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RESEARCH

Exploring the subjective and objective characteristics affecting the frequency of human-nature interactions in urban green spaces: a case study from Finland

Anita Poturalska[1] · **Terhi Ala-Hulkko**[2,3] · **Janne Artell**[4] · **Artti Juutinen**[5] · **Katja Kangas**[6]

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Abstract

Green urban and peri-urban spaces are important sites for human-nature interactions, providing countless ecosystem services to support the wellbeing of urban populations. In an era of rapid urbanization, understanding human-nature interactions requires considering both subjective, user-specific perspectives and the objective measures of environmental and infrastructural features of these green spaces. In this case study we explore how different groups of characteristics impact the number of visits and, consequently, human-nature interactions frequency in urban and peri-urban spaces across three Finnish cities: Espoo, Kuopio, and Jyväskylä. We used Public Participatory Geographic Information Systems survey data of which respondents marked the green urban and peri-urban spaces they visit annually. A panel generalized linear modelling approach was used to analyze the roles of four groups of subjective and objective characteristics on the visit frequency, including: the socio-demographic background of survey respondents; the cultural ecosystem services they consume; the perceived accessibility characteristics of the marked locations; and the presence of objectively measured environmental and infrastructure features of these locations. Our findings underline the importance of perceived accessibility and availability of infrastructure for more frequent interactions with nature. Additionally, they emphasize the need of urban residents for access to biodiverse green spaces within closer proximity to their homes. Ensuring the availability of green spaces and preserving their ability to provide ecosystem services is essential for maintaining the well-being of urban populations now and in the future.

Keywords Green urban and peri-urban green spaces · Nature interactions · Visit frequency · Public participatory geographic information systems · Panel generalized linear models

Introduction

Urban and peri-urban green spaces are valuable sites for human-nature interactions (Li et al. 2025), offering a range of benefits to growing urban populations (Bertram and Rehdanz 2015; WHO 2023; Zhao et al. 2024). These spaces deliver vital ecosystem services that strengthen human well-being (La Rosa et al. 2016; Veerkamp et al. 2021; Xia et al. 2024). The provision of these ecosystem services and human-nature interactions are directly improving both physical and mental health of urban populations (Wolch et al. 2014), for example, by reducing stress or enhancing physical activity (Bratman et al. 2012; Sia et al. 2023; WHO 2023).

However, intensifying urbanization poses challenges to maintaining equal opportunities for interaction with nature

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✉ Anita Poturalska
anita.poturalska@oulu.fi

[1] University of Oulu, Geography Research Unit, Oulu, Finland

[2] Department of Built Environment, Spatial Planning and Transportation Engineering, Aalto University, Espoo, Finland

[3] University of Oulu, Kerttu Saalasti Institute, Nivala, Finland

[4] Natural Resources Institute Finland, Latokartanonkaari 9, Helsinki, Finland

[5] Formerly, Natural Resources Institute Finland, Paavo Havaksen tie 3, Oulu, Finland

[6] Natural Resources Institute Finland, Paavo Havaksen tie 3, Oulu, Finland

in urban and peri-urban green spaces (Holt et al. 2015; Thapa et al. 2021; Plieninger et al. 2022; Krsnik & Illán-Fernández 2024). The expansion of densely built-up areas can lead to degradation of urban ecosystems, reducing their capacity to provide services and potentially causing a decline in human well-being (Thapa et al. 2021; Plieninger et al. 2022). Understanding the factors that shape human-nature interactions in rapidly urbanizing cities promotes the development of effective planning strategies, enhances ecosystem service provision, benefits public health, and raises environmental awareness (Xia et al. 2024; Joo et al. 2024; Li et al. 2025). This knowledge supports the design of more inclusive and resilient cities, by identifying how people perceive and value green spaces, enabling planning strategies to align with the diverse preferences and needs of urban communities (Holt et al. 2015; Krsnik & Illán-Fernández 2024).

One useful way to examine human-nature interactions is by studying the number of visits to green spaces (Joo et al. 2024; Romelli et al. 2025). The intensity of visits in a certain green space represents its' level of popularity and attractiveness among the users (Huai et al. 2023; Li et al. 2025) and exemplifies the direct outdoor interactions with nature. Therefore, it can be used to assess user-specific subjective patterns in human-nature interactions (Romelli et al. 2025). The number of visits to green spaces can be influenced by a range of characteristics related to subjective needs and desired benefits from nature, as well as by objective environmental and infrastructure features of these spaces (Neuvonen et al. 2007; Plieninger et al. 2013; Hegetschweiler et al. 2017).

Previous studies have shown that the visit frequency to green spaces may be influenced by the visitors' socio-demographic background (e.g., Wolch et al. 2014; Gottwald et al. 2022; Aghabozorgi et al. 2023; Nowak-Olejnik et al. 2024; Romelli et al. 2025). This includes, for example, users' age, gender, social status, cultural background, personal preferences, heritage values, feelings or disabilities and health-related factors. Together with socio-demographic characteristics, the self-reported perceptions towards green spaces and ecosystem service consumed may impact the visit intensity therein (e.g., Fischer et al. 2018; Romelli et al. 2025). Studies have found that high visit intensity may be related to the direct consumption of ecosystem services, especially considering cultural ecosystem services (CES), such as recreational activities and spiritual interactions with nature (La Rosa et al. 2016; Xia et al. 2024). CES reflect both direct interactions with the environment and perceptions of its contribution to individuals' well-being through activities with which the user engages (Nowak Olejnik et al. 2024). CES have a special emphasis over other ecosystem services in urban settings (Andersson et al. 2015; Xia et al. 2024). Urban dwellers feel generally less reliant and affected by regulating and provisioning services provided by nature, whereas cultural services are tangibly present in day-to-day activities and public discourse within urban green spaces.

Visit intensity is also driven by how people perceive the geographic surroundings, a factor long recognized as shaping human spatial behavior (Kirk et al. 1963; Pot et al. 2021). Because of the effect of distance decay, the spaces that are perceived as accessible or close, are usually more often visited than those located farther away (Pot et al. 2021). Soga & Gatson (2020) emphasize that the geographic distribution of interactions with nature is shaped by spatial dynamics, driven by factors such as the availability and accessibility of natural spaces or the distribution of human populations. These factors include a variety of accessibility indicators, such as perceived or measured distance to spaces, nearby facilities (e.g., parking lots), or the availability and affordability of transportation options to reach desired locations (Phillips et al. 2023). For example, Phillips et al. (2023) states, that urban green spaces perceived as close, are often subjectively associated with higher health benefits by green space users.

In addition to subjective, user-dependent characteristics, environmental and infrastructure features of the surrounding landscape may influence visitation rates to green spaces. Spatial data related to the quantity and quality of biophysical features (e.g., tree species, forest cover, or biodiversity measures) or built environments (e.g., length of recreational roads) are commonly used in visitor rate assessments. For instance, Agimass et al. (2018) examined the preferences of forest visitors regarding biophysical characteristics and determined that area size, the presence of broad-leaved species, and tree density are preferred by visitors of the studied areas. In contrast, Baumeister et al. (2020) found that human-made infrastructure, including trails and recreational roads, plays a more significant role in interactions with nature in urban forests than measured forest features. These somewhat contradictory findings suggest that the impact of biophysical and infrastructure characteristics is case- and area-specific and should be considered alongside other variables that might impact visit frequency.

Despite the increasing amount of research on human-nature interactions, studies rarely consider the impact of user-specific characteristics and objective biophysical features simultaneously. While many studies have emphasized the importance of green space structure, biodiversity, and spatial accessibility, fewer have combined these with people's self-reported preferences and usage patterns (Raymond et al. 2017). Integrated, case- and area-specific research exploring patterns of human-nature interactions is needed, as these interactions depend not only on the presence of specific biophysical structures but also on how people perceive and use them (Kabisch et al. 2015). Furthermore, recent evidence suggests that positive perceptions of nature, combined with high-quality biophysical features, are associated with better population well-being (Vanhöfer et al. 2025). This highlights the importance of studying the combined influence of objective and subjective factors on human-nature interactions to better manage urban green spaces that support public health and well-being.

In this study we aim to bridge this research gap, by examining the impact of both subjective and objective factors on the number of visits to urban and peri-urban green spaces across three Finnish cities. More specifically we choose to explore what are the roles of the following characteristics on the number of visits: (1) sociodemographic background of green space users, (2) reported CES consumption and perception of the surrounding environmental features, (3) perceived accessibility characteristics, and (4) objectively measured environmental and infrastructure characteristics, such as biodiverse forests, distance to nearest waterbodies and walking roads availability around used green spaces.

We use data collected via a public participatory geographic information system (PPGIS) survey, a reliable tool for exploring spatial patterns and perceptions (Fagerholm et al. 2021), alongside spatial data on the biophysical features and available infrastructure surrounding green urban and peri-urban locations marked in the survey. We analyze the data using a panel generalized linear modeling (PGLM) approach. PGLMs allow us to account for differences in PPGIS survey respondents' preferences and consider unobservable factors influencing personal decisions to visit green spaces. We created four separate models for the groups of characteristics studied. This enables us to examine the impact of each group, compare the effects of subjective and objective variables on green space visit frequency, and identify similarities in their influence.

Materials and methods

Study areas

The research was conducted in the Finnish cities of Jyväskylä, Kuopio and Espoo (Fig. 1). Compared to many European cities, studied locations are characterized by good availability of green spaces, which is related to the historical foundations of Finnish urban planning, that acknowledges the close relationship between humans and nature (Hautamäki 2021). Finnish urban areas contain on average 30–40% of different types of green spaces and are among the greenest in Europe (Hautamäki 2021; Copernicus Land Monitoring Service 2021; European Environmental Agency 2022). Alongside green areas, blue spaces, including lakes, rivers, and seascapes, are common components of the landscape of Finnish cities (Hautamäki 2021). Studied cities and municipalities of Espoo, Kuopio and Jyväskylä are no exceptions, containing relatively many green and blue spaces, which availability increases with the distance from city centers (European Environmental Agency 2022). Based on the current municipal borders, green spaces cover over 60% of Kuopio and Jyväskylä municipalities (62.3% and 67%, respectively) and 33.5% of municipality of Espoo (Fig. 1, CLC 2018).

Although green and blue areas are more abundant in studied urban areas compared to many other European cities, rapid urbanization can impact equal opportunities for daily human-nature interactions. The population has steadily grown in all the studied urban areas in recent years (Statistics Finland 2025). The most substantial increase in population density was observed in Espoo, where the number of residents grew by 2.9% just in one year between 2023 and 2024. A less intensive yet still significant increase was observed in Kuopio and Jyväskylä, with the population growing by 1.2% and 1.3%, respectively, in the same year (Statistics Finland 2025).

PPGIS survey design and variables

Sample approach

PPGIS survey data was collected between November 2020 and February 2021 with the Maptionnaire tool (Maptionnaire 2021). The web-based survey was distributed in two ways: by invitation (random sample of 1500 households, per city) and by open-ended web survey, advertised via social media (Juutinen et al. 2023). In this study we use answers from both invitation and open surveys.

In the survey, the respondents were first asked to provide information related to their social and economic backgrounds. This information includes gender (male, female, other), education (elementary school, high school, professional, bachelor's, master or higher degree), housing type (apartment building, more than 3 floors, small apartment building, less than 3 floors, row or twin house, detached house), municipality of residence and age (Table 1).

The survey included respondents from Espoo (35%), Kuopio (35%) and Jyväskylä (30%). 52.1% were female, 47.3% male, and 0.6% identified as other or preferred not to disclose. The average age was 45.6 years (*SD* = 15.01, [19, 81] years old). Most respondents came from the invitation survey (71.9% compared to 28.1% of responses from open surveys). 35.1% of respondents reported living in apartment houses, followed by detached (32.9%), terrace (21.4%), and small apartment (10.6%). Most of the respondents had a

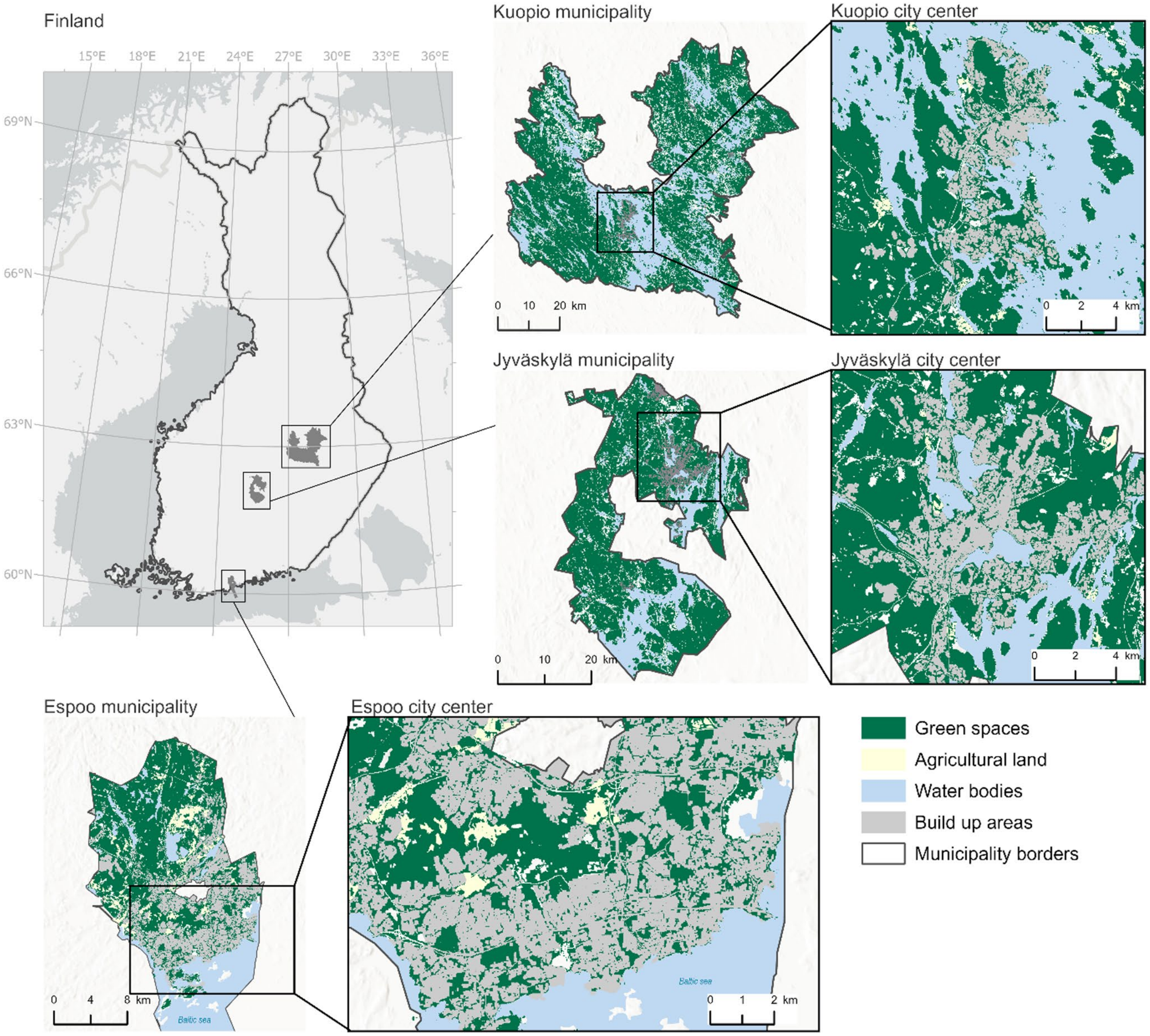

Fig. 1 The locations of the cities studied together with the visual representation of the coverage of green spaces within their municipalities and city centers of Kuopio, Espoo and Jyväskylä. (source: Corine Land Cover 2018, 20 × 20 m resolution).

master's (43.5%), followed by bachelor's (25.1%) or college (10.8%) degree. Only a few held a vocational (9.6%), upper secondary (8.8%), or comprehensive (2.2%) school degree. The representativeness of this sample relative to the general population of the studied cities has been established in a previous study where this data was used (see Juutinen et al. 2023). Compared to the responses from the invitation survey, the answers from the open survey showed greater variation between cities. In the open survey sample, females and respondents aged 30–39 were overrepresented compared to those aged 70 and older. Additionally, participants were more likely to hold academic degrees than basic education.

Subjective characteristics from PPGIS data

After providing socio-demographic background information, the respondents were asked to mark on the map the locations of important green urban and peri-urban spaces, and provide details related to the site, such as how often they visit it annually (the number of visits), and how far the site is from their home (self-reported distance). Respondents could mark an unlimited number of green spaces important to them.

Respondents were also asked to explain why the place is important for them, by selecting reasons from a list of pre-selected options representing CES consumed in marked

Table 1 Summary of PPGIS data variables used in this study, related to sociodemographic background of the survey respondents, CES consumed in marked green spaces and perceived characteristics of marked locations, and the perceived accessibility characteristics of those locations (*locations n* = 1721, *respondents n* = 499)

SOCIODEMOGRAPHIC CHARACTERISTICS			
Variable		*Variable type*	*Number of respondents, (%)**
survey type	open	categorical	140 (28.1%)
	invited		359 (71.9%)
municipality	Kuopio		174 (34.9%)
	Espoo		175 (35.1%)
	Jyväskylä		150 (30%)
gender	male		236 (47.3%)
	female		260 (52.1%)
	other		3 (0.6%)
education	elementary school		11 (2.2%)
	upper secondary school		44 (8.8%)
	high school		48 (9.6%)
	professional degree		54 (10.8%)
	bachelor's degree		125 (25.1%)
	master's or higher degree		217 (43.5%)
	other education		10 (2.0%)
housing	apartment building, more than 3 floors		175 (35.1%)
	small apartment building, less than 3 floors		53 (10.6%)
	row or twin house		107 (21.4%)
	detached house		164 (32.9%)
age		continuous ***	*min* = 19, *max* = 81, *md* = 45, *mean* = 45.7
CES AND PERCEIVED ENVIRONMENTAL CHARACTERISTICS			
Variable		*Variable type*	*Number of locations, (%)***
recreation		binary (yes (1) or no (0))	887 (13.8%)
hunting			25 (0.4%)
fishing			94 (1.5%)
berry picking			376 (5.9%)
biodiversity			513 (8.0%)
peaceful			889 (13.8%)
beautiful scenery			1087 (16.9%)
cultural history			191 (3.0%)
other			147 (2.3%)
PERCEIVED ACCESSIBILITY CHARACTERISTICS			
accessible		binary (yes (1) or no (0))	994 (15.5%)
easy terrain			395 (6.1%)
facilities			826 (12.9%)
self-reported distance (km) from home		continuous ***	*min* = 0.1, *max* = 100, *md* = 3, *mean* = 7.7

*Values are presented as n (%), where n is the number of responses and percentages are shown in parentheses

** Values are presented as n (%), where n is the number of locations and percentages are shown in parentheses

*** For continuous variables the descriptive statistics (minimum, maximum, median and mean values) are given

green spaces, i.e. recreation (walking, hiking, biking, etc.), hunting, fishing, berry picking, cultural history, peaceful and quiet environment, and beautiful landscape as well as the perception of place as biodiverse to support CES provision (CES and perceived environmental characteristics), and representing the sites perceived accessibility (Table 1.). The list of CES considered in this study, alongside their corresponding class numbers based on the Common International Classification of Ecosystem Services (CICES V 5.2, Haines-Young 2023), can be found in Supplementary Materials S1.

To exclude planned overnight trips outside of the home province, we removed points where the distance to the visited place was greater than 100 km (11 points marked by 5 respondents). We further limited the maximum number of visits to two per day (max. 730 trips annually; excluding 8 points marked by 2 respondents). Ultimately, we filtered out all rows with missing information from the PPGIS data. A total of 1721 points, marked by 499 respondents, remained in the data structure and were used for statistical analysis (the number of respondents in Kuopio: $n = 174$; Espoo: $n = 175$ and Jyväskylä: $n = 150$).

Objective environmental and infrastructures variables

In addition to the subjectively reported characteristics from PPGIS survey, we calculated objective spatial variables representing the characteristics of the local environment and infrastructure around the marked points. We used a circular buffer with a 500-meter radius surrounding the marked green spaces. The buffer is useful for explaining spatial patterns and identifying landscape characteristics around the mapped location (Fagerholm et al. 2021). A 500-meter buffer is commonly applied in the literature (e.g., Kyttä et al. 2016; Brown and Hausner 2017), particularly in urban contexts.

We initially calculated seven environmental characteristics including: mean tree volume and forest cover indicating the quantity of forest; area of highly biodiverse forests (top 10% of biodiverse forests) and area of moderately to highly biodiverse forests (top 30% of biodiverse forests), indicating the quality of forests; built green urban areas including parks and sport and leisure areas; the distance to nearest waterbodies and the distance to nearest lake indicating the proximity to blue spaces. For representation of infrastructure characteristics, two variables we calculated: recreational roads availability (total length) and paved walking roads availability (total length). Variables moderately to highly biodiverse forest, distance to lake and forest cover were excluded from further analyses due to high correlations with other predictors (*Spearman's* $r \geq 0.6$, Supplementary materials S2), which could compromise the interpretability and stability of the models. The details of the final environmental and infrastructure characteristics used in this study are presented in Table 2.

Table 2 Summary details regarding spatial data used to assess the role of the objective environmental and infrastructure characteristics on the number of visits at locations marked by PPGIS survey respondents

OBJECTIVE ENVIRONMENTAL AND INFRASTRUCTURE CHARACTERISTICS

Variable	Variable description	Unit	Original resolution	Data source
Highly biodiverse forests	High biodiversity value forests data from 2018, representing the top 10% values of highly biodiverse forests area within 500 m buffer from visited location. The data considers landscape-level estimation of forests' conservation potential with added long-distance connectivity to permanently protected areas.	$\%/km^2$	96 m	Mikkonen et al. 2018 version 6, Finnish Environmental Institute 2018
Distance to waterbodies	Distance to the nearest waterbody (class 5, all waterbody types) from the location visited, within the 500 m buffer	km	-	Corine Land Cover (CLC) 2018, EEA 2024
Mean tree volume	Mean volume of the growingstock, in 500 m buffer from the marked location	m^3/ha	16 m	the Finnish Multi-Source National Forest Inventory (MS-NFI) database, Natural Resource Institute Finland 2021
Recreational roads availability	Length of recreational roads within 500 m buffer from marked location (incl. biking, canoe, cross country biking, hiking, horse track, jogging, nature trail, snowmobile and ski tracks)	km	-	Lipas database (University of Jyväskylä) 2024
Walking roads availability	Length of paved walking roads in 500 m buffer from marked location	km	-	Digiroad (Finnish Transport Infrastructure Agency) 2023
Build green urban areas	The cover of green urban areas such as parks (class 141) and outdoor sport and leisure areas (class 142) within 500 m from the marked locations	km^2	20 m	Corine Land Cover (CLC) 2018, EEA 2024

Data pre-evaluation and statistical analysis

Before examining how the studied groups of characteristics affect the number of visits, we assessed multicollinearity among them using Spearman's correlation. Correlation analysis also helped us determine whether the effect of distance decay was present in the PPGIS data. We ran correlations using the R package *corrplot* (Wei and Simko 2024).

After data pre-evaluation the associations of the studied variables with the number of visits to green areas were analyzed using the panel generalized linear modeling (PGLM) approach with the *pglm* R package (Croissant and Millo 2019; Croissant 2021). PGLM is an extension of the generalized linear model (GLM), accounting for panel data collected over multiple entities (reported by many people) and multiple observations per entity (many places marked at once). We selected this method to account for the nested structure of the data, wherein individual respondents to the PPGIS survey could mark multiple locations, resulting in repeated observations per individual. Panel modeling allows us to explicitly account for within-person variation while controlling unobserved individual-level characteristics such as values, preferences, familiarity with the area, or the impact of other people on individual choices (Wooldridge 2010). These factors are not directly measured, yet they could influence spatially observed behavior.

We applied a fixed effects negative binomial model in the analysis. Fixed effects account for unobserved heterogeneity when it is constant over time and might be correlated with the independent variables analyzed (Croissant 2021; Hanck et al. 2024). Fixed effects allow each respondent to have their own baseline tendency for marking visited places, thereby reducing omitted variable bias. Negative binomial regression is used for count data, where the outcome variable represents the number of times an event occurs, and it accounts for overdispersion, or variance greater than the mean (Wooldridge 2010; Croissant 2021; Hastie and Tay 2023). Since overdispersion was present in the dependent variable (number of visits), the negative binomial model was chosen for the analysis. Details of the overdispersion assessment of the number of visits are presented in Supplementary materials S3, and include the variance and mean ratio, Poisson model fit, and formal dispersion test run with the *dispersiontest()* function from the *AER* R package (Kleiber and Zeileis 2008).

Several diagnostic tools were used to assess model fit including: comparison of the log likelihoods of panel and non-panel baseline generalized linear models, run with *glm2* R package (Marschner 2011); assessment of the Akaike information criterion (AIC) value for model comparison using the *stats* package in R (R Core Team 2024); calculation of the McFadden's pseudo R-squared value ($R^2 = 1 - \log L \text{ model n}/\log L \text{ model null}$) to estimate explained variance; and finally, likelihood-based tests using the *lmtest* R package (Zeileis and Hothorn 2002) to evaluate model significance and improvements across specifications.

Model estimation was conducted using the *pglm()* function, with individual respondent IDs defined as the panel index. We created four separate panel models, aiming to explain the role of studied variable groups on the number of visits in a marked location. Model 1 includes only the relationship between the number of visits and the dummy-coded sociodemographic categorical variables of the respondents, with coefficients interpreted relative to a reference group. The socio-demographic background is included in each model to control for individual-level differences, allowing clearer interpretation of other variables' effects. Model 2 examined the role of CES and perceived environmental characteristics. Model 3 analyzed the role of perceived accessibility variables. Finally, Model 4 included the effect of objectively measured environmental and infrastructure variables. The continuous variables included in Models 3 and 4 were standardized using *scale()* function in R, prior to running the models.

The models' results include regression coefficients (estimates), which represent the log-transformed effect of a variable on the expected count (in this case, the number of visits); standard error values; as well as z-scores and p-values, which account for the statistical significance of the variables' role for the number of visits. To make the results easier to interpret, we exponentiated the coefficients and calculated incidence rate ratios (IRRs). The IRRs show how the expected number of visits changes multiplicatively with a one-unit increase in the dependent variable (IRR = 1 means no difference in visit rate, IRR < 1 shows lower rate of visits, IRR > 1 shows higher rate of visits).

Results

Insights from data pre-evaluation

Spearman's correlation analysis showed a highly statistically significant correlation ($r = -0.5$, $p < 0.001$), between the reported distance from home [0.1, 100] in kilometers and visit frequency [1, 600]. Most of the visits occurred within a short self-reported distance from home (Supplementary materials S4). The correlation coefficient between the number of visits and the other studied variables was very low, never exceeding 0.3 (see Supplementary materials S5, S6, S7 and S8). The highest positive correlations were found between visits and the availability of walking roads ($r = 0.3$) and perceived accessibility ($r = 0.2$). The highest negative correlations were observed for biodiverse

Table 3 Summary of fit statistics for PGLMs

Model	LogLik non-panel GLM	LogLik	AIC non-panel GLM	AIC	ΔDf	ΔLL	LRT p-value	Pseudo R^2
null model	—	−4836.7	—	9675.427	—	—	—	0.000
Model 1	−15610.43	−4823.0	15628.0	9661.957	+7	+27.5	0.00027 ***	0.0028
Model 2	−15560.72	−4812.4	15597.0	9658.706	+9	+21.3	0.0116 *	0.005
Model 3	−15413.52	−4756.1	15440.0	9536.227	−5	+112.5	<2e−16 ***	0.015
Model 4	−15361.56	−4782.5	15392.0	9592.978	+2	+52.8	3.5e−12 ***	0.011

Significance codes: *** $p<0.001$, ** $p<0.01$, * $p<0.05$

forests ($r = -0.1$), tree volume ($r = -0.1$), and male respondents ($r = -0.1$).

Statistical models

Model fit evaluation

All models showed statistically significant improvements over the null model, as confirmed by likelihood ratio tests (Model 1 $\Delta LL = +20.5$, Model 2 $\Delta LL = +30.3$, Model 3 $\Delta LL = +50.5$, Model 4 $\Delta LL = +40.8$). Model fit was also better according to log-likelihood and AIC comparisons (Table 3). AIC values of the panel model were considerably smaller than AIC values of non-panel model indicating a better fit for the data analysis. Although pseudo-R^2 values were relatively low (Table 3), this does not indicate poor model fit. A substantial portion of the variation is already captured by person-specific intercepts through the inclusion of individual fixed effects, which limits the incremental gain reflected in the pseudo-R^2. These values reflect improvements in deviance rather than explained variance and must be interpreted together with log-likelihood ratio tests and AIC reductions, which indicate that the model fit the data better than the null model.

The roles of the subjective and objective characteristics on the visit frequency

Model 1 showed that the number of visits was significantly associated with survey mode, education level, and study area (see Table 4). Those who responded via invitation survey reported less visits compared to open survey respondents (IRR = 0.73, $\beta = -0.32$, $p < 0.001$). Respondents with a higher education reported fewer visits than those with other educational backgrounds (IRR = 0.86, $\beta = -0.15$, $p < 0.05$). Residents of Espoo reported the highest number of visits, compared to residents of Jyväskylä and Kuopio (IRR = 0.83, $\beta = -0.18$ for Kuopio and $\beta = -0.19$ for Jyväskylä, $p < 0.05$).

Table 4 PGLM results for model 1: the roles of sociodemographic characteristics for the number of visits to marked locations

MODEL 1: sociodemographic characteristics

Variable	Estimate	Std. error	Statistic (z-score)	p-value	IRR
(Intercept)	0.23	0.140	1.64	0.1007	1.26
Kuopio	−0.18	0.081	−2.26	0.0236 *	0.83
Jyväskylä	−0.19	0.084	−2.20	0.0277 *	0.83
age	0.00	0.003	1.45	0.1465	1.00
male (gender)	0.04	0.071	0.61	0.5386	1.04
Master's (education)	−0.15	0.069	−2.22	0.0263 *	0.86
apartment (housing)	−0.02	0.070	−0.34	0.7305	0.98
invitation responses (survey mode)	−0.32	0.071	−4.48	7.34e-06 ***	0.73

respondents $n = 499$, locations $n = 1721$ Significance codes: *** $p<0.001$, ** $p<0.01$, * $p<0.05$,. $p<0.1$

Model 2 (Table 5) considered the CES and perceived environmental characteristics that respondents reported in marked locations, along with their sociodemographic background. The number of visits to marked locations had a statistically significant negative association with peacefulness (IRR = 0.9, $\beta = -0.10$, $p < 0.05$) and cultural heritage (IRR = 0.85, $\beta = -0.16$, $p < 0.05$). Additionally, there was a weak negative association between beautiful scenery and number of visits (IRR = 0.92, $\beta = -0.09$, $p < 0.1$). Although some CES indicated slight increases or decreases in visits to certain locations, these changes were not statistically significant (Table 5). Associations between number of visits and sociodemographic background variables were like those in Model 1.

The strongest model explaining the number of visits to marked locations was Model 3 (Table 6), where perceived spatial and accessibility characteristics were considered. In this model, perceived accessibility had the highest positive and statistically significant association with the number of visits (IRR = 1.47, $\beta = 0.38$, $p < 0.001$), and it was the highest of all variables compared to other models. Additionally, the self-estimated distance from respondent's home to the marked location had significant negative association with the number of visits (Table 6) indicating that the greater the distance, the less frequently the place is visited (IRR = 0.86, $\beta = -15$, $p < 0.001$). Associations between the number of visits and sociodemographic background variables were similar than in Model 1.

Finally, Model 4 (Table 7) evaluated the impact of objective environmental and infrastructure characteristics on the

Table 5 PGLM results for model 2: the roles of CES and perceived environmental characteristics for the number of visits at marked locations

MODEL 2: CES and perceived environmental characteristics

Variable	Estimate	Std. error	Statistic (z-score)	*p*-value	IRR
(Intercept)	0.39	0.148	2.62	0.0087 **	1.48
Kuopio	−0.20	0.082	−2.41	0.0160 *	0.82
Jyväskylä	−0.21	0.085	−2.50	0.0124 *	0.81
age	0.00	0.003	1.90	0.0581.	1.00
male (gender)	0.02	0.073	0.31	0.7549	1.02
master's (education)	−0.16	0.070	−2.37	0.0178 *	0.85
apartment (housing)	−0.02	0.072	−0.25	0.7990	0.98
invitation responses	−0.32	0.072	−4.49	7.2e-06 ***	0.72
recreation	−0.08	0.051	−1.64	0.1011	0.92
hunting	−0.22	0.201	−1.11	0.2649	0.80
fishing	0.05	0.109	0.45	0.6533	1.05
berry picking	0.01	0.059	0.22	0.8234	1.01
biodiversity	−0.03	0.056	−0.61	0.5409	0.97
peaceful	−0.10	0.050	−2.03	0.0424 *	0.90
beautiful scenery	−0.09	0.052	−1.66	0.0973.	0.92
cultural history	−0.16	0.078	−2.08	0.0377 *	0.85
other CES	0.09	0.087	0.99	0.3211	1.09

respondents $n=499$, locations $n=1721$ Significance codes: *** $p<0.001$, ** $p<0.01$, * $p<0.05$,. $p<0.1$

Table 6 PGLM results for model 3: the roles of perceived accessibility characteristics for the number of visits in marked locations

MODEL 3: perceived accessibility characteristics

Variable	Estimate	Std. error	Statistic (z-score)	*p*-value	IRR
(Intercept)	0.16	0.142	1.10	0.2734	1.17
Kuopio	−0.16	0.080	−2.06	0.0395 *	0.85
Jyväskylä	−0.21	0.084	−2.57	0.0102 *	0.81
age	0.00	0.002	1.24	0.2164	1
male (gender)	0.08	0.070	1.16	0.2456	1.09
master's (education)	−0.20	0.070	−2.81	0.0049 **	0.82
apartment (housing)	−0.05	0.070	−0.70	0.4842	0.95
invitation responses	−0.32	0.071	−4.48	7.37e-06 ***	0.73
distance	−0.15	0.034	−4.54	5.53e-06 ***	0.86
accessible	0.38	0.053	7.27	3.73e-13 ***	1.47
easy terrain	0.03	0.058	0.51	0.6093	1.03
facilities	−0.02	0.048	−0.44	0.6589	0.98

respondents $n=499$, locations $n=1721$ Significance codes: *** $p<0.001$, ** $p<0.01$, * $p<0.05$,. $p<0.1$

Table 7 PGLM results for model 4: the roles of objective environment and infrastructure characteristics of the surroundings of marked locations for the number of visits therein

MODEL 4: objective environmental and infrastructure characteristics

Variable	Estimate	Std. error	Statistic (z-score)	*p*-value	IRR
(Intercept)	0.21	0.141	1.46	0.1431	1.23
Kuopio	−0.10	0.089	−1.15	0.2485	0.90
Jyväskylä	−0.16	0.086	−1.85	0.0640.	0.85
age	0.01	0.002	2.19	0.0283 *	1.01
male (gender)	0.09	0.071	1.30	0.1951	1.10
master's (education)	−0.19	0.069	−2.69	0.0071 **	0.83
apartment (housing)	−0.05	0.070	−0.68	0.4942	0.95
invitation responses	−0.37	0.072	−5.13	2.83e-07 ***	0.69
Walking Roads	0.19	0.027	7.16	7.80e-13 ***	1.22
Recreational Roads	0.03	0.025	1.17	0.2422	1.03
tree volume	0.06	0.034	1.73	0.0829.	1.06
waterbody	−0.01	0.027	−0.23	0.8216	0.99
biodiverse forest	−0.13	0.030	−4.17	3.06e-05 ***	0.88
Built urban green spaces	0.00	0.022	−0.01	0.9899	1.00

respondents $n=499$, locations $n=1721$ Significance codes: *** $p<0.001$, ** $p<0.01$, * $p<0.05$,. $p<0.1$

number of visits to marked locations. This was the second strongest model after Model 3. The number of visits had statistically significant positive relationship with walking roads (IRR = 1.22, $\beta=0.19, p<0.001$), and there was a trend of positive relationship with a higher volume of trees characterizing the marked location (IRR = 1.06, $\beta=-0.06, p<0.1$). Meanwhile, the number of visits had significant negative association with the presence of biodiverse forests (IRR = 0.88, $\beta=-0.13, p<0.001$). Associations between the number of visits and sociodemographic background variables were a bit different than in Model 1, as age appeared a statistically significant factor for the number of visits ($p<0.05$). However, the coefficient and simultaneously IRR of age remains low, with IRR rising by 0.01 (IRR = 1.01, $\beta=0.01$).

Discussion

Green urban and peri-urban spaces are vital for fostering leisure and human-nature interactions, offering a wide range of ecosystem services that support the wellbeing of urban populations. This study examined the roles of subjective and objective groups of characteristics on the visit frequency in green urban and peri-urban spaces, across three Finnish cities. Our results highlight the importance of perceived accessibility of urban and peri-urban green spaces for frequent human-nature interactions. Despite the presence of both subjectively and objectively valuable ecosystems, such as beautiful landscapes and biodiverse forests, people may interact with them less often due to the determining role of spatial perceptions on their visitation choices.

Based on our results, green urban or peri-urban spaces that were perceived as accessible received the highest positive, statistically significant score for frequent visits compared to all the other subjective variables considered. Consequently, we found that green spaces located farther from residential areas are visited less often than those close by. Additionally, out of the objective variables, the availability of walking roads was significant in increasing the frequency of human-nature interactions across the studied cities. These findings are aligned with previous research (e.g., Phillips et al. 2023; Sia et al. 2023; Fleming & Schwartz 2023; Zhao et al. 2024) and imply the determining role of perceived accessibility, supported by availability of infrastructure, on human spatial behavior across the studied areas.

It should be acknowledged that in this survey respondents weren't asked to specify which aspect of accessibility they were referring to. Perceived accessibility differs from spatial accessibility measures. It reflects the mental picture people form of their environment. This picture is shaped by people's experiences, the information they receive, and how they interpret it (Pot et al. 2021). Rather than describing spatial opportunities for reaching a location via the transportation network (Paéz et al. 2012), perceived accessibility refers to how a person thinks they can reach a location. This perception is shaped by their understanding of where destinations are located, how the transportation system works, and how much time they have to get there (Pot et al. 2021). However, in our results, the availability of paved walking roads was also linked to more visits across studied green space. This finding highlights the central role of accessibility indicators (both perceived and measured, including transportation networks) on the frequency of human-nature interactions and spatial behavior (Phillips et al. 2023; Li et al. 2023).

Considering other studied variables, the association between the number of visits and the self-reported distance from home aligns with the concept of distance decay. According to this concept, the likelihood or frequency of interaction with a location decreases as the distance from it increases. This study only included self-reported distance estimation in the analysis, nevertheless, the effect of distance decay is visible, further confirming that aspects of perception are vital for spatial behavior (Pot et al. 2021) which aligns with previous research (Žlender and Ward Thompson 2017; Phillips et al. 2023).

Also, a number of subjective variables that were found to have negative association with the visit frequency to green spaces are related to certain CES characteristics. These include peacefulness of the location, its cultural heritage and to some extent also perceiving it as beautiful. Interestingly, comparable patterns were observed for objective environmental characteristics like highly biodiverse forests. Meanwhile, perceived biodiversity was not found significant at all. However, these results do not necessarily indicate that the characteristics mentioned are less valued by individuals. In fact, they might suggest that the use of these CES requires longer travel time, which could explain the lower visitation rate at these sites. After all, beautiful scenery and peacefulness were among the most commonly mentioned attributes of marked locations in the PPGIS survey (see Table 1), indicating their importance for green space users in general. However, the number of visits to those places is less frequent than in the locations perceived as accessible.

Biodiverse and peaceful spaces, such as protected areas or larger green spaces with dense vegetation, are often located in peri-urban zones, away from traffic, urban noise or densely populated neighborhoods (Schindler et al. 2022). Although fewer, the interactions with nature in further green spaces may be more intense and last longer amount of time (Fleming & Schwartz 2023). From a conservation perspective, the lower visitation rates to biodiversity-rich areas can be beneficial, as it reduces pressure on their ecosystems and supports their protection and restoration actions (Tolvanen and Kangas 2016; Littlewood et al. 2020). Additionally, lack of a significant relationship between perception of biodiversity and visit intensity may be explained by the presence of urban noise or traffic near biodiverse urban areas, which can diminish the perception of biophysical quality (Simkin et al. 2021). These sites may be primarily perceived as important for reasons other than biodiversity, such as recreational activities (Tolvanen et al. 2020) or accessibility. Furthermore, the perceptions of biodiversity in urban settings may be sometimes low, even if the green space is of a high biophysical quality (e.g., old urban forests stand) as stated by Simkin et al. (2021). Nevertheless, our results may also indicate the difficulties in the provision of high-quality CES by green spaces close to the residential areas in studied cities. Perhaps they do not fully support people's wellbeing and need maintenance in enhancing biodiversity and CES provision.

Regarding the socio-demographic characteristics of PPGIS survey respondents, we did not find many of them to have a significant impact on visitation rates. Respondents to the open survey tended to be more interested in participating in the study; therefore, their answers may have been more significant. Additionally, the number of visits was affected by respondents' city of residence, possibly due to differences in population structure and the topography of green spaces in the studied urban areas.

Critical reflections and suggestions for further research

In this study we relied on self-reported estimation of the accessibility characteristics and studied their role on the visitation rate in green spaces. Spatial accessibility measures could not be verified due to the lack of home location data. Nevertheless, comparing spatial perceptions with precise spatial variables, such as identification of respondents' home locations or transportation modes used to reach the marked green spaces, could enable opportunities to explore people's movements related to human-nature interactions. Additionally, investigating the role of transportation is particularly crucial to understanding accessibility dynamics and promoting equal opportunities for interactions with nature, especially in overcrowded, densely populated urban areas (Phillips et al. 2023). Moreover, when evaluating the accessibility of urban and peri urban green spaces, it could be beneficial to explore access restrictions related to the quality of the recreational road network. These restrictions might impact the ability of vulnerable groups, such as disabled or elderly people, to visit green spaces (Terefe and Hou 2024). Finally, the concept of accessibility was not explicitly defined in the PPGIS survey. Accessibility can be interpreted in multiple ways, e.g., precise measured proximity, estimated proximity, availability of transport modes or facilities enhancing the opportunities to reach the desired location (Paéz et al. 2012; Pot et al. 2021). Recent evidence (Battiston & Schifanella, 2024) suggests that future studies could incorporate the aforementioned accessibility elements, both perceived and spatial, into the assessment of human-nature interactions.

This study offers static information about the annual visitation rates in sites important for nature interactions, without accounting for seasonal variation, which was out of the scope of this study. However, temporal dynamics can significantly impact patterns of these interactions in the studied Finnish cities (Vierikko and Yli-Pelkonen 2019; Schirpke et al. 2020; Siltanen and Puhakka 2025). In addition, information regarding the quality or user satisfaction with the green spaces were not captured in the data. Nevertheless, the characteristics of the quality (ecological, perceived functionality etc.) and satisfaction, as well as the information regarding the length of the interactions, are important for better understanding the green space use patterns (Huai et al. 2023; Fleming & Schwartz 2023; Li et al. 2025). Future work should integrate longitudinal data to capture variations in visitation rates, measure ecosystem quality and user satisfaction from nature interactions.

Furthermore, the total sample is enough for general analyses of the roles of the variables across all studied cities; however, the number of respondents per city is relatively small, and therefore it was out of the scope of this study to perform separate city-specific analysis. Unfortunately, a part pf the data with missing variables had to be excluded, further reducing the usable sample. Nevertheless, the study was still able to identify meaningful associations across the areas studied; however, future research with a larger dataset could yield even stronger results.

Despite the aforementioned limitations, our study is a step towards better understanding the roles of both subjective and objective characteristics that influence visitation rates in green spaces. Our results reveal connections between subjective, self-reported characteristics of green spaces and their objective environmental and infrastructure features, which play an important role for human-nature interactions. Using a panel model approach, we accounted for variations among respondents and unobservable factors impacting their decisions to visit green sites. Our findings confirm the importance of accessibility, environmental, and infrastructure characteristics on visit intensity (e.g., Hegetschweiler et al. 2017; Li et al. 2025) and highlight their significance for human-nature interactions in urban and peri-urban green spaces.

While our models offer useful insights into individual-level preferences regarding visits to marked locations, there is still a substantial scope of expanding this approach. Future studies could continue evaluating subjective perceptions of environments alongside their objective characteristics, including green, blue spaces and elements of human-built infrastructure. PPGIS, a well-established tool for exploring human perceptions (Fagerholm et al. 2021), can continue to be used to study visitation rates across green areas, with surveys designed to address complex patterns of subjectivity and objectivity of spaces (Plieninger et al. 2013; Nowak-Olejnik et al. 2024). In addition to variables studied in this paper, other subjective reasons impacting visitation rates, such as for example, the feeling of insecurity in green spaces, could be also further examined in future studies (e.g. Evensen et al. 2021). Asking more targeted questions about perceived and spatial accessibility, quality, or satisfaction with human-nature interactions, could develop a richer, more context-sensitive understanding of how green spaces are used and valued.

Conclusions

For the rapidly growing population of Finnish cities, urban and peri-urban green spaces are the main locations of human-nature interactions. This study examined the impact of subjective and objective characteristics on visit frequency in these spaces. Panel modeling approach was used to capture variation in unobserved individual-level factors within the data structure. The results of this study highlight the importance of perceived accessibility characteristics for more frequent interactions with nature in urban and peri-urban areas. Additionally, our findings exemplify the importance of maintaining and managing the quality and biodiversity of urban and peri-urban green spaces located near urban residents' homes, as well as improving their accessibility, because these spaces are highly valued by citizens. Our results exemplify how the phenomenological qualities of green spaces impact their usage patterns in urban and peri urban settings. Future studies and urban development strategies should incorporate analyses of the roles of subjective, user-reported variables and objective features of green spaces to gain a more coherent understanding of people's demand for areas that facilitate human-nature interactions.

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Data availability The data that support the findings of this study are available from Dr Katja Kangas upon request.

Declarations

Competing interests The authors declare no competing interests.

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