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Research Paper

Seeing through their eyes: Revealing recreationists' landscape preferences through viewshed analysis and machine learning

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HIGHLIGHTS

- Accurate models of recreation achieved with machine learning and viewshed analysis.
- Blue space, infrastructure and deciduous forests are preferred.
- Noise, built-up areas and younger forests are avoided.
- Management to address these aspects could improve quality of recreation.

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ABSTRACT

Planning for outdoor recreation requires knowledge about the needs and preferences of recreationists. While previous research has mainly relied on stated preferences, recent advances in spatial data collection and analysis have enabled the assessments of actual usage patterns. In this study, we explored how landscape characteristics interact with the attributes of recreationists to determine their area choice for recreation. Using a public participation GIS (PPGIS) approach we asked residents of a Swedish city in the boreal region to draw typical recreational routes and identify favourite places for recreation on a digital online map (1389 routes, 385 individuals). We employed a novel methodology, where LiDAR data was used to calculate what was visible along all routes and at favourite places (viewsheds) in order to more realistically capture the landscape that each recreationist had experienced. Using machine learning modelling, we compared landscape characteristics of experienced areas with areas available to each recreationist. Our novel approach yielded accurate models that revealed that water environments, recreational infrastructure and deciduous forests increased the probability of choosing an area for recreation, while urban environments, noise, forest clearcuts and young forests had the opposite effect. Characteristics of the recreationists such as age, gender, level of education, or of the activity, such as type of activity performed, did not meaningfully influence area choice. Our findings suggest that it is possible to improve the conditions for recreation by developing recreational infrastructure, maintaining recreation opportunities close to waters, and adapting forest management in areas important for recreation.

1. Introduction

Urban and near-urban green spaces are in decline globally (Richards & Belcher, 2020). A reason for this is the undervaluation of green space in decision-making processes due to the challenges of incorporating cultural ecosystem services, such as the provision of opportunities for outdoor recreation (Fish, Church, & Winter, 2016). To address this issue, there have been suggestions to incorporate green space indicators into physical planning, such as residents having at least a certain amount of green space within an accessible distance (Ekkel & de Vries, 2017). While such efforts emphasize the importance of quantity, it's also crucial to consider the quality of green space. Higher quality has been linked to both increased visitation (Kajosaari et al., 2024) and improved health outcomes for recreationists (Nguyen, Astell-Burt, Rahimi-Ardabili, & Feng, 2021). To be able to assess the quality of greenspace however, which characteristics that are attractive for recreationists need to be

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understood.

Research on landscape preferences of recreationists has shown that, for instance, forest characteristics (Gundersen, Köhler, & Myrvold, 2019), landscape heterogeneity (Filyushkina, Agimass, Lundhede, Strange, & Jacobsen, 2017), and presence of water (White et al., 2010) can affect willingness to access a specific area. Most research has relied on *stated preferences*, mainly studied by showing recreationists pictures of landscapes and asking them to rate them. The results from such studies have been synthesized to map the supply of recreational landscapes (e.g. Paracchini et al., 2014; Walz & Stein, 2018). With recent technological advancements, particularly the widespread adoption of smartphones, an increasing number of studies have been performed on *revealed preferences*, i.e. how recreationists actually utilize landscapes. Various methods have been employed, such as GPS tracking (Korpilo, Virtanen, & Lehvävirta, 2017), data scraping from social media (Karasov, Vieira, Külvik, & Chervanyov, 2020), and implementations of public participation geographic information systems (PPGIS), wherein online surveys are deployed to collect spatial data from respondents (Brown & Fagerholm, 2015).

Most PPGIS studies correlate landscape utilization with remote sensing data, such as land cover maps. Often the studies do not control for effects stemming from spatial heterogeneity (e.g. Kienast, Degenhardt, Weilenmann, Wäger, & Buchecker, 2012; Baumeister, Gerstenberg, Plieninger, & Schraml, 2020; De Valck et al., 2016), such as what has been termed *distance-decay*, which means that areas further away are less likely to be visited (De Valck & Rolfe, 2018). How easily accessible an area is has shown to have a strong influence on to what degree it is used for recreation, with recreationists tending to utilize landscapes that are in close proximity (Grahn & Stigsdotter, 2003; Hörnsten, 2000; Lehto, Hedblom, Öckinger, & Ranius, 2022; Neuvonen, Sievänen, Tönnes, & Koskela, 2007). To be able to tease apart the effect of preference with that of accessibility it is important to control for this. A further methodological obstacle is defining what landscape the recreationist perceived, with a common approach being sampling a buffer around respondent's locations (e.g. Baumeister et al., 2020). An alternative (or complement) is to calculate viewsheds, using topography to estimate what landscape was visible to the recreationist (e.g. Schirpke, Tasser, & Tappeiner, 2013; Yoshimura & Hiura, 2017). This approach increases the realism of the analysis, but has rarely been utilized in PPGIS studies, probably due to its higher computational cost.

Landscape preferences of recreationists have been found to be heterogeneous, with variation in preference due to the type of preferred activity (De Valck et al., 2017), socio-demographic factors (van Zanten, Verburg, Koetse, & van Beukering, 2014), held beliefs (Kearney & Bradley, 2011) and attitudes (such as nature relatedness: Nisbet, Zelenski, & Murphy, 2009; Elbakidze et al., 2022; Flowers, Freeman, & Gladwell, 2016), cultural differences (Gosal et al., 2021), user typology (Komossa, van der Zanden, & Verburg, 2019), age, gender (Gunnarsson, Knez, Hedblom, & Sang, 2017), or group identity (Scott, Carter, Brown, & White, 2009). However, heterogeneity of preference has mainly been shown in studies of stated preferences (e.g. De Valck et al., 2017), while only a few studies have revealed differences in actual patterns of recreational usage of landscapes (e.g. De Valck et al., 2016; Kienast et al., 2012).

The goals with this study were:

I. Exploring which landscape characteristics (e.g. land cover, heterogeneity, topography, recreational infrastructure, forest characteristics) are important determinants of the choice of area for recreation.
II. Investigating to what degree the preference for these landscape characteristics depends on attributes of the recreationist (age, gender, level of education, nature relatedness), or attributes related to the recreational visit (type of activity, frequency of visit, time spent, time of week/year).
III. Furthering the field of PPGIS analysis of recreation by developing and implementing a more advanced approach, based on the inclusion of viewsheds, network analysis, and machine learning.

To achieve these goals, we employ a PPGIS survey to collect spatial data on *typical routes* and *favourite places* of recreationists in and around the city of Umeå, Sweden. The reason for including both modes of recreation was that we expected the routes to give a more complete picture of where daily recreation is performed, while the favourite places to a higher degree would exhibit which landscape characteristics are preferable (Frick, Degenhardt, & Buchecker, 2007).

We employ a novel methodology, in which we firstly control for the effect of accessibility using network analysis, to properly compare the areas used by the recreationists to areas that were available to them. Secondly, we capture the perceived recreational experience in a more realistic manner through estimating what landscape was visible to the recreationist using LiDAR data. Finally, we use flexible machine learning modeling in the form of Boosted Regression Trees, capable of handling a large number of map covariates.

2. Materials and methods

2.1. Survey

2.1.1. Study area

The study was performed in Umeå municipality, Sweden (Fig. 1). It covers an area of approximately 2300 km^2 with a population of 131 000, yielding a population density of 56/km^2 (Umeå municipal government, 2022). Its seat, the city of Umeå, is the 13th most populous city in Sweden and harbors the largest university in northern Sweden. The climate is cold continental, with freezing winters and mild summers. The surrounding landscape is dominated by managed forest land (mainly coniferous), but with some remnants of unmanaged forest as well as arable land, wetlands, and lakes. Sweden has a right of public access that encompasses almost all land, both public and private, which means that there are very few restrictions on where people can engage in outdoor recreation.

2.1.2. Survey design

An invitation to participate in our survey was sent to 3,000 residents over 18 years of age of the Umeå postal area via mail in September 2021, with a reminder sent three weeks later. 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 regards to gender and age. The invitation contained a link to the digital survey, which was implemented using the online survey tool Maptionnaire.

In the survey, the respondents were asked to provide background personal data (age, gender, and level of education). Furthermore, they were asked to assess to what degree they were a *nature-oriented* and an *urban-oriented* person, using two respective sliders with a range between 0 and 100, where 0 represented "Not at all" and 100 "Fully". The terms were not defined further to the survey respondents, and was included as it had affected perception of green space in a previous study (Gunnarsson et al., 2017).

The main part of the survey was divided into two sections. In the first section, the respondents were asked to summarize their outdoor recreation by drawing typical routes on a map of Umeå municipality. The respondents were asked to only draw what they experienced as the recreational route, and not including the travel route. For each route drawn, follow-up questions were asked, such as what type of activity was performed, the mode of transportation used to reach the area, and the frequency and duration of visits. This procedure was done separately for summer and winter recreation. The second section of the survey tasked the respondents with marking the locations of their favourite places when engaging in recreation. A favourite place was defined as a

Fig. 1. Land cover types of the study area (Umeå municipality, Sweden). Blue is water, light blue is wetland, green is forest, yellow is arable land, and grey is built-up areas. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

place “holding any specific importance, such as a place of beauty or somewhere you often stop and spend time in”. The participants were also asked to mark a location as close to their home location as they felt comfortable with. Prior to deployment, the survey was tested on a convenience sample of 45 friends and colleagues to assess its clarity and adjusted accordingly. Supplementary materials S1 contains an English translation of the survey.

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 authorization from the Swedish Ethical Review Authority. Collected data was handled in accordance with the General Data Protection Regulation (Regulation (EU) 2016/679). At the start and the end of the survey, the respondents were provided information on how the collected data would be handled and consent was asked.

2.1.3. Summary of responses

Of the 3,000 invited participants, 658 (22 %) opened the link to the digital survey, and 285 (10 %) finished the entire survey. Data from respondents who drew at least one route or placed one favourite place was kept and used in the analysis. The routes were manually screened to assess data quality, with 15 erroneous routes removed. The basis for removal was that the route had crossed itself, had many acute angles, or had unrealistically long distances between vertices. The final sample was 1389 routes within Umeå municipality (947 summer, 442 winter) from 358 individuals (mean 3.88 routes/individual, std. dev 4.1). For the favourite places within Umeå municipality, the final sample consisted of 275 from 181 individuals. The routes and favourite places are visualized in supplementary materials S2.

Of the respondents, 47 % were male and 53 % female. Median age was 48 (std. dev. 17), which is similar to the Umeå average (49 $\pm$ 18, Umeå kommuns demografidatabas 2023). The respondents were more educated than the Swedish average; 70 % had attended higher education for at least one year, compared to the Swedish average of 45 % (SCB, 2021).

2.2. Modelling recreational choice

With the collected spatial data, we analyzed which factors were most important in the choice of location for outdoor recreation. We did this in three steps: first we defined which areas the respondents had available to them; then we sampled various map data in both the used area and the available area; and finally we trained a machine learning model to compare the characteristics of the areas visited by the recreationists with those that were available to them.

2.2.1. Use-available framework

The routes and favourite places were analyzed in a use-available framework, where characteristics of the use sample are compared to those of the availability sample (Northrup, Hooten, Anderson, & Wittemyer, 2013). Here, our use sample consisted of the routes and favourite places marked by the survey respondents. To construct the availability sample for the routes, first a spatial network analysis was performed. This analysis used path and road map data to determine which areas could have been reached in the same time it took to reach the beginning of the route from the home of the respondent, utilizing the same mode of transportation as the respondent (on foot, by bike, or by car/public transportation). A random point was then placed along the edge of this area, and at that point a copy of the route was placed rotated 180 degrees (Fig. 2). The route was rotated to minimize the risk of overlap between the performed and random route. For the respondents that drew a route but did not mark their home location (101 people, 204 routes), the geographic median of all other home locations was used. The placement of the random routes were constrained so that the starting point of a route was not placed in water, and the entire route was always inside the municipal borders.

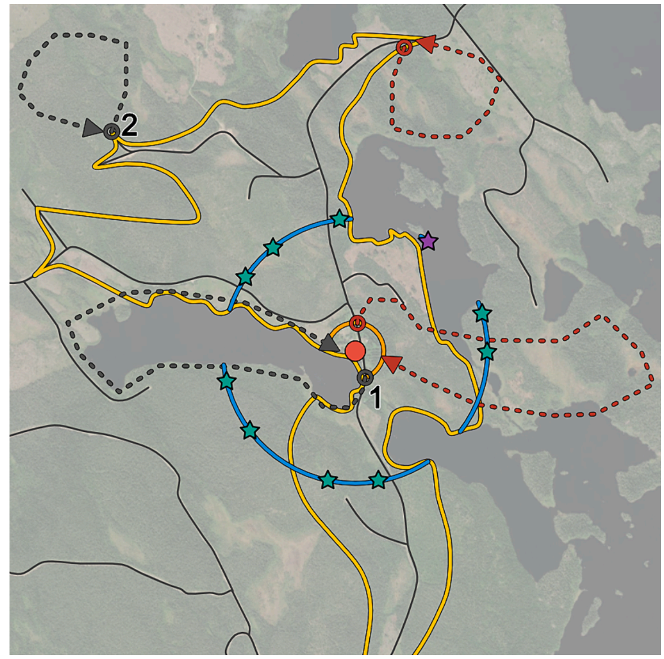

Fig. 2. An example of how the availability sample was created for one respondent. The respondent had placed the home location (red dot), drawn two routes (grey dashed lines), and placed one favourite place (purple star). For the routes, the availability sample was created by copying the shape of each route, flipping it (red dashed lines), and placing it in a random position that could be reached in the same amount of time as the performed route, taking into account the mode of transportation. All equidistant locations from the home location are represented by the orange circle. The availability sample was randomly placed at a terrestrial point along this circle. For the favourite place, nine random locations (teal stars) were placed at an equal distance from the home location (blue circle) as the favourite place (purple star). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

To construct the availability sample for the favourite places, random points were placed around each home location within a distance equal to the distance to the favourite place. Network analysis was not applied here, since information on the mode of transportation was not requested for the favourite places. We evaluated the sensitivity of the model predictions to the size of the availability sample by creating models with either one, three or all nine random points included, as suggested by Northrup et al. (2013). The random points were constrained to not be placed in water or outside the municipal borders. This sensitivity analysis was not performed for the routes, due to the assumption that a 1:1 matched sample was enough due to the larger sample size.

2.2.2. Defining the area experienced by the respondents

To define the spatial extent of what recreationists experienced, a combination of two approaches was employed. First, a buffer with a radius of 50 m was created around each favourite place and along each route, representing the immediate surroundings (cf. Baumeister et al., 2020). This distance was chosen as a conservative estimate of a ’perceptual horizon’, ensuring our analysis captures the core of the recreational experience without extending into possibly unexperienced areas. Secondly, a viewshed was calculated at each favourite place and along each route, representing the area that was visible. The viewsheds were constructed using LiDAR data (Lantmäteriet, 2023), which provide high resolution heightmaps of both the ground terrain and any obstacles that block vision (trees, buildings etc.). On the one hand, treating trees as complete visual barriers yields unrealistically small viewsheds, since vision is often only partially obscured by foliage. On the other hand, not accounting for trees would instead lead to unrealistically large viewsheds. As a compromise, we treated trees outside the 50 m buffer as a visual barrier and assumed full visibility within this distance (Fig. 3). For the favourite places, the viewshed was calculated from the point of the place, while for the routes it was calculated every 100 m along the routes, and then summed into a total viewshed. The viewsheds were calculated from a height of 1.5 m, with a maximum sight distance of 1 km. The distance between calculations was chosen partly for computational cost reasons, but also so that the 50 m buffer where we assume full visibility would exactly lie tangent with the next calculated viewshed.

2.2.3. Model predictors

Landscape characteristics were sampled using several map sources. In addition to landscape predictors, characteristics of the respondents and of the activity were included as predictors (Table 1). Most landscape predictors were sampled in both the viewshed and the buffer, while those assumed to be more related to the immediate experience (e.g. noise) were exclusively sampled in the buffer.

Land cover was extracted from the CadasterENV Sweden map (Swedish Environmental Protection Agency, 2023) and reclassified from 25 original classes into 13 classes (Supplementary materials S3). The fractions of each land cover of the buffer and the viewshed, respectively, were used as predictors. They were also used to estimate landscape heterogeneity of viewsheds and buffers by calculating the Shannon-Wiener diversity index, which reflect how many land cover types there are and how evenly the area is divided into these types (Shannon, 1948).

The Swedish Agricultural University forest map added nuance to the land cover maps in forested areas by supplying estimates of the mean tree height and volumes of different tree species, as well as total tree biomass volume (SLU, 2015). Conservation value of land was included as a predictor by combining several sources of map data: formally protected areas (nature reserves and protected forest biotopes) sourced from the Swedish Environmental Protection Agency, woodland key habitats from the Swedish Forestry Agency (i.e. forests with high conservation values; Timonen et al. (2010)), and areas with high conservation values identified by the Umeå municipal government. The predictor used in the model was the percentage overlap between the buffer and any of these maps.

We included noise level as a predictor using three maps of estimated average daily noise levels (Lden) due to road traffic, railroad traffic, and industry, respectively (Umeå Municipal government, 2016). 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. To include recreational infrastructure, data on amenities (shelters, toilets, and fireplaces) from the municipal government was used as a predictor by calculating the average distance to the nearest recreational amenity, while paths and roads were extracted from OpenStreetMap, and densities of each were calculated within the buffer. As topographical measures, we used the median, standard deviation, and range (largest difference) of elevation above sea level within buffer and viewshed.

2.2.4. Modeling: boosted regression trees

Statistical modeling was performed using boosted regression trees (BRT), also known as gradient boosting machines, or generalized boosting models. BRT is a machine learning approach that can be used both for regression or classification, where the 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

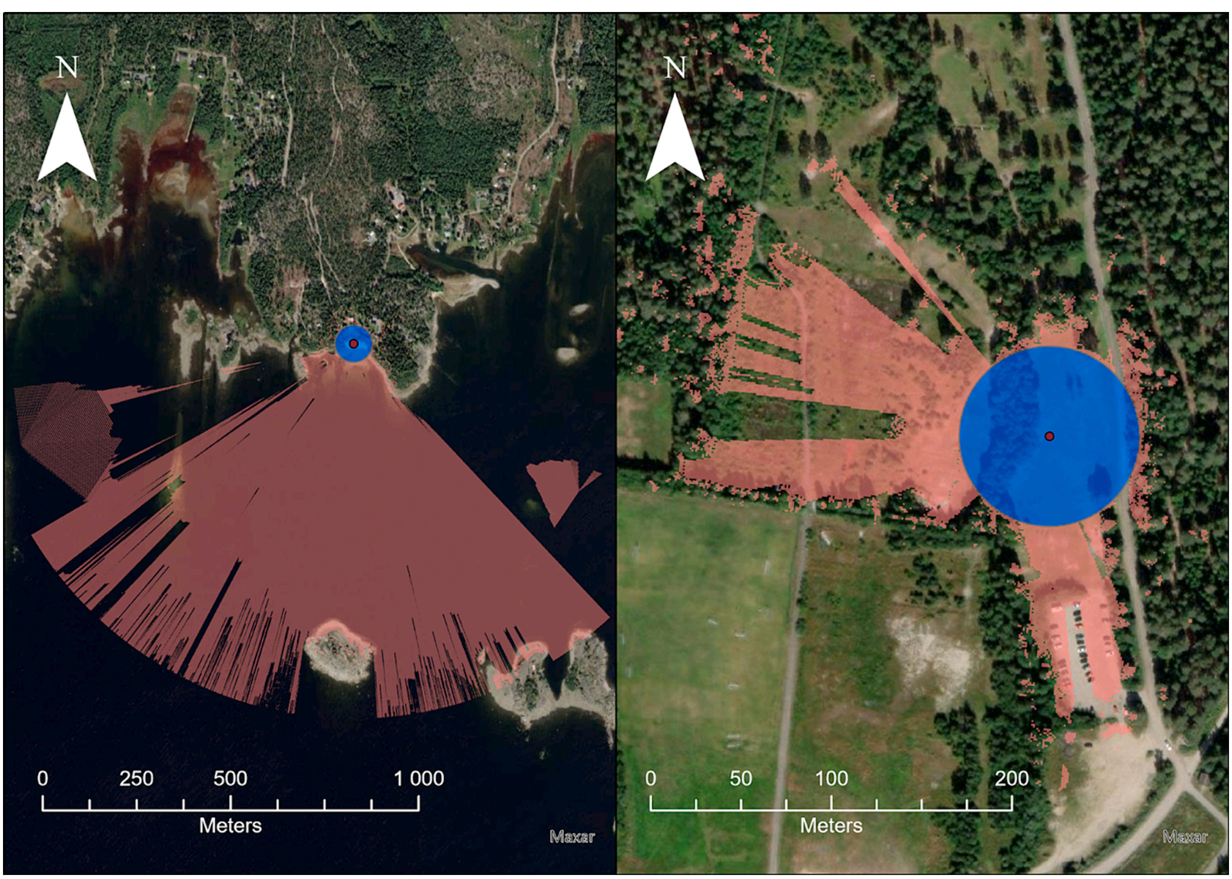

Fig. 3. Example of the sampled landscape around two favourite places. The red point is the favourite place provided by the survey respondent, the blue circle is the 50 m buffer, and red areas are the calculated visible landscape when standing at the point (viewshed). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Predictors Used in the Machine Learning Models.

Predictor	Description	Unit
Land cover(13 predictors)[a,b]	Composition of reclassified land cover types	%
Shannon-Wiener diversity[a,b]	Landscape heterogeneity, calculated using the reclassified land cover classes	Unitless
Tree height[a,b]	Average height of trees	m
Spruce volume[a,b]	Average standing volume of Norway spruce	m^3/ha
Pine volume[a,b]	Average standing volume of Scots pine	m^3/ha
Birch volume[a,b]	Average standing volume of birch	m^3/ha
Biomass volume[a,b]	Average volume of all vegetation	m^3/ha
Elevation (3 predictors)[a,b]	Median, standard deviation and range of elevation	m
Noise[a]	A-weighted day noise level	Lden dB(A)
Area of conservation concern[a]	Overlap of buffer with areas of high nature conservation values	%
Path/road density[a]	Density of paths and roads within buffer	m/m^2
Distance to amenities	Average distance to the closest recreational amenity	m
Age	The age of the respondent	years
Gender	The gender of the respondent	Male; Female; Other
Education	Highest level of finished education	Elementary School; Secondary School; University 2 yrs or less; University > 2 yrs; Folk high school
Urban person	To what extent the person self-identified as an "Urban person"	Unitless [0–100]
Nature person	To what extent the person self-identified as a "Nature person"	Unitless [0–100]
Activity[*]	Type of activity engaged in	Walking; Walking with dog; Jogging/running; Cycling; Ice skating; Cross-country skiing
Season[*]	Time of year	Summer; Winter
Transportation[*]	The mode of transportation used to get to the route from home	On foot; Bicycle; Car; Public transportation
Weekday/ Weekend[*]	Whether the route primarily is performed during weekdays, the weekend, or both	Weekday; Weekend; Both
Time usually spent[*]	The average visit duration	Minutes
Visit frequency[*]	How often the route is performed	Times per year

[*] Predictor only used for route model.
[a] Predictor was sampled within the 50 m buffer.
[b] Predictor was sampled within the viewshed.

multicollinearity; and it eschews the need for model selection or pre-specifying interaction effects. The main disadvantage of BRT is a lower interpretability of the final models, being more of a "black box" than traditional regression models such as GAMs or GLMs. However, with recent methodological advances (e.g. the Interpretable Machine Learning package for R applied here; Molnar, Casalicchio, & Bischl, 2018), these shortcomings are mitigated. For a more detailed exploration of BRT, see Elith, Leathwick, and Hastie (2008).

All analyses and visualizations were carried out in R version 4.0.3 (R Core Team, 2020). Boosted regression trees were constructed using a Bernoulli distribution with Use/Available as the response variable, and hyperparameters were set using a grid-search to find the optimal values, with models being evaluated on their cross-validated accuracy. Feature (predictor) importance, interaction effects and accumulated local effect (ALE) plots were evaluated using the iml package (Molnar et al., 2018). A more detailed account of the modeling is presented in Supplementary materials S4.

3. Results

3.1. Model validity

The route model yielded a cross-validated accuracy of 0.78, meaning that 78 % of the time the model correctly differentiated between an actual route by a recreationist and a randomly placed route. The model for favourite places was similarly accurate regardless of the size of the availability sample: the accuracy was 0.83, 0.82, and 0.84 respectively for 1, 3, or 9 random points per used point. As the three models also were consistent in predictor effects, we concluded that an availability sample with one random point was sufficient, and present results only from that model.

To evaluate BRT model effects, the first step is to calculate a feature importance table, which ranks each predictor (i.e. "feature") according to its influence on model accuracy. The effect size is normalized across all predictors to produce a relative influence in percent for each predictor. This relative influence provides information on how important each predictor is for model accuracy, but does not inform on the specific relationship between the predictor and the response variable. To understand how the likelihood that a route or favourite place was used by a recreationist related to the value of the predictor, we produced accumulated local effects (ALE) plots, which are 2D representations of this relationship. As BRT models can have multidimensional interactions between predictors, ALE plots are valid only when the predictor is not strongly affected by such effects. This can be investigated using the H statistic, which estimates how much of a predictors relative influence is due to interactions with other predictors. In the route model, the fractions of built-up area within the viewshed and within the buffer were the only predictors showing an H statistic >10 %. The H statistic can be decomposed in a second stage to see which other predictors that the predictor is interacting with; decomposing the H statistic for these predictors showed that they mainly interacted with each other. For the favourite place model, only the distance to recreational amenities showed H > 10 %, which when decomposed revealed only weak interactions with many other predictors in the model. The presented ALE plots (Section 3.2) for individual predictors are thus mostly unaffected by interactions, and accurately depict how each predictor affects model output.

3.2. Predictors' effect on the choice of recreational location

When evaluating predictors of BRT models, a common rule of thumb is to only investigate predictors that have a relative influence larger than expected by chance, which is the inverse of the number of predictors. Due to the large number of predictors in our models (53 and 51) this cut-off was low (~1.9 %), with 23 predictors having a higher influence than the cut-off for the route model and 12 for the favourite places model. We created ALE plots for all predictors above the cut-off, but present only the interpretable ALE plots (i.e. mainly plots with a clear direction of the relationship between the variables, and for which the relationship could not easily be explained as an artifact due to confounding variables) for the two models in Figs. 4 and 5, while the plots for the remaining predictors are included in Supplementary materials S5.

3.2.1. Predictors affecting selection of routes

For the route model, proximity to recreational amenities (shelters, fireplaces, and toilets) had the strongest positive effect, where shorter distances increased the probability that a route was used (Fig. 4). The amount of built-up area in the viewshed had a strongly negative effect, while for the amount of built-up area in the buffer, the relationship was inversely u-shaped. Path density, deciduous forest in the buffer, open area without vegetation (both buffer and viewshed), tree height, and

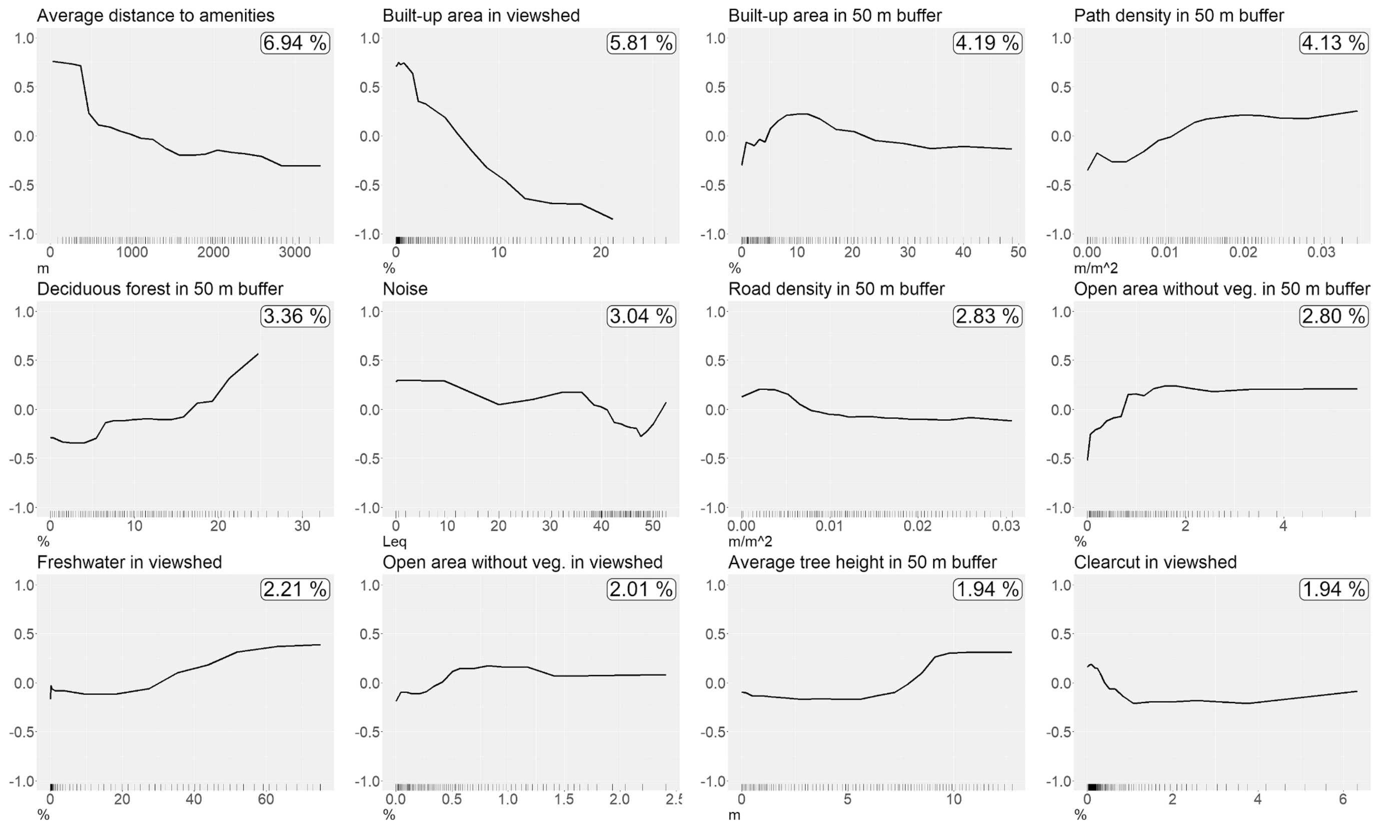

Fig. 4. Accumulated local effects for 12 of the most influential predictors in a model comparing landscape characteristics of routes used by recreationists to random routes. A higher value on the y-axis represents a higher likelihood that it is a used route. The relative influence of each predictor on model outcomes is shown in the boxes in the upper right corner of each graph. Above the x-axis is a rug plot, which shows the distribution of values within the dataset, with each notch representing one percentile. The x-axis has been cut off at 95 % of the range of each variable within the dataset to remove outliers.

freshwater in the viewshed were all positively related with route use. Noise and clearcuts in the viewshed showed negative correlations.

3.2.2. Predictors affecting selection of favourite places

In the model predicting favourite places, two predictors were considerably more influential than the others and strongly positively correlated with being a favourite place: the amount of freshwater in the viewshed, and proximity to the nearest amenity (Fig. 5). Freshwater within the 50 m buffer was also positive, along with the standard deviation of elevation. In the viewshed, the fraction of sea and median elevation were positive, while the fraction built-up area and pine forest was negative. Moreover, viewshed size was positively correlated with being a favourite place.

4. Discussion

Here we employed a novel approach to analysis of PPGIS survey data. By including viewsheds and controlling for accessibility when analyzing landscapes around favourite places and along recreational routes, we created high-accuracy models that revealed which landscape characteristics are important to recreationists. Environments with recreational infrastructure, water elements and deciduous forests were preferred, while noisy, built-up areas, young forests, and clearcuts were avoided. The analysis revealed that the routes and the favourite places had some commonalities in what features were important, showing preference for recreational infrastructure and avoidance of urban areas. There were also some differences, with the route model emphasizing forest attributes, whereas the favourite place model was more influenced by water elements and topography. Contrary to expectation, we did not find more pronounced landscape preferences in the favourite places model, with both models instead being similarly accurate.

4.1. What landscape characteristics matter for recreationists?

4.1.1. Preference for recreational infrastructure

Proximity to a shelter, fireplace, or toilet had a strong positive effect on the likelihood of an area being used by recreationists in both models. Correlations between recreational infrastructure and visits have been revealed also in previous studies (De Valck et al., 2017; Giergiczny, Czajkowski, Żylicz, & Angelstam, 2015; Kienast et al., 2012). Such a pattern can be either because the recreational infrastructure attracts visitors, or because it is built in already popular places. A study of American national parks suggested the former (Donovan, Cerveny, & Gatziolis, 2016). We argue that our results also support this view, as the large number of predictors leaves little room for the effect of recreational infrastructure to be only a proxy for other qualities in these areas. The magnitude of the effect in our study underscores the importance of incorporating recreational infrastructure in physical planning.

The density of paths and trails showed a positive effect in the route model. The role of paths and trails have rarely been studied, but Gundersen and Vistad (2016) have highlighted the importance of path quality for recreationists, finding that less developed paths (in terms of size, paving, signage etc.) were preferred in an experimental setting (rating photographs), but that more developed paths was utilized more frequently when studying actual behavior. We did not study the effect of path quality, but conclude that the occurrence of paths attract recreationists.

4.1.2. Importance of water elements

We found a strong preference for recreation close to water elements in the favourite place model. Moreover, in the route model the land cover class “Open area without vegetation” had a strong positive effect, which in the study area mostly represents rocky and sandy coastal areas.

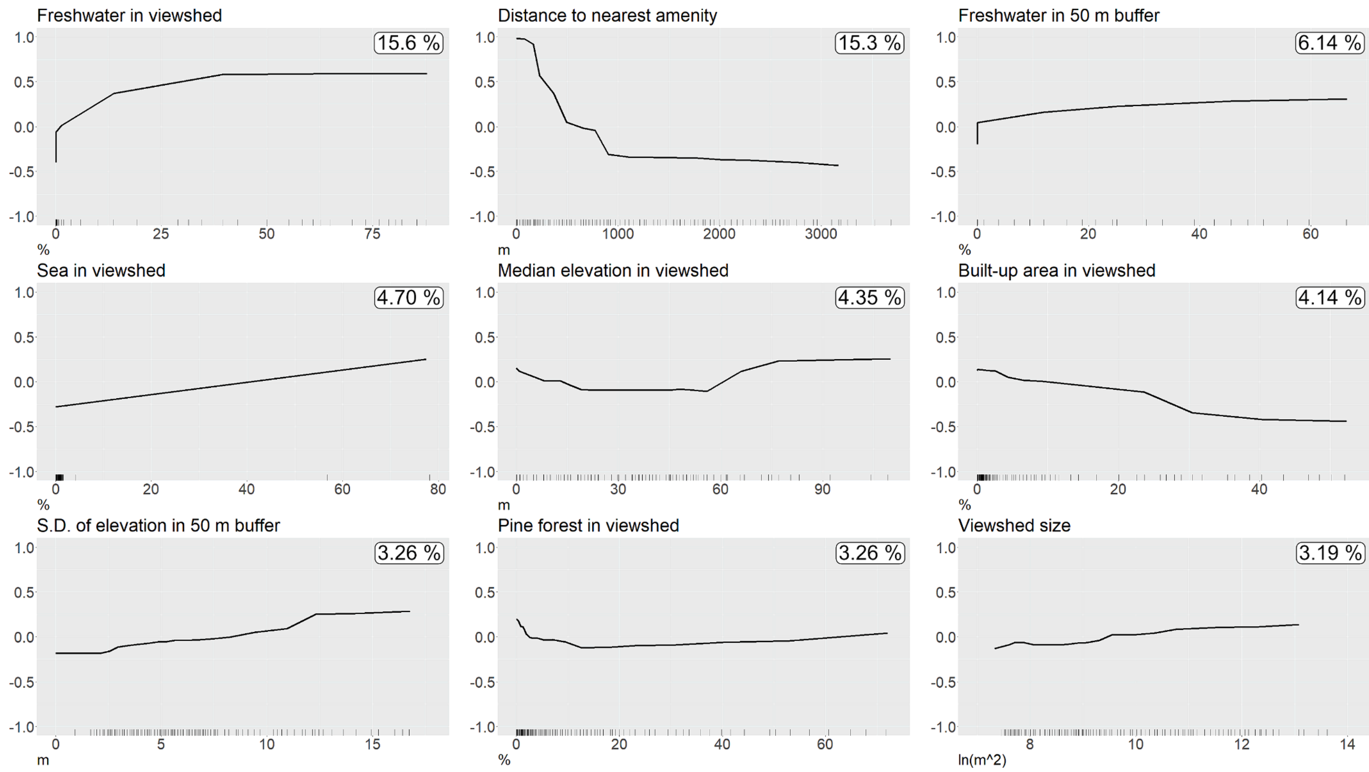

Fig. 5. Accumulated local effects for the 9 most influential predictors of the model comparing landscape characteristics of favourite places stated by recreationists to random places. A higher value on the y-axis represents a higher likelihood that it is a favourite place. The relative influence of each predictor on model outcomes is shown in the boxes in the corner of each graph. Above the x-axis is a rug plot, which shows the distribution of values within the dataset, with each notch representing one percentile. The x-axis has been cut off at 95 % of the range of each variable within the dataset to remove outliers.

These results are consistent with previous studies of both stated (De Valck et al., 2017; Kaplan & Kaplan, 1989; White et al., 2010) and revealed preferences (Baumeister et al., 2020; Kienast et al., 2012; Laatikainen, Piiroinen, Lehtinen, & Kyttä, 2017). Our results highlight the importance of preserving water environments for recreational use. Recreational opportunities around water elements can be further improved by establishing recreational infrastructure in the vicinity or adapting management to increase viewsheds towards them.

4.1.3. *Preferences for specific forest characteristics*

Forest-related predictors were important in both models, but especially in the route model. Deciduous forest and taller trees had a positive effect, while clearcuts had a negative effect. The fraction of deciduous forest within the buffer around routes ranged between 0 and 30 % in the dataset, and within this range we observed a linear positive effect. A preference for deciduous forest stands has been shown in previous preference research (Gundersen et al., 2019). The observed effect may arise from an inherent preference for deciduous trees, or it could be attributed to the predominance of conifers in the boreal landscape, where the introduction of deciduous trees contributes to greater heterogeneity—which has been shown to be preferable (Filyushkina et al., 2017). Regardless of mechanism, our results show that increasing the fraction of deciduous trees increases recreational values.

The observed preference for taller trees and avoidance of clearcuts is consistent with previous studies on stated preferences (Gundersen et al., 2019). The positive effect of tree height leveled off at around 10 m, suggesting that recreationists avoid young forests formed after clearfelling, which thus typically are even-aged. This result supports the claims of higher recreational values when applying methods such as continuous cover forestry rather than even-aged forestry with clearcuts, which currently is the prevalent method in Fennoscandia (Pukkala, Lähde, & Laiho, 2012).

4.1.4. *Avoidance of noise and urban areas*

Both models indicated that recreationists avoid urban areas, and the route model further revealed a negative impact of noise. Noise, especially from anthropogenic sources such as traffic, have been shown to negatively affect perceptions of natural environments in experimental settings (Benfield, Rainbolt, Troup, & Bell, 2020; Li et al., 2018) and in situ (Krog, Engdahl, & Tambs, 2010). A national survey conducted in Sweden found that approximately 50 % of recreationists perceived negative effects of noise during outdoor activities (Naturvårdsverket, 2019). Results such as these have spurred research on the role of what has been termed ‘soundscapes’, and has been incorporated in PPGIS methodology to map where people experience positive and negative sounds (Korpilo et al., 2023). A related concept that has been shown to be important to recreationists is ‘tranquility’, which denotes not only an absence of noise, but also how restorative a landscape is perceived (Purves & Wartmann, 2023). In a large Danish study where recreationists were asked to map ‘good locations’ they experienced along their walking routes, 40 % of these were described as having a tranquil quality (Christiansen, Klein-Wengel, Koch, Høyer-Kruse, & Schipperijn, 2023). Our result shows that noise also affects actual landscape usage, i.e. that recreationists choose areas that have less noise. Our findings also demonstrate the utility of spatial noise modelling, and underscores the recent efforts made to map and protect “quiet areas” (Cerwén & Mossberg, 2019).

4.1.5. *Preference for a varied topography and viewshed size*

The influence of predictors related to elevation and viewshed size revealed that topography was important: people preferred a landscape of varying height that also yielded a large view, but avoided views of urban areas or clearcuts. We found that both a high elevation and a low elevation were positive, which we interpret as representing both a preference for height and for close-to-sea areas, both of which yield large views with long sight lines. Earlier studies have also found a preference for views (Gundersen et al., 2019; Kaplan & Kaplan, 1989; Kienast et al., 2012). Thus, views is an important aspect to consider in landscape planning for recreation, and viewshed analysis is a possible route to identify them. Existing views can be improved by management, for instance by opening up views towards water elements, obscuring views towards buildings, or through the construction of lookouts.

4.2. Are recreationists' preferences homogeneous?

Our models had very weak interaction effects, implying that characteristics of the recreationists did not influence which landscape characteristics they sought out (Fig. 4). This was also the case for predictors related to the activity (e.g. type of activity, time spent on location, frequency of visit) or the season (winter/summer). In contrast, other studies have provided evidence for the influence of socio-demographic factors on landscape preference and utilization. Kienast et al. (2012) found that older people tended to visit places with more distinct characteristics compared to younger people. However, socio-demographic characteristics appear to have a weaker explanatory power in determining landscape preferences compared to environmental attitudes, nature relatedness or ideology (Eriksson, Nordlund, Olsson, & Westin, 2012; Juutinen, Kosenius, Ovaskainen, Tolvanen, & Tyrväinen, 2017; Ode Sang, Knez, Gunnarsson, & Hedblom, 2016; Scott et al., 2009). This could explain the weak effects seen here, as we only included one questions on attitudes and ideology, namely on to what degree the respondent identified as an "urban person" and "nature person". The type of activity has also been found to affect preferences and behaviors (De Valck et al., 2016, 2017; Korpilo et al., 2017). However, only some variation related to preferences related to characteristics of the landscape have been observed (De Valck et al., 2016), and the main effects appear to be driven by preferences for different types of recreational infrastructure (Abildtrup, Garcia, Olsen, & Stenger, 2013; De Valck et al., 2017). User typology, i.e. defining archetypes of recreationists related to their typical patterns of recreational use (e.g. preferred activity, willingness to travel, visit frequencies etc.), has been suggested as an approach to analyze the heterogeneous preferences of recreationists (Komossa et al., 2019). As the BRT models employed here can handle multiple predictors interacting concurrently, our methodology should be able to identify such user groups. Yet, the results did not identify such groups, implying that preferences for the landscape characteristics we used as predictors do not vary, or only vary a little, between user types.

Interestingly, we did not see any difference in preference for landscape characteristics between winter and summer recreation. Seasonal effects on outdoor recreation have rarely been studied, but a small study in Utah revealed that the winter landscape was perceived as drastically different, and that recreational patterns and experiences changed (Gatti, Brownlee, & Bricker, 2022). Moreover, a study on tourists' perceptions in Finland showed that forest characteristics were less important when snow was present, whereas the presence of long sight lines was more important (Tyrväinen, Silvennoinen, & Hallikainen, 2017). Our lack of pattern was surprising, given that our study area is dramatically changed in winter, with most water elements freezing, deciduous trees losing their leaves, and large quantities of snow blanketing the landscape, making some types of activities possible (e.g. cross-country skiing and ice skating) while others become more difficult (e.g. cycling). A possible issue with our methodology was the timing of survey deployment: since data was collected in September, summer recreation would have been easier to recall for the respondents.

4.3. Improved methodology for PPGIS landscape preference analysis

Here, we further PPGIS research through a novel combination of three approaches: firstly, through the calculation of viewsheds at the locations of recreation; secondly by performing a network analysis to define what landscape was available to each recreationist; and thirdly via the inclusion of flexible machine learning methods.

Viewshed analysis has been employed previously in outdoor recreation research, such as when modeling the aesthetic value of landscapes using crowdsourced photographs (Karasov et al., 2020; Tenerelli, Püffel, & Luque, 2017; Yoshimura & Hiura, 2017). Here we included viewsheds to estimate what each recreationist experienced. Viewshed analysis has some prerequisites, such as a digital surface model (DSM) with high spatial accuracy (Lagner, Klouček, & Šímová, 2018), and it has relatively high demands on computing power. We believe that continued development of viewshed analysis in recreation research will yield results closer to the ground truth, and recommend researchers to experiment with possible implementations.

Most PPGIS studies we could find have not properly controlled for accessibility (e.g. Kienast et al., 2012; Baumeister et al., 2020; De Valck et al., 2016), or have done so only to a certain extent (Agimass, Lundhede, Panduro, & Jacobsen, 2018). We believe our approach of using network analysis (see 2.2.1, Fig. 2) is a good solution to this issue.

Machine learning has been suggested to be particularly useful in ecosystem service research (Scowen, Athanasiadis, Bullock, Eigenbrod, & Willcock, 2021). The modelling performed here, using boosted regression trees, is not novel in itself, (Friedman, 2001), but as with most innovations in statistical methods, adoption by researchers is slow (Sharpe, 2013). Our results here are a showcase for how this type of modelling can be advantageous compared to traditional alternatives such as GLMs. Here, we had few prior hypotheses on which landscape characteristics to be most predictive, and for many predictors non-linear relationships were expected. Since collinearity of predictors is not an issue for model fitting, and there is no need for model selection or pre-specifying interactions, we were able to add all available map data that could be relevant to the analysis. This type of modelling is thus very useful for exploratory studies. The main drawback is that the models can be harder to interpret than e.g. GLMs, but with newer tools (e.g. the *iml* R package used here; Molnar, 2018) these issues can be overcome.

We can compare the outcome from this study with our previous study on Swedish recreationists (Lehto et al., 2022). That study analyzed a spatial dataset on recreation in a similar manner to here, but without letting the respondents draw full routes, without viewsheds, and with less adequate control for what landscape was accessible to the recreationist, which resulted in much weaker models despite a much larger sample size.

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, Connelly, Heberlein, Decker, & Allred, 2019), especially for web-based surveys (Daikeler, Bošnjak, & Lozar Manfreda, 2020). On the other hand, surveys with a strong local connection, as here, usually have higher response rates (Stedman et al., 2019). There might be a degree of self-selection bias in that people who were more interested in outdoor recreation chose to finish the survey to a higher degree. However, our sample relatively closely matched the population under study regarding age and gender, so for those characteristics we were able to compare, our sample was representative for the population as a whole.

5. Conclusions

Our study has successfully developed new methods for studying revealed preferences among recreationists. We have improved on existing PPGIS methods of outdoor recreation in three ways. Firstly, we included viewsheds, which brings the analysis closer to the recreationists' experience by attempting to see the landscape through their eyes. Secondly, we controlled for accessibility by using network analysis, to properly compare the area used by the recreationist with an area that was equally accessible. Thirdly we employed flexible machine learning methods, capable of handling a large number of map covariates.

Our results yield actionable results on recreation. Water environments, recreational infrastructure, and deciduous forests were selected for, while urban environments, noise, forest clearcuts, and young forest were avoided. These outcomes suggest that increased recreational infrastructure could improve the conditions for recreation, especially in proximity to water. This also ties into policy, showing the importance of providing access to and hindering the exploitation of water environments and minimizing noise pollution. To manage forests for recreation, deciduous trees should be favored and clearcuts avoided, whereas felling trees to create viewsheds toward water could be positive for recreation.

CRediT authorship contribution statement

Carl Lehto: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Marcus Hedblom:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Anna Filyushkina:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Thomas Ranius:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2024.105097.

References

Abildtrup, J., Garcia, S., Olsen, S. B., & Stenger, A. (2013). Spatial preference heterogeneity in forest recreation. *Ecological Economics, 92*, 67–77. https://doi.org/10.1016/j.ecolecon.2013.01.001

Agimass, F., Lundhede, T., Panduro, T. E., & Jacobsen, J. B. (2018). The choice of forest site for recreation: A revealed preference analysis using spatial data. *Ecosystem Services, 31*, 445–454. https://doi.org/10.1016/j.ecoser.2017.11.016

Baumeister, C. F., Gerstenberg, T., Plieninger, T., & Schraml, U. (2020). Exploring cultural ecosystem service hotspots: Linking multiple urban forest features with public participation mapping data. *Urban Forestry & Urban Greening, 48*, Article 126561. https://doi.org/10.1016/j.ufug.2019.126561

Benfield, J. A., Rainbolt, G. A. N., Troup, L. J., & Bell, P. A. (2020). Anthropogenic noise source and intensity effects on mood and relaxation in simulated park environments. *Frontiers in Psychology, 11*. https://doi.org/10.3389/fpsyg.2020.570694

Brown, G., & Fagerholm, N. (2015). Empirical PPGIS/PGIS mapping of ecosystem services: A review and evaluation. *Ecosystem Services, 13*, 119–133. https://doi.org/10.1016/j.ecoser.2014.10.007

Cerwén, G., & Mossberg, F. (2019). Implementation of Quiet Areas in Sweden. *International Journal of Environmental Research and Public Health, 16*(1), 134. https://doi.org/10.3390/ijerph16010134

Christiansen, L. B., Klein-Wengel, T. T., Koch, S., Høyer-Kruse, J., & Schipperijn, J. (2023). Recreational walking and perceived environmental qualities: A national map-based survey in Denmark. *International Journal of Health Geographics, 22*(1), 21.

Daikeler, J., Bošnjak, M., & Lozar Manfreda, K. (2020). Web versus other survey modes: An updated and extended meta-analysis comparing response rates. *Journal of Survey Statistics and Methodology, 8*(3), 513–539.

De Valck, J., Broekx, S., Liekens, I., De Nocker, L., Van Orshoven, J., & Vranken, L. (2016). Contrasting collective preferences for outdoor recreation and substitutability of nature areas using hot spot mapping. *Landscape and Urban Planning, 151*, 64–78. https://doi.org/10.1016/j.landurbplan.2016.03.008

De Valck, J., Landuyt, D., Broekx, S., Liekens, I., De Nocker, L., & Vranken, L. (2017). Outdoor recreation in various landscapes: Which site characteristics really matter? *Land Use Policy, 65*, 186–197. https://doi.org/10.1016/j.landusepol.2017.04.009

De Valck, J., & Rolfe, J. (2018). Spatial heterogeneity in stated preference valuation: Status, challenges and road ahead. *International Review of Environmental and Resource Economics, 11*(4), 355–422.

Donovan, G. H., Cerveny, L. K., & Gatziolis, D. (2016). If you build it, will they come? *Forest Policy and Economics, 62*, 135–140. https://doi.org/10.1016/j.forpol.2015.11.002

Ekkel, E. D., & de Vries, S. (2017). Nearby green space and human health: Evaluating accessibility metrics. *Landscape and Urban Planning, 157*, 214–220. https://doi.org/10.1016/j.landurbplan.2016.06.008

Elbakidze, M., Dawson, L., Milberg, P., Mikusiński, G., Hedblom, M., Kruhlov, I., & Grodzynskyi, M. (2022). Multiple factors shape the interaction of people with urban greenspace: Sweden as a case study. *Urban Forestry & Urban Greening, 74*, Article 127672. https://doi.org/10.1016/j.ufug.2022.127672

Elith, J., Leathwick, J. R., & Hastie, T. (2008). A working guide to boosted regression trees. *Journal of Animal Ecology, 77*(4), 802–813. https://doi.org/10.1111/j.1365-2656.2008.01390.x

Eriksson, L., Nordlund, A., Olsson, O., & Westin, K. (2012). Beliefs about urban fringe forests among urban residents in Sweden. *Urban Forestry & Urban Greening, 11*(3), 321–328. https://doi.org/10.1016/j.ufug.2012.02.004

Filyushkina, A., Agimass, F., Lundhede, T., Strange, N., & Jacobsen, J. B. (2017). Preferences for variation in forest characteristics: Does diversity between stands matter? *Ecological Economics, 140*, 22–29. https://doi.org/10.1016/j.ecolecon.2017.04.010

Fish, R., Church, A., & Winter, M. (2016). Conceptualising cultural ecosystem services: A novel framework for research and critical engagement. *Ecosystem Services, 21*, 208–217.

Flowers, E. P., Freeman, P., & Gladwell, V. F. (2016). A cross-sectional study examining predictors of visit frequency to local green space and the impact this has on physical activity levels. *BMC Public Health, 16*(1), 420. https://doi.org/10.1186/s12889-016-3050-9

Frick, J., Degenhardt, B., & Buchecker, M. (2007). Predicting local residents' use of nearby outdoor recreation areas through quality perceptions and recreational expectations. *Forest Snow and Landscape Research, 81*(1–2), 31–41.

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *The Annals of Statistics, 29*(5). https://doi.org/10.1214/aos/1013203451

Gatti, E. T. J., Brownlee, M. T. J., & Bricker, K. S. (2022). Winter recreationists' perspectives on seasonal differences in the outdoor recreation setting. *Journal of Outdoor Recreation and Tourism, 37*, Article 100366. https://doi.org/10.1016/j.jort.2021.100366

Giergiczny, M., Czajkowski, M., Żylicz, T., & Angelstam, P. (2015). Choice experiment assessment of public preferences for forest structural attributes. *Ecological Economics, 119*, 8–23. https://doi.org/10.1016/j.ecolecon.2015.07.032

Gosal, A. S., Giannichi, M. L., Beckmann, M., Comber, A., Massenberg, J. R., Palliwoda, J., & Ziv, G. (2021). Do drivers of nature visitation vary spatially? The importance of context for understanding visitation of nature areas in Europe and North America. *Science of The Total Environment, 776*, Article 145190. https://doi.org/10.1016/j.scitotenv.2021.145190

Grahn, P., & Stigsdotter, U. A. (2003). Landscape planning and stress. *Urban Forestry & Urban Greening, 2*(1), 1–18. https://doi.org/10.1078/1618-8667-00019

Gundersen, V., Köhler, B., & Myrvold, K. M. (2019). Seeing the forest for the trees: A review-based framework for better harmonization of timber production, biodiversity, and recreation in boreal urban forests. *Urban Science, 3*(4), 113. https://doi.org/10.3390/urbansci3040113

Gundersen, V., & Vistad, O. (2016). Public opinions and use of various types of recreational infrastructure in boreal forest settings. *Forests, 7*(12), 113. https://doi.org/10.3390/f7060113

Gunnarsson, B., Knez, I., Hedblom, M., & Sang, Å. O. (2017). Effects of biodiversity and environment-related attitude on perception of urban green space. *Urban Ecosystems, 20*(1), 37–49. https://doi.org/10.1007/s11252-016-0581-x

Hörnsten, L. (2000). *Outdoor recreation in Swedish forests: implications for society and forestry* (Swedish University of Agricultural Sciences). Swedish University of Agricultural Sciences, Uppsala. Retrieved from http://urn.kb.se/resolve?urn=urn:nbn:se:slu:epsilon-e-5406.

Juutinen, A., Kosenius, A.-K., Ovaskainen, V., Tolvanen, A., & Tyrväinen, L. (2017). Heterogeneous preferences for recreation-oriented management in commercial forests: The role of citizens' socioeconomic characteristics and recreational profiles. *Journal of Environmental Planning and Management, 60*(3), 399–418. https://doi.org/10.1080/09640568.2016.1159546

Kajosaari, A., Hasanzadeh, K., Fagerholm, N., Nummi, P., Kuusisto-Hjort, P., & Kyttä, M. (2024). Predicting context-sensitive urban green space quality to support urban green infrastructure planning. *Landscape and Urban Planning, 242*, Article 104952.

Kaplan, R., & Kaplan, S. (1989). *The experience of nature: A psychological perspective*. CUP Archive.

Karasov, O., Vieira, A. A. B., Külvik, M., & Chervanyov, I. (2020). Landscape coherence revisited: GIS-based mapping in relation to scenic values and preferences estimated with geolocated social media data. *Ecological Indicators, 111*, Article 105793.

Kearney, A. R., & Bradley, G. A. (2011). The effects of viewer attributes on preference for forest scenes: Contributions of attitudes, knowledge, demographic factors, and stakeholder group membership. *Environment and Behavior, 43*(2), 147–181. https://doi.org/10.1177/0013916509353523

Kienast, F., Degenhardt, B., Weilenmann, B., Wäger, Y., & Buchecker, M. (2012). GIS-assisted mapping of landscape suitability for nearby recreation. *Landscape and Urban Planning, 105*(4), 385–399. https://doi.org/10.1016/j.landurbplan.2012.01.015

Komossa, F., van der Zanden, E. H., & Verburg, P. H. (2019). Characterizing outdoor recreation user groups: A typology of peri-urban recreationists in the Kromme Rijn area, the Netherlands. *Land Use Policy, 80*, 246–258. https://doi.org/10.1016/j.landusepol.2018.10.017

Korpilo, S., Nyberg, E., Vierikko, K., Nieminen, H., Arciniegas, G., & Raymond, C. M. (2023). Developing a Multi-sensory Public Participation GIS (MSPPGIS) method for integrating landscape values and soundscapes of urban green infrastructure. *Landscape and Urban Planning, 230*, Article 104617. https://doi.org/10.1016/j.landurbplan.2022.104617

Korpilo, S., Virtanen, T., & Lehvävirta, S. (2017). Smartphone GPS tracking—Inexpensive and efficient data collection on recreational movement. *Landscape and Urban Planning, 157*, 608–617. https://doi.org/10.1016/j.landurbplan.2016.08.005

Krog, N. H., Engdahl, B., & Tambs, K. (2010). Effects of changed aircraft noise exposure on experiential qualities of outdoor recreational areas. *International Journal of Environmental Research and Public Health, 7*(10), 3739–3759. https://doi.org/10.3390/ijerph7103739

Laatikainen, T., Piiroinen, R., Lehtinen, E., & Kyttä, M. (2017). PPGIS approach for defining multimodal travel thresholds: Accessibility of popular recreation environments by the water. *Applied Geography, 79*, 93–102. https://doi.org/10.1016/j.apgeog.2016.12.006

Lagner, O., Klouček, T., & Šímová, P. (2018). Impact of input data (in)accuracy on overestimation of visible area in digital viewshed models. *PeerJ, 6*, e4835.

Lantmäteriet. (2023). *National Elevation Model*. Retrieved from https://www.lantmateriet.se/en/geodata/geodata-products/product-list/terrain-model-download-grid-1/.

Lehto, C., Hedblom, M., Öckinger, E., & Ranius, T. (2022). Landscape usage by recreationists is shaped by availability: Insights from a national PPGIS survey in Sweden. *Landscape and Urban Planning, 227*, Article 104519. https://doi.org/10.1016/j.landurbplan.2022.104519

Li, J., Burroughs, K., Halim, M. F., Penbrooke, T. L., Seekamp, E., & Smith, J. W. (2018). Assessing soundscape preferences and the impact of specific sounds on outdoor recreation activities using qualitative data analysis and immersive virtual environment technology. *Journal of Outdoor Recreation and Tourism, 24*, 66–73. https://doi.org/10.1016/j.jort.2018.08.001

Molnar, C., Casalicchio, G., & Bischl, B. (2018). iml: An R package for interpretable machine learning. *Journal of Open Source Software, 3*(26), 786.

Naturvårdsverket. (2019). *Friluftsliv 2018: nationell undersökning av svenska folkets friluftslivsvanor* (No. 6887). Stockholm: Naturvårdsverket. Retrieved from Naturvårdsverket website: https://www.naturvardsverket.se/978-91-620-6887-5.

Neuvonen, M., Sievänen, T., Tönnes, S., & Koskela, T. (2007). Access to green areas and the frequency of visits – A case study in Helsinki. *Urban Forestry & Urban Greening, 6*(4), 235–247. https://doi.org/10.1016/j.ufug.2007.05.003

Nguyen, P. Y., Astell-Burt, T., Rahimi-Ardabili, H., & Feng, X. (2021). Green space quality and health: A systematic review. *International Journal of Environmental Research and Public Health, 18*(21), 11028.

Nisbet, E. K., Zelenski, J. M., & Murphy, S. A. (2009). The nature relatedness scale: Linking individuals' connection with nature to environmental concern and behavior. *Environment and Behavior, 41*(5), 715–740. https://doi.org/10.1177/0013916508318748

Northrup, J. M., Hooten, M. B., Anderson, C. R., & Wittemyer, G. (2013). Practical guidance on characterizing availability in resource selection functions under a use–availability design. *Ecology, 94*(7), 1456–1463. https://doi.org/10.1890/12-1688.1

Ode Sang, Å., Knez, I., Gunnarsson, B., & Hedblom, M. (2016). The effects of naturalness, gender, and age on how urban green space is perceived and used. *Urban Forestry & Urban Greening, 18*, 268–276. https://doi.org/10.1016/j.ufug.2016.06.008

Paracchini, M. L., Zulian, G., Kopperoinen, L., Maes, J., Schägner, J. P., Termansen, M., & Bidoglio, G. (2014). Mapping cultural ecosystem services: A framework to assess the potential for outdoor recreation across the EU. *Ecological Indicators, 45*, 371–385. https://doi.org/10.1016/j.ecolind.2014.04.018

Pukkala, T., Lähde, E., & Laiho, O. (2012). Continuous cover forestry in Finland – Recent research results. In T. Pukkala & K. von Gadow (Eds.), *Continuous Cover Forestry* (pp. 85–128). Dordrecht: Springer Netherlands. doi 10.1007/978-94-007-2202-6_3.

Purves, R. S., & Wartmann, F. M. (2023). Characterising and mapping potential and experienced tranquillity: From a state of mind to a cultural ecosystem service. *Geography Compass, 17*(11), e12726.

R Core Team. (2020). *R: A language and environment for Statistical Computing*. Vienna, Austria. Retrieved from https://www.R-project.org/.

Richards, D. R., & Belcher, R. N. (2020). Global changes in urban vegetation cover. *Remote Sensing, 12*(1), 23. https://doi.org/10.3390/rs12010023

SCB. (2021). Utbildningsnivån i Sverige. Retrieved 7 July 2023, from Statistiska Centralbyrån website: https://www.scb.se/hitta-statistik/sverige-i-siffror/utbildning-jobb-och-pengar/utbildningsnivan-i-sverige/.

Schirpke, U., Tasser, E., & Tappeiner, U. (2013). Predicting scenic beauty of mountain regions. *Landscape and Urban Planning, 111*, 1–12.

Scott, A., Carter, C., Brown, K., & White, V. (2009). 'Seeing is not everything': Exploring the landscape experiences of different publics. *Landscape Research, 34*(4), 397–424. https://doi.org/10.1080/01426390903009289

Scowen, M., Athanasiadis, I. N., Bullock, J. M., Eigenbrod, F., & Willcock, S. (2021). The current and future uses of machine learning in ecosystem service research. *Science of the Total Environment, 799*, Article 149263.

Shannon, C. E. (1948). A mathematical theory of communication. *The Bell system technical journal, 27*(3), 379–423.

Sharpe, D. (2013). Why the resistance to statistical innovations? Bridging the communication gap. *Psychological Methods, 18*(4), 572–582. https://doi.org/10.1037/a0034177

SLU. (2015). *SLU Forest map*. Retrieved from https://www.slu.se/en/Collaborative-Centres-and-Projects/the-swedish-national-forest-inventory/foreststatistics/slu-forest-map/.

Stedman, R. C., Connelly, N. A., Heberlein, T. A., Decker, D. J., & Allred, S. B. (2019). The end of the (research) world as we know it? Understanding and coping with declining response rates to mail surveys. *Society & Natural Resources, 32*(10), 1139–1154.

Swedish Environmental Protection Agency. (2023). CadasterENV Sweden. https://www.naturvardsverket.se/verktyg-och-tjanster/kartor-och-karttjanster/nationella-marktackedata/.

Tenerelli, P., Püffel, C., & Luque, S. (2017). Spatial assessment of aesthetic services in a complex mountain region: Combining visual landscape properties with crowdsourced geographic information. *Landscape Ecology, 32*(5), 1097–1115. https://doi.org/10.1007/s10980-017-0498-7

Timonen, J., Siitonen, J., Gustafsson, L., Kotiaho, J. S., Stokland, J. N., Sverdrup-Thygeson, A., & Mönkkönen, M. (2010). Woodland key habitats in northern Europe: Concepts, inventory and protection. *Scandinavian Journal of Forest Research, 25*(4), 309–324. https://doi.org/10.1080/02827581.2010.497160

Tyrväinen, L., Silvennoinen, H., & Hallikainen, V. (2017). Effect of the season and forest management on the visual quality of the nature-based tourism environment: A case from Finnish Lapland. *Scandinavian Journal of Forest Research, 32*(4), 349–359. https://doi.org/10.1080/02827581.2016.1241892

Umeå municipal government. (2016). Umeå Municipality. Retrieved 7 July 2023, from https://www.umea.se/byggaboochmiljo/boendemiljobullerochluftkvalitet/buller/bullerberakningar.4.250f9659174ae4b97941386.html.

Umeå municipal government. (2022). Umeå municipality. Retrieved 7 July 2023, from https://www.umea.se/kommunochpolitik/kommunfakta/statistikochanalyser/befolkningochbefolkningsprognoser.4.2bd9ced91726ea4d7b49.html.

van Zanten, B. T., Verburg, P. H., Koetse, M. J., & van Beukering, P. J. H. (2014). Preferences for European agrarian landscapes: A meta-analysis of case studies. *Landscape and Urban Planning, 132*, 89–101. https://doi.org/10.1016/j.landurbplan.2014.08.012

Walz, U., & Stein, C. (2018). Indicator for a monitoring of Germany's landscape attractiveness. *Ecological Indicators, 94*, 64–73. https://doi.org/10.1016/j.ecolind.2017.06.052

White, M., Smith, A., Humphryes, K., Pahl, S., Snelling, D., & Depledge, M. (2010). Blue space: The importance of water for preference, affect, and restorativeness ratings of natural and built scenes. *Journal of Environmental Psychology, 30*(4), 482–493. https://doi.org/10.1016/j.jenvp.2010.04.004

Yoshimura, N., & Hiura, T. (2017). Demand and supply of cultural ecosystem services: Use of geotagged photos to map the aesthetic value of landscapes in Hokkaido. *Ecosystem Services, 24*, 68–78. https://doi.org/10.1016/j.ecoser.2017.02.009