for PSDs *Natural*, *Cultural* and *Social*, although still having low explanatory power, showed some interesting patterns. The *Natural* PSD had several expected effects, such as being negatively affected by built-up areas and noise. The strongest effect, however, was the degree to which the survey respondent identified as a nature-oriented person, with a strong positive correlation. In previous studies (Gunnarsson et al., 2017), highly nature-oriented persons were shown to perceive more urban greenery-related aesthetics, more greenery-related sounds and greater importance of trees and plants for their perception of bird species in urban greenery compared to less nature-oriented persons. Thus, there seems to potentially be a stronger link between the way people define themselves and the perception of the environment compared to landscape characteristics such as composition of land cover, or type of forest.

The *Cultural* and *Social* models had many commonalities, as expected by their adjacency in the PSD model, and high degree of covariance in the data set. Both were positively correlated with the degree to which the respondent identified as urban-oriented, an increased fraction of built-up area and increased landscape heterogeneity (as measured by Shannon's index). This while increased distance to recreational infrastructure was negatively associated with both qualities. These effects are not surprising, being connected to urban areas or developed recreational areas, which expectedly would score higher on both the *Cultural* and *Social* PSD. The positive correlation with Shannon's index is probably due to the higher heterogeneity of land cover classes within urban and peri-urban areas compared to more natural environments.

It is still possible that each PSD depends reliably on some objective landscape features, only that these were not included in our analysis here. Qiu and Nielsen (2015) suggested that differences regarding factors such as size, location, vegetation structure and management level of green spaces are likely to be the most decisive factors for people's perceptions of the PSDs. They concluded that more diversity of biotopes leads to a greater number of strongly experienced PSDs. This is in line with findings by Plieninger et al. (2013), who concluded that the assignment of perceived landscape values is closely related to biophysical landscape features and spatial properties. Similarly, Björk et al. (2008) and Annerstedt van den Bosch et al. (2015) suggested that the PSDs might be reliably described by similar landscape data as employed in our study here. However, their employed models have not been directly validated against people's perceptions of the PSDs.

Here, we have used similar map data (although with higher spatial resolution) as in the latter studies, together with powerful modelling techniques and with more variables. Our results suggest that the PSDs cannot be easily predicted by such structural parameters alone. Instead, they indicate that the degree to which a PSD is perceived as strong in an environment largely depends on individual factors, such as the degrees to which a person identifies as nature or urban oriented. Other such individual factors might be of a more momentary nature, such as current mood or stress levels, while others might reflect more permanent personality traits. Neither respondents' gender nor educational level, however, significantly influenced the strength of the models in our study, in line with the findings presented by Qiu and Nielsen (2015). This warrants further research into how individual characteristics might shape perceptions of the PSDs. Overall, our results highlight the relevance of an ecological approach to perception (Chemero, 2009; Gibson, 1979) when interpreting perceived qualities such as the PSDs, that is, to regard them as perceived qualities highly dependent on the needs, abilities and perceptual framework of the individual and not on structural landscape characteristics alone.

According to Leslie et al. (2010), a general lack of agreement between objective and perceived measures is not surprising, since the two kinds of measures highlight different aspects of the world. There is, however, a commonly expressed need among various societal actors to translate key perceived qualities into quantifiable factors to create generally applicable design and planning guidelines and reliable tools for environmental evaluations. For such endeavours, results such as ours here present a challenge, as they suggest the need for finer levels of analysis when determining the strengths of PSDs for users in environmental planning. They arguably also put into question the validity of some past claims surrounding the PSDs, where these have been assumed to describe a more objective or universal truth about the landscape, presumably relevant for all users. Even if general connections between objective landscape features and people's perceptions of qualities such as the PSDs could be established, the influence of individual characteristics on such experiences is still likely significant.

4.4 | Strengths and weaknesses of the study

There are some caveats to our presented analyses. In the survey, we chose to count all untouched sliders as having been left in the middle deliberately (counted as 50) as long as any other slider had been interacted with. Likely, some of these sliders were left untouched because the respondent did not understand the statement, or felt that it could not be answered in a meaningful way for their favourite place and should thus have been removed from the analysis. We made the judgement, however, that the respondents leaving them in the middle due to such reasons was still less likely than the alternative, that they were left there on purpose. Qiu and Nielsen (2015) utilised a Yes/No/Don't know structure to their survey of PSDs and had only 8% 'Don't know' answers, showing that in general people can be expected to understand descriptions of these qualities. Furthermore, which qualities that are perceived at favourite places might not only reflect people's preferences but could also depend on the overall supply of qualities in the landscape. We did not ask the survey participants about how they experience the supply situation for each PSD in the available recreational landscape, and thus have no baseline to compare the favourite places to. Our survey also did not offer the opportunity for participants to enter additional information regarding perceived qualities other than the eight PSDs measured through the 0–100 sliders. We thus do not know whether these eight PSDs offer a sufficient basis for covering the main perceived qualities at favourite places in our study.

The response rate of our survey was rather low, with 20% starting the survey and 9% filling it out in full. Decreasing response rates to surveys is a trend (Stedman et al., 2019), especially for web-based surveys (Daikeler et al., 2020). Surveys with a strong local connection, as here, usually have higher response rates (Stedman et al., 2019). We believe the main issue here was technical: To reach the survey, the respondent had to either enter a URL by hand or scan a QR code. The survey was functional on mobile devices, but it was slightly more difficult to fill out; during data collection, we received several emails and phone calls from survey respondents who experienced difficulties. The data used for the analysis here stemmed from the second part of the survey, so was also subject to respondent attrition.

Due to the relatively small sample size, spatial and cultural delimitation etc., the generalisability of our findings to other cohorts or geocultural conditions could be questioned. More research is needed to determine the general validity of our results, and to further investigate the relations between structural landscape characteristics, perceived qualities and people's recreational needs. Methodologically the study might be interesting to replicate with a higher number of participants, across different geocultural conditions. Our predictive models suggest a strong influence on individual characteristics in shaping perceptions of the PSDs, emphasising the need for an ecological approach to perception when analysing such qualities, that is, to also consider how individual abilities and needs shape associated perceptions. The nature and extent of such individual factors are interesting for future studies to investigate further, since only a limited set was employed here. Future studies could also remedy our study's limitations regarding sample size and geocultural extension and include even more detailed landscape data to potentially identify stronger and more fine-tuned recreation indicators.

5 | CONCLUSIONS

Regarding physical landscape characteristics, our study suggests a general importance of forest and water for people when choosing a favourite site for recreation. It also largely confirms the overall relationships between perceived qualities suggested by previous research, while also indicating a division between two basic recreational attitudes. One seems more oriented towards outward-directed activities, with an emphasis on social experiences in cultivated or human-influenced settings. The other seems more rest-oriented, focused on experiences of serenity and freedom from disturbances in landscapes perceived as natural and free from human influence. Moreover, people commonly associate their favourite places with experiences related to vistas and openness, often while simultaneously being provided a sense of safety and shelter.

Our results also suggest that readily available landscape data might be insufficient to provide general predictions of the PSDs, possibly due to the importance of still largely unknown individual factors in shaping such perceptions. This might indicate broader limitations in how perceived qualities such as the PSDs can be represented in, for example, mapping or modelling scenarios. It presents a challenge for various aspects of, for example, landscape architecture, urban planning, rural development etc., where there is a wish to include such qualities side by side with other landscape measures to account for health and well-being effects. Further research is needed to increase the understanding of population- level relationships between structural landscape features, individual characteristics and perceived qualities of potential importance to support health and well-being. However, our results here might indicate a standing need for dialogue and engagement with local users as a complement to structural analyses when planning landscapes for recreational outcomes.

AUTHOR CONTRIBUTIONS

Jonathan Stoltz, Carl Lehto and Marcus Hedblom conceived the research idea and designed the methodology; Carl Lehto collected the data and ran the statistical analyses; Jonathan Stoltz, Carl Lehto and Marcus Hedblom interpreted the results. Jonathan Stoltz led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data and code used in the analysis are accessible at https://zenodo.org/doi/10.5281/zenodo.10060677.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Supplementary materials S1: Reclassification of CadasterENV land cover classes.

Supplementary materials S2: Lists of all influential predictors in boosted regression tree models.

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APPENDIX A

Original survey statements, in Swedish

1. Platsen inger en känsla av vild och orörd natur
2. Platsen inger en känsla av att vara formad av människans hand
3. Platsen inger en känsla av öppenhet och ger möjlighet till utsikt och vyer
4. Platsen är en social yta som ger möjligheter att interagera med andra människor
5. Platsen inger en känsla av en helhet, av att vara en värld i sig själv
6. Platsen inger en känsla av mångfald och variation
7. Platsen inger en känsla av trygghet
8. Platsen inger en känsla av rofylldhet