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Landscape usage by recreationists is shaped by availability: Insights from a national PPGIS survey in Sweden

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HIGHLIGHTS

- Outdoor recreation is highly geographically aggregated to urban and periurban areas.
- Selection of landscape type follow availability - recreationists use what is nearby.
- Longer than preferable travel distances suggest possible recreational deficit.
- Landscape characteristics weak predictor of where recreation is conducted.

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ABSTRACT

Areas suitable for outdoor recreation are in decline due to urbanization and land-use intensification. To provide people with access to recreational areas, it is imperative to understand what characterizes areas attractive to recreationists. In this study we explore patterns of outdoor recreation visits on a national scale, using a large (n = 3853) Public Participatory GIS survey in Sweden. We analyze land cover of areas visited in comparison to landscape composition across a gradient from urban to rural areas. Additionally, we employ machine learning models to compare attributes of areas visited to random areas in the available landscape. We found that the geographical distribution of outdoor recreation was highly aggregated, with 57 % of recreation occurring in urban and periurban areas, which together cover 5 % of the total land area. Landscape characteristics were weak predictors of where outdoor recreation took place. The median travel distance to the area where recreation was conducted was 2 km, which is longer than what recreationists prefer according to previous studies. We argue that this is indicative of a recreational deficit in Sweden, with recreationists' preferences not being expressed due to lack of access to suitable areas close to home. This highlights the importance for physical planners to consider spatial accessibility when planning for outdoor recreation.

1. Introduction

Urbanization and intensified land use has led to a decrease in the supply of outdoor recreation opportunities globally (Hedblom, Andersson, & Borgström, 2017; IPBES, 2019). Recreational opportunities are difficult to plan for, since they encompass a wide range of activities, each with different demands on the landscape (Juutinen, Kosenius, Ovaskainen, Tolvanen, & Tyrväinen, 2017). To be able to provide recreational opportunities, it is important to understand what factors are most important in shaping recreational usage of landscapes. Previous studies on recreational preference have mostly relied on stated preference, i.e. the outcome when asking people to rate pictures or other descriptions of real or hypothetical landscapes. These studies have found effects of e.g. forest types (Gundersen & Frivold, 2008), biodiversity levels (Qiu, Lindberg, & Nielsen, 2013) and landscape heterogeneity (Filyushkina, Agimass, Lundhede, Strange, & Jacobsen, 2017). Preferences have been shown to vary between individuals, influenced by e.g. socio-demographic factors (van Zanten, Verburg, Koetse, & van Beukering, 2014), held beliefs and attitudes (Kearney & Bradley, 2011), cultural differences (Gosal et al., 2021), and group identity (Scott, Carter, Brown, & White, 2009). The outcomes have been used in other studies to make spatial predictions of where high recreational values are located (e.g. Norton, Inwood, Crowe, & Baker, 2012; Komossa, van der Zanden, Schulp, & Verburg, 2018).

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Fewer studies (e.g. Agimass, Lundhede, Panduro, & Jacobsen, 2018; De Valck et al., 2017; Kienast, Degenhardt, Weilenmann, Wäger, & Buchecker, 2012) have assessed revealed preference at the landscape level, i.e. the patterns of actual landscape use by recreationists. Observing actual usage is a more difficult undertaking, but an important complement to stated preference studies in order to see how held preferences are realized in recreational patterns. With the advent of new technologies it has become easier to obtain large amounts of spatial data on recreation, with researchers using approaches such as GPS tracking (Korpilo, Virtanen, & Lehvävirta, 2017), data scraping of social media (Yoshimura & Hiura, 2017), or online surveys with elements of public participatory GIS (PPGIS) (Brown & Fagerholm, 2015).

Using PPGIS, outdoor recreation has been analyzed with different research questions and on various, but mostly local, scales. Examples include estimating the usage of a city park (Korpilo, Virtanen, Saukkonen, & Lehvävirta, 2018), analyzing access to aquatic environments (Laatikainen, Tenkanen, Kyttä, & Toivonen, 2015), modeling recreation around small Swiss towns (Kienast et al., 2012), or examining how residents of a large city (Antwerp) utilize the surrounding region (De Valck et al., 2016). The local scale is relevant when studying patterns of recreation; for instance, Kienast et al. (2012) revealed significant model differences between each town they studied, suggesting that local conditions make these patterns unique for every town. Large-scale studies are still mainly lacking, but could potentially reveal broader patterns of outdoor recreation, i.e. how recreationists in general utilize landscapes available to them. This could inform higher-level public policy and help in the prioritization of land use for recreation, even in areas where no local-scale studies have been conducted.

The preferences for recreation is not only a question of what is required of the landscape, but also of where it should be located. Recreation has been shown to be highly influenced by geographic accessibility: recreational areas are visited more often the closer they are to peoples' home (Neuvonen, Sievänen, Tönnes, & Koskela, 2007; SEPA, 2019), and most people prefer shorter distances than they currently have to their closest recreational forest (Hörnsten & Fredman, 2000). The interplay between distance and landscape characteristics have been explored in several willingness-to-pay studies, often analyzing how far recreationists are willing to travel to experience areas with certain characteristics (Ezebilo, Boman, Mattsson, Lindhagen, & Mbongo, 2015; Giergiczny, Czajkowski, Żylicz, & Angelstam, 2015). Again, as with studies on landscape characteristics, studies on travel distances have mainly relied on asking recreationists about preferences (e.g. Hörnsten & Fredman, 2000) and have not assessed actual movement patterns of recreationists. Further, research on the availability of recreational areas has primarily focused on urban and periurban areas, with few studies including rural areas. This is possibly due to an assumption that rural areas have a higher availability of natural areas suitable for recreation. This assumption might be unfounded, with high-intensity agriculture and silviculture dominating many landscapes.

In this study, we attempt to fill in some of the above-mentioned knowledge gaps by analyzing a large-scale PPGIS survey on recreational habits across Sweden. We employ a novel approach, combining the ability of PPGIS to yield a large amount of spatial data with the flexibility of machine learning in the form of Boosted Regression Trees (BRT). BRT modeling is particularly useful when faced with large amounts of data and many possible predictors, yielding high predictive power paired with simple model selection (Elith, Leathwick, & Hastie, 2008), but has to our knowledge not been used in the research field of recreation. Using biophysical landscape characteristics (such as land cover, heterogeneity, and topology), combined with socio-demographic attributes (such as age, gender, and degree of education) and characteristics of recreational visits (season, duration and type of activity), we explore what factors affect the choice of location for recreation on a national scale. We investigate the difference in landscape composition and frequency of recreation on a gradient from rural areas to urban areas. We also investigate travel distances to recreational areas. More specifically, we aim to answer the following questions:

I. Does the availability and recreationists' selection for different land cover types vary between urban and rural areas?
II. How do typical travel distances from home to recreational areas vary in relation with type of outdoor recreation and time of the year?
III. What biophysical characteristics of landscapes (i.e. land cover, heterogeneity, topology, path and road density, forest characteristics, and protected areas) are most important in shaping where outdoor recreation is conducted, and how do these effects depend on individual attributes of the recreationist (i.e socio-demographics or type of recreation performed)?

2. Materials and methods

2.1. Study area

This study is based on survey data on outdoor recreational habits collected across Sweden. In Sweden, most outdoor recreation is performed in natural or semi-natural environments, with 50 % of residents spending time in nature on weekdays. The most common activities are walking, spending time in forests, and cycling (SEPA, 2019). Recreationists often utilize the right of public access, which allows access to almost all property except arable land to anyone, and is enshrined in law. Sweden is a relatively sparsely populated country (25.5 inhabitants/km^2). It has followed a similar trajectory to the rest of the world of increased urbanization, with 87 % living in urban areas as defined by the Swedish Bureau of Statistics (SCB, 2018), i.e. sites with more than 200 inhabitants with a distance of $<$ 200 m from their closest neighbouring house within the urban area. In addition to being clustered around urban areas, the population density is also skewed towards the south of Sweden, and towards the coasts.

2.2. Survey design

The data used in this study was collected as part of a national survey on Swedish residents' recreational habits (SEPA, 2015). Twelve digital panel surveys were performed, totaling 8410 responses during the period of December 2013 – November 2014. Each survey was initially sent to 340 people drawn from a panel of 80 000 each day over the first week of every month. The sample was stratified to be representative of the Swedish population in regard to age, sex and region of Sweden. Extra invitations to participate in the survey were sent as needed during each month, weighted on the response rate of the group quotas. Participants were anonymous and able to participate in multiple months, but not more than one time each month. Respondent IDs were lost during data handling, thus the number of unique respondents is unknown; however the large panel size made repeat participants presumably rare.

The survey tasked the respondents with marking the location of their latest outdoor recreational visit on a map, and to provide details of the visit, such as the time spent, the distance from home to the location, how often they visit this location, and the type of activity. If they had visited a larger area they were instructed to mark the center point of the area. In the survey, outdoor recreation was defined as "any activity performed outdoors in a natural or cultural landscape for the purpose of well-being and experiencing nature". This broad definition encompassed almost all kinds of outdoor activities, which was reflected in the extensive list of activities the respondents could choose between (Supplementary materials S1). Simple activities such as walking, jogging or cycling made up the majority of responses, while more complicated activities such as roller-skating or horse riding were rarer. For our analysis, we chose to exclude responses where the performed activity restricted the ability to choose freely where to conduct the activity, such as alpine skiing, gardening, or golf.

Due to programming errors in the survey website the first two months (December and January) of the spatial data were lost. Additionally, not all survey participants chose to mark a location. The dataset was further reduced by removing 12 visits outside of Sweden; 482 visits longer than 24 h (to distinguish outdoor recreation from tourism (Bell, Tyrväinen, Sievänen, Pröbstl, & Simpson, 2007)); and 51 visits where the respondent had indicated it was their first visit to the location (i.e. this was not a location preferred due to experiences from earlier visits). The final sample size was 3853 (Fig. 1). The reduction in sample size did not lead to a significant geographical skew, moving the mean center of the dataset only 6.3 km southwest. Gender and age distributions were similar to national demographics in 2014 (Supplementary materials S2).

2.3. Availability and selection of land cover types across the urban–rural gradient

To evaluate availability and selection of different land cover types along an urban–rural gradient, we divided the dataset into four categories. The first category consisted of recreational visits within urban areas, using the definition of the Central Bureau for Statistics (SCB, 2018): any area of at least 200 residents with < 200 m to their closest neighbour. The second category consisted of visits within periurban areas, where periurban was defined using the definition by the National Forest Inventory of Sweden (2009): a buffer around each urban area (200–7500 m) with an increasing radius with increasing population size of the urban area. The third category consisted of all visits outside periurban areas but <10 km from any urban area, and the fourth category consisted of all visits more than 10 km from any urban area. Land cover data was extracted using the high-resolution satellite-based CadasterENV raster (Swedish Environmental Protection Agency, 2018). The 25 land cover classes were reclassified into 13 classes to aggregate classes that we believed were similar in recreational aspects (Supplementary materials S3). In each of the four urban–rural categories, the land cover composition was compared to the land cover at the locations of the recreational visits using the Manly-Chesson selection index. The index is calculated by dividing the fraction of each used land cover with the fraction of available land cover, to see which land cover types are selected for or against (Manly, McDonald, Thomas, McDonald, & Erickson, 2002).

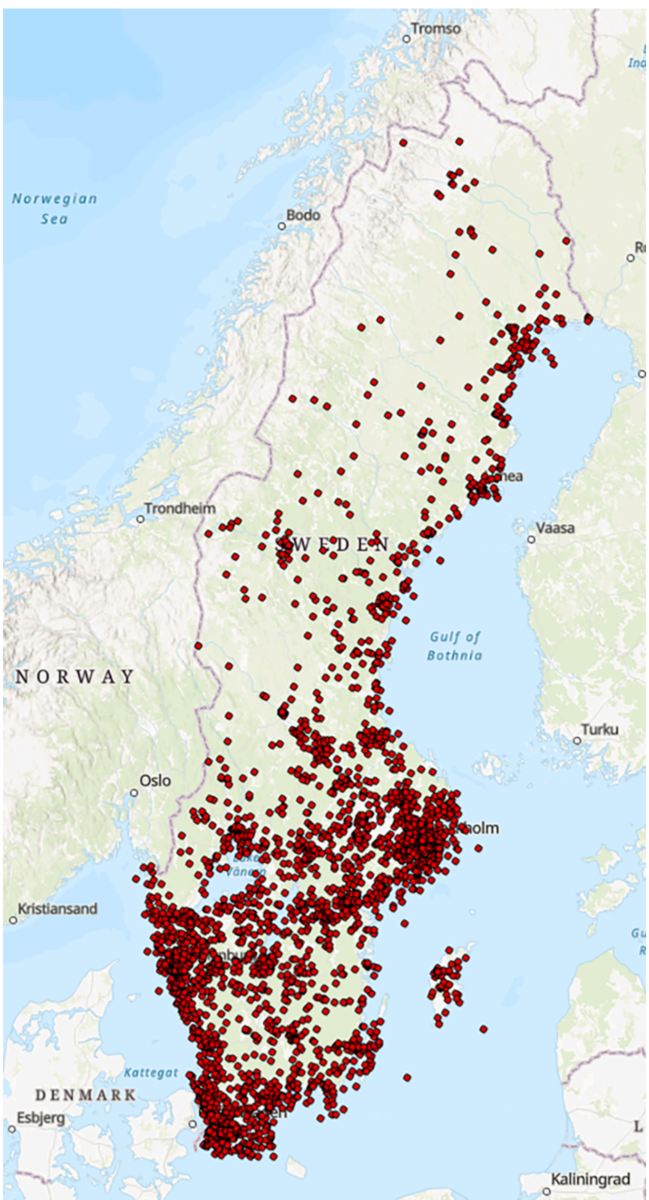

Fig. 1. Distribution of the recreational visits across Sweden.

2.4. Predictive modeling of outdoor recreation

2.4.1. Use-available framework

To explore how landscape characteristics and individual attributes of recreationists affect where outdoor recreation was conducted, we applied a use-available framework. This is a common approach in studies of animal habitat selection, where spatial data on the movements of animals (the use sample) is contrasted with locations drawn randomly from the surrounding landscape (the availability sample) (Northrup et al., 2013). Here, our use sample consisted of a single point from each survey respondent representing their last recreational visit. The availability sample was placed at a point randomly within twice the travel distance of each visited point. This approach was used since the starting point of the travel (the respondents' home) was unknown.

Since the exact extent of the area the respondent had experienced was unknown, we created five different models sampling landscape characteristics on different spatial scales. The first model only used the point given by the recreationist, while the second employed a circular buffer of 100 m around each point, reflecting an assumed minimum area the recreationists had experienced. The final three models employed a buffer with a varying radius, with the radius increasing with increasing time spent during the recreational visit. The buffer radius was constrained to reach its maximum at 120 min time spent on location, and the maximum radius was set to roughly yield a tripling of the area compared to the previous model (200 m, 340 m, and 570 m respectively for model 3–5). The reason for constraining the buffer radius in this way was due to the many outliers in regards to visit duration, which would have yielded unreasonably large buffers; 120 min corresponded to the third quantile of respondents.

2.4.2. Predictors

We used all sources of map data we believed could affect outdoor recreation, and that covered our entire study area (Table 1). We extracted map data within the buffers (or, at the point for model 1) using ArcGIS Pro 10.7. Land cover data was extracted from the CadasterENV satellite-based raster (Swedish Environmental Protection Agency, 2018). We reclassified the 25 land cover classes into 13 (Supplementary materials S3) to simplify model interpretation. Land cover was used both as a predictor by itself (fraction of each land cover class within the buffer), but was also used to estimate landscape heterogeneity (see *Estimation of landscape heterogeneity*). Forest data was included by extracting tree height and volumes of different tree species from the SLU forest map (SLU, 2015). Elevation was extracted from the Swedish National Land Survey ground topology map (Lantmäteriet, n.d.) using both the median and the standard deviation of height above sea level within the buffers as separate predictors. As a proxy for biodiversity, we calculated the overlap of protected areas (National parks, nature

Table 1
Predictors related to biophysical landscape characteristics included in the machine learning models.

Predictor	Description	Levels
Land cover (13 predictors)	Percentage cover of each land cover type. Data source CadasterENV raster.	% [0, 100]
Q index	Landscape heterogeneity defined via CadasterENV land cover classes, see *Estimation of landscape heterogeneity.*	Continuous [0, 1]
Shannon-Weaver index	Landscape heterogeneity defined via CadasterENV land cover classes	Continuous [0, 1.85]
Recreational quality dimensions (6 predictors)	The mean value of each recreational quality dimension, see *Estimation of landscape heterogeneity* and supplementary materials S4.	Continuous [0, 10]
Tree height	Average height of trees (m). Data source SLU Forest map.	Continuous [0, 23]
Spruce volume	Average volume of Norway spruce per square meter (m^3/ha). Data source SLU Forest map.	Continuous [0, 232]
Pine volume	Average volume of Scots pine per square meter (m^3/ha). Data source SLU Forest map.	Continuous [0, 167]
Deciduous tree volume	Average volume of deciduous trees (m^3/ha). Data source SLU Forest map.	Continuous [0, 41]
Total biomass volume	Average volume of all biomass (m^3/ha). Data source SLU Forest map.	Continuous [0, 196]
Elevation (2 predictors)	Median and standard deviation of elevation within buffer. Data source Swedish Geological Survey elevation map.	Continuous [0,1461]/[0, 61]
Path/road density (2 predictors)	Length of paths/roads per square meter (m/m^2). Data source Lantmäteriet path and road maps.	Continuous [0, 0.1]/[0, 0.2]
Protected area	Percentage cover of legally protected areas (Nature reserves, national parks, protected biotopes).	% [0, 100]

reserves, protected biotopes and Natura 2000 area). Using OpenStreetMap data (OpenStreetMap Foundation, n.d.), we calculated path and road density.

Predictors related to socio-demographic characteristics of the respondent, along with the type of recreational activity they were engaged in, the visit duration, and the season of the visit were also included in the models (Table 2).

2.4.3. *Estimation of landscape heterogeneity*

Since landscape heterogeneity has been shown to influence recreational preference (Filyushkina et al., 2017), we included it as a predictor using land cover classes. We calculated heterogeneity with two methods: firstly the Shannon-Weaver index, which has been commonly used to estimate landscape heterogeneity previously. Secondly we employed the index Q, which in contrast to Shannon-Weaver accounts for heterogeneity not reflecting only the proportion and number of classes within a patch, but also of the qualitative differences between different classes (Díaz-Varela, Roces-Díaz, & Álvarez-Álvarez, 2016). The advantage of Q is that it can better estimate perceived heterogeneity when certain land cover classes are more similar to each other (e.g. different forest classes) while others classes are more distinct (e.g. sea, alpine). For a description of how we estimated Q, see Supplementary materials S4.

2.4.4. *Boosted regression trees*

Statistical modeling was performed using boosted regression trees (BRT). BRT is a decision tree-based machine learning approach where a predictive model is created by iteratively building an ensemble of many decision trees, each with a low weight (Friedman, 2001). The method has several advantages over traditional regression methods such as GLMs or GAMs: it does not assume linear relationships between predictor variables and response variables, and can handle a large number of predictors regardless of multicollinearity. Further, there is no need for model selection or specifying interaction effects in advance, while at the same time yielding models with high predictive power. The main disadvantage of BRT is the lower interpretability of the final models. However, with recent methodological advances, such as the Interpretable Machine Learning package for R (Molnar, 2018), these shortcomings can be overcome to a large degree.

All analysis and visualization was carried out using the gbm package (Greenwell, Boehmke, & Cunningham, 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 Bernoulli

Table 2
Predictors related to the recreationist and the recreational visit included in the machine learning models.

Predictor	Description	Levels
Education	The highest education level obtained by respondent.	Primary education Secondary education Bachelor's degree or equivalent Master's degree or equivalent
Income	Gross household income per year	0–100000 SEK 100001–200000 SEK […] 1,000,001 SEK or more
Rural or Urban*	Whether the respondent lived in an urban or rural area.	Stockholm City with at least 100 000 inhabitants City with 50000–99999 inhabitants Town with 5000–49999 inhabitants Rural area
Boreal or Boreo-Nemoral + Nemoral	Whether the respondent lived north or south of the boreo-nemoral boundary, as defined by Rydin et al. (1999) (roughly equivalent to latitude 60° N in Sweden).	Boreal Boreo-Nemoral + Nemoral
Gender	The gender of the respondent.	Male Female
Ageclass	The age of the respondent, divided into four classes of equal number of respondents.	16–35 years 36–50 years 51–66 years 67–84 years
Disability	Whether the recreationist experienced themselves to have a disability that decreased their ability to conduct outdoor recreation to any degree	Yes No
Immigrant (3 predictors)	Whether the recreationist or either of their parents were born in Sweden.	Sweden Nordic country except Sweden Europe Rest of world
Activity	Type of recreational activity performed.	35 different activities (Table 1)
Season	Season of the year, defined by calendar month.	Spring (March, April, May) Summer (June, July, August) Autumn (September, October, November) Winter (December, January, February)
Visit duration	How long the recreationist spent during the visit	Discrete [5,1440] min

*N.B. that this definition of urban and rural is different from the definition used for the analysis described under *Availability and selection of land cover types across the urban–rural gradient*.

distribution with used area/available area as the response variable. When fitting boosted regression trees, three hyperparameters that affect model fitting are set: Tree complexity (how many splits are allowed in each tree); learning rate (how quickly the algorithm converges, with lower values leading to better models at the cost of computing time); and bag fraction (how large a fraction of the dataset to use in each iteration). We created models with combinations of four different tree complexities (1, 3, 5 and 7) and two bag fractions (0.5 and 0.75) and lowered the learning rate until a model of at least 1000 trees were fitted. Model performance was evaluated using cross-validated AUC. Feature importance, interactions and partial dependence plots were produced using the iml package (Molnar, 2018).

In total, the models were fitted with 44 predictors, except for the point model for which heterogeneity and averages of quality dimensions could not be assessed, and land cover was used as a single categorical predictor instead of 13 continuous predictors.

3. Results

3.1. The urban–rural gradient of outdoor recreation

57 % of the respondents most recent recreational visits were in urban and periurban areas (Table 3). Landscape composition changed along the urban–rural gradient. Urban areas had a higher proportion of built-up area and open area with vegetation, while areas more than 10 km from an urban area had a higher proportion of sea (Fig. 2). In total, across the whole dataset, 44 % of recreational visits were in forested land cover types, 13 % in built-up areas, 12 % in bodies of water, 11 % in arable land and 4 % in wetlands. Overall, the proportion of visits among land cover classes was strongly correlated with available land cover (Pearson's R-value = 0.94), suggesting that across the four urban–rural categories, selection for different land cover types was weak. However, for some land cover types there was a clear difference between the proportion of visits and the availability. The strongest selection (defined using the Manly-Chesson index: the proportion of recreational visits within each land cover class divided by that land cover class' proportion of the total area) was for arable land and built-up areas in rural areas, followed by freshwater and sea in urban areas (Fig. 2). Among forest types, temperate deciduous forests were most selected for, followed by deciduous forests, mixed forests and pine forests. Spruce forests and clearcuts were selected against.

3.2. Travel distance

The overall median distance from the respondents' home to the recreational area was 2 km, but the distance varied depending on the type of activity (Fig. 3). The median distance was longest for swimming and berry/mushroom picking, and shortest for walking and jogging. There were no significant differences in distances between men and women or any other socio-demographic characteristic. Travel distances varied over the year, with longer distances during summer and shorter during winter (median distance for July 3 km, for December 500 m; see Supplementary materials S5). Travel distances were positively correlated with duration of the recreational visit (linear regression, $p < 0.001$, $r^2 = 0.18$).

Table 3
The distribution of recreational visits and land area across four categories, representing a gradient from urban areas to rural areas. For definitions of the four categories, see Survey data.

Urban-rural category	Recreational visits (% of total)	Land area (% of Sweden)
Urban	27	1.4
Periurban	30	3.6
<10 km	36	48
>10 km	5.8	47

3.3. Predicting outdoor recreation using landscape characteristics

The BRT models performed poorly, with cross-validated AUC scores of 0.55 for the model only sampling the points (model 1) and 0.58–0.6 for the models sampling a buffer around the points (models 2–5, Supplementary materials S6). This suggests all models were only slightly better than chance (corresponding to AUC = 0.5) at distinguishing between the use sample and the availability sample. Which predictors had the largest effect on the outcome of each model was evaluated by calculating the relative influence of each predictor. Model 1 had only one influential predictor, land cover, which had a 95 % influence on model accuracy. Model 2–5 exhibited similar patterns to each other, with type of activity being most influential (18–19 %), followed by the same 7–8 predictors, each with low influence (Supplementary materials S7).

The relationship between each predictor and the probability that an area was selected for recreation was investigated through partial dependence plots. These evaluate the effect of a predictor by setting all other predictors to their median value, and examining how model outcomes change as the predictor of interest changes. Model 1′s only influential predictor, land cover, showed that open areas without vegetation, built-up areas, temperate deciduous forests, and deciduous forests increased the probability that an area would be selected for recreation the most, while the presence of sea, arable land, wetlands, freshwater, or clearcuts lowered the probability (Fig. 4). Note that both terrestrial and water habitats were included in these analyses, and thus the low probability for sea and freshwater simply reflect that most recreation activities in the dataset took place on land.

The partial dependence plots for the influential predictors of model 2–5 revealed almost flat responses, suggesting that model predictions were based on many weak effects (Supplementary materials S8). Interaction effects between predictors were analysed by calculating H-statistics. Model 1 lacked interaction effects due to its tree complexity being 1. The strongest interaction found in model 2–5 was between type of activity and other predictors, and accounted for 15–19 % of the variance of the model prediction. Investigating these interactions yielded no interpretable effects due to the weak main effects of the predictors. There were no clear interactions between landscape predictors and socio-demographic predictors.

4. Discussion

We found that recreation in Sweden was highly aggregated geographically, with 57 % of the recreation occurring in urban or periurban areas, despite these areas only constituting 5 % of the total land area. The median distance from the respondent's home to the site of recreation was 2 km, with the distances varying depending on activity. Further, there was a high correlation between the land cover types that were used and the availability of these types, indicating low levels of selection for most land cover types. Our predictive models had low accuracy, suggesting that the included predictors (land cover, heterogeneity, topology, path and road density, forest characteristics and protected areas) were not important for why an area was chosen for recreation.

4.1. Availability and utilization of land cover types across the urban–rural gradient

The utilization of land cover types for recreation was highly correlated with the land cover composition across the four urban–rural categories. This suggests that there was overall only a weak selection for land cover types, with most being used proportionally to their frequency within each urban–rural category. Selection was only observed for certain land cover types, with temperate deciduous forests and

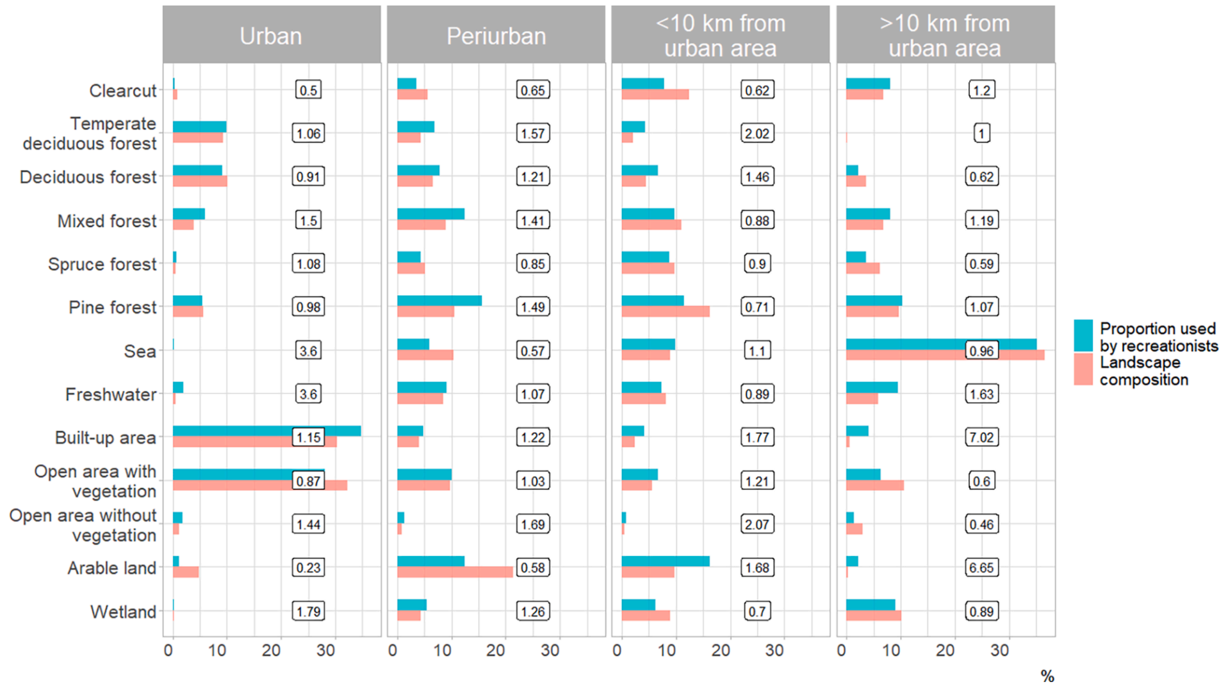

Fig. 2. Landscape composition compared to the proportion of visits by outdoor recreationists of land cover types along the urban–rural gradient. By dividing the used proportion with the landscape composition the Manly-Chesson selection index is calculated, which is presented in the boxes. A value greater than 1 implies selection for the land cover type, a value < 1 selection against.

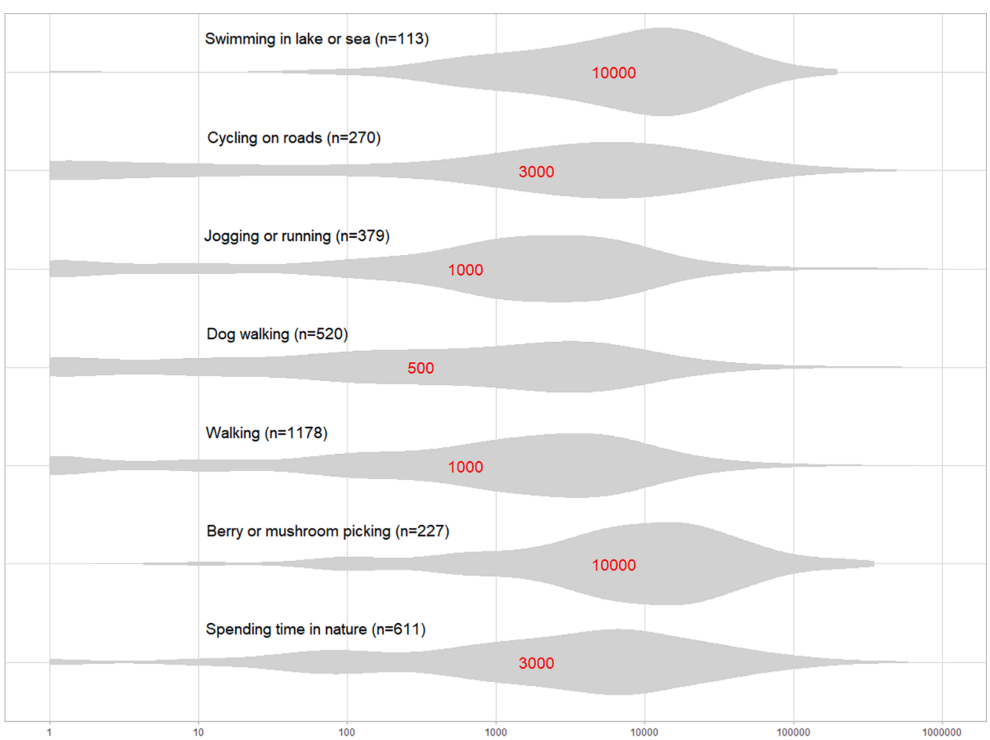

Fig. 3. The distribution of distances from home to the location where recreation occurred for the most common types of recreational activities. The area of each violin is equal. Numbers in red are median distance values; numbers within parentheses are number of responses.

deciduous forests used most, followed by mixed forests and pine forests, while spruce forests and clearcuts were selected against. These results are in agreement with previous stated preference studies of forest types (Gundersen & Frivold, 2008). Water environments in urban areas showed high levels of selection (i.e. the respondent selected a point situated in the water), despite their importance likely being underestimated in this analysis. This is due to recreation occurring close to water being counted as terrestrial, even though the purpose of the visit might have been to experience the water environment, e.g. by taking a walk along a river or a lake. Our result confirms the strong preference for

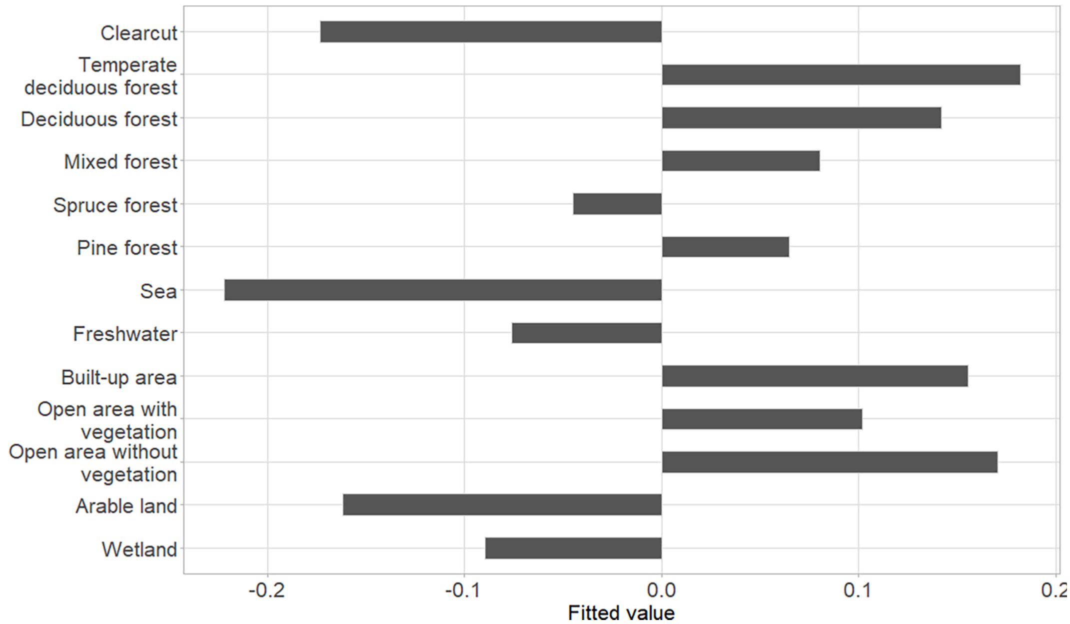

Fig. 4. Partial dependence plot for the land cover predictor of model 1, showing how land cover type affects the probability that an area is chosen for recreation. Positive values represent an increased probability.

water environments for recreation within urban areas, which has been shown in stated preference studies (Schneider, 2009). The high selection values for built-up areas and arable land in the most rural category could be explained by these land cover types being clustered around settlements, and thus frequently visited because they occur close to home.

4.2. Travel distances for recreational activities

To be able to plan for recreation, an understanding of what distances people are willing to travel to reach a recreational area is paramount. We found that the overall median distance from home to the recreational area was 2 km, with some variation between types of activities and seasons. To note here is that the survey asked the respondents to state the distance from their home to the point they had defined as the center of the recreational area they had visited, and it may have varied among the respondents to what extent this travel distance was regarded as a part of the recreational experience or not.

Studies of actual movement patterns of a broader range of recreational activities and landscapes are rare. A survey of Helsinki residents showed that two thirds of respondents traveled <100 m for their latest "close-to-home" recreational visit (Neuvonen et al., 2007). A study on recreational visits to forests in Denmark estimated the median travel distance to 4 km (Agimass et al., 2018), while an Australian study showed a mean of 5.5 km to pre-defined recreational facilities such as parks, beaches, or rivers (McCormack, Giles-Corti, Bulsara, & Pikora, 2006). All these studies were restricted in the types of locations studied, whereas we have analyzed all recreation conducted in any environment. It has also been shown that travel distance is a key factor in the choice of recreational area. For instance, forests closer to home are much more likely to be chosen (Agimass et al., 2018), and people with access to fewer recreational facilities travel longer distances (McCormack, Giles-Corti, Bulsara & Pikora, 2006). This is also supported by studies in Sweden: a survey on the frequency of recreational visits to the closest forest showed a dramatic decline in frequency when the distance from home exceeded 2 km (Hörnsten, 2000), while Grahn and Stigsdotter (2003) showed that the frequency of visits to the closest recreational area was halved if the distance increased from 300 m to 1000 m. These findings suggest that the longer distances in our study could be a sign of a recreational deficit, with people traveling further than they would prefer to reach their recreational areas. In another study, almost 50 % of Swedes reported some degree of deficit in their access to recreational areas (Petersson-Forsberg, 2014).

We observed that travel distances varied depending on which activity was performed. Travel distances in our study were shorter (500–1000 m) for walking, running and "spending time in nature", while they were longer for activities such as swimming and berry/mushroom picking. The former can be performed in most environments, imposing few specific demands of the landscape, while the latter require certain landscape features to be performed, which could explain the difference in travel distances. They are also activities that are more associated with longer visits, which presumably increases the willingness to travel further. The traveling distances varied over the year, reaching a minimum in the winter months and a maximum in July. This could be an effect of most people having vacation in July, increasing the time available for recreational activities.

4.3. Predicting recreational use from landscape characteristics

Our five models performed poorly, being only slightly better than chance at classifying the used points from the random availability sample. The models that employed a buffer around each point (model 2–5) were a minor improvement to the point-based model (model 1). The outcome was not sensitive to the scale of the buffer, with model 2–5 having similar predictive power. For model 1 there was only one influential predictor, land cover type, while model 2–5 each had sets of 7 or 8 predictors that were mainly the same for all models. The land cover predictor of model 1 aligned with previous stated preference research, with e.g. the rankings of different forest types being the same as in Gundersen and Frivold (2008). Model 2–5 had many influential predictors, but all with almost flat responses: they each influenced the predicted outcomes only to a small degree (Supplementary materials S8). Although the models performed slightly better, the weak effects of each variable made them hard to draw any meaningful conclusions from.

The poor predictive power of the machine learning models suggests that the landscape characteristics we investigated (land cover, heterogeneity, topology, path and road density, forest characteristics and protected areas) are weak predictors of actual landscape usage. This came as a surprise, as previous stated preference research has revealed a multitude of effects of different aspects of landscape characteristics, e.g.

indicating what kinds of forests are preferred (Gundersen & Frivold, 2008), the role of landscape heterogeneity (Dronova, 2017; Filyushkina et al., 2017), or the importance of different kinds of infrastructure such as paths and roads (De Valck et al., 2017). Our modeling results are contrary not only to these studies, but also to some studies of revealed preferences. Kienast et al. (2012) showed that biophysical landscape characteristics, such as land cover, could explain patterns of recreation in landscapes around Swiss towns. Their models also showed that travel distance was the most influential factor; similar results could be seen in patterns of usage of a national park in France (Tardieu & Tuffery, 2019). In a study on urban forests in Germany, the strongest predictors of recreational supply were related to human infrastructure, such as monuments, and bluespace (Baumeister, Gerstenberg, Plieninger, & Schraml, 2020). However, similar to our study, they found weak predictive powers of forest characteristics. A study on recreationists in Hamburg showed no correlation between the characteristics of sites and the frequency of visit, and also a disconnect between the preferences stated by the recreationists and which site they visited (Boll, von Haaren, & von Ruschkowski, 2014). Similarly, Bagstad et al. (2016) found no correlations between perceived aesthetic values of landscapes and modeled values based on biophysical characteristics. Taken together, this paints a muddled picture of the relationship between recreationists and the landscape, with some disconnect between results of different studies, warranting further research.

Given that earlier studies on stated preferences have shown preferences for many biophysical characteristics included in our models (e.g. Gundersen & Frivold, 2008), it was unexpected that these preferences were not manifested in our analyses. One possible explanation is linked to the long travel distances observed in this study: it could be that the recreationists' preferred landscape is not accessible enough, and that they instead choose a location that is closer to home, even though it is not their most preferred option. There are however other possible explanations for the lack of clear patterns: Firstly, in Sweden, recreation can be performed on any land, public or private, while in other countries recreation to a higher extent is restricted to certain areas, which might be more homogenous in their attributes. This makes it less likely to find strong effects of certain biophysical characteristics in Sweden, especially if people enjoy variation, and choose areas because they have different characteristics to what they have visited previously. Secondly, the land cover map data used here is coarse in its categorization: each land cover class contains a range of different environments, for example the class "Open area with vegetation" includes both urban lawns and semi-natural grasslands. The SLU forest map adds some nuance, at least for forested environments, by supplying information on tree height, tree species composition and volume; still, this might not be enough to properly characterize how the landscape is experienced by recreationists. We used all the spatial data that was available on a national scale, however, there are several other aspects that might be important for recreationists, which mainly can be studied at a smaller spatial scale. For instance, recreational infrastructure, such as campgrounds (Donovan, Cerveny, & Gatziolis, 2016) and perceived safety (Lis & Iwankowski, 2021) has been shown to influence outdoor recreation.

Due to the weak main effects, it was difficult to draw any conclusions from the interaction effects between predictors of the models. Type of activity performed was the predictor with most interaction effects, which is not surprising, since this has previously been shown to alter how landscapes are used (De Valck et al., 2016). In our models there were only weak interactions between landscape characteristics and gender, age, income, disability and level of education. Previous research has shown that preference can be influenced by socio-demographic factors (van Zanten et al., 2014), cultural differences (Gosal et al., 2021) or group identity (Scott et al., 2009). Since the main effects of the landscape characteristics were weak, and we do not expect the interaction effects to be stronger than the main effects, we cannot say in what manner individual attributes or type of activity affects the choice of recreational location.

Despite our under-performing models, we believe that overall our methodology is sound. A weakness is our estimate of what landscape the recreationists experienced, where the respondent only provided the center point of the area they had visited. Since we did not know how large an area they had visited, we sampled circular buffers of various sizes around this point. For the large fraction of the data set where the recreationists moved over a larger area (e.g. walking, cycling) our approach sampled a smaller part of their experience. We argue that this approach is valid, in that we are contrasting a part of the landscape experienced by the recreationists to a landscape they did not experience. An improvement would have been to collect data on the exact route each recreationist had taken. We further lacked exact information on where the recreationist had traveled from, which would have improved our estimate of what landscape was available, instead of having to rely on the destination point combined with the travel distance.

We believe BRT modeling to be a very well suited tool for analyzing a complex phenomenon such as recreation. It has generally high predictive power, combined with flexibility and the ability to handle any number of predictors (regardless of collinearity). It does not require the specification of interaction effects in advance, nor assume linear relationships between predictors and response. Its main problem of producing models that are harder to interpret can be overcome, and is in our view worth the drawback.

5. Conclusions

We have found that recreationists in Sweden travel farther to recreational areas than what previous research has suggested is preferred. At the same time, we found only weak signals of recreationists having selected the area due to its biophysical characteristics. Thus, recreationists' preferences are not manifested, and one explanation for that is that a low availability of closely situated areas are limiting their choice. This indicates a possible recreational deficit, making it important for policy-makers to take into account the need for recreational opportunities in physical planning, even in a sparsely populated country such as Sweden.

We found that a large proportion of recreation occurs on a small proportion of the total land area (i.e. urban and periurban areas). This is because the population is clustered towards urban areas, combined with the fact that most recreation occurs close to home. This has implications for planning: recreational opportunities can be improved for half of the Swedish population by focusing on these areas, however to improve them for the other half would affect much larger areas.

The outcomes from studies of stated preferences and revealed preferences seem contradictory. To achieve a better understanding of this, a combination of stated preference and revealed preference could be applied in future studies by asking recreationists about their preferences, while at the same time studying their actual recreational patterns.

Conclusively, it is important to take spatial accessibility into account, both when performing research and during physical planning. Recreationists use the landscape that is available to them, which in our study were on average one or two kilometers from home for the most common activities.

CRediT authorship contribution statement

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

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2022.104519.

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