

Original Article

Urban green infrastructure and recreational patterns: A 3D geospatial data analysis

Nora Fagerholm^{a,1,*}, Topi Tanhuanpää^{b,c,2}, Kamyar Hasanzadeh^{d,3}, Anna Kajosaari^{e,4},
Tiina Rinne^{f,g,5}, Markus Holpainen^{h,i,6}, Marketta Kyttä^{j,7}

^a Department of Geography and Geology, University of Turku, University of Turku, 20014, Finland

^b Department of Geographical and Historical studies, University of Eastern Finland, Finland

^c Department of Forest Sciences, University of Helsinki, Finland

^d Department of Geosciences and Geography, University of Helsinki, Finland

^e Institute for Urban and Regional Research, Austrian Academy of Sciences, Austria

^f Transport Research Center Verne, Tampere University, Finland

^g Department of Built Environment, Aalto University, Finland

^h Department of Forest Sciences, University of Helsinki, Helsinki 00014, Finland

ⁱ Department of Remote Sensing and Photogrammetry, Finnish Geospatial Research Institute, Espoo 02150, Finland

^j Department of Built Environment, Aalto University, Finland

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ABSTRACT

This study investigates the potential of 3D geospatial data to explain the spatial distribution of outdoor leisure-time activities in Helsinki, Finland, as mapped through Public Participation GIS (PPGIS). By integrating airborne laser scanning (ALS) data with traditional land cover data derived from satellite imagery, we provide complementary insights into urban green infrastructure (UGI) characteristics. Key findings reveal that features such as Relative canopy cover and Average crown area are associated with outdoor activity distribution, particularly for social interactions and nature enjoyment. Proximity to rivers and the sea also emerged as crucial factors, highlighting the importance of blue spaces for recreational activities. However, the relatively low explained variance for some activities suggests a complex interplay of factors, including built infrastructure and socio-demographic characteristics, influencing urban outdoor recreation behavior. This study highlights the value of high-resolution 3D data for urban planning and UGI research, providing detailed insights into the vertical structure of urban greenery, which are not captured by traditional satellite imagery-based greenness indices. In this paper, we present details of our analytical approach, share the results, discuss the observations, and envision future research directions.

1. Introduction

As the global population shifts increasingly towards urban living, the challenge of creating sustainable and livable urban environments becomes more pressing. The compact city approach, which advocates for

the densification of urban areas, has been widely endorsed as a strategy for sustainable urban development (OECD, 2012). This model seeks to optimize land use, reduce urban sprawl, and promote efficient public transportation. However, urban densification must be carefully managed to ensure that cities remain livable, vibrant, and conducive to

* Corresponding author.

E-mail address: nora.fagerholm@utu.fi (N. Fagerholm).

¹ <https://orcid.org/0000-0001-5020-0746>

² <https://orcid.org/0000-0002-5509-6922>

³ <https://orcid.org/0000-0002-0705-7662>

⁴ <https://orcid.org/0000-0001-8165-6770>

⁵ <https://orcid.org/0000-0001-8680-2263>

⁶ <https://orcid.org/0000-0001-6489-8671>

⁷ <https://orcid.org/0000-0001-9969-8194>

the well-being of the residents. There is a wide agreement that a critical component of achieving this balance is the preservation and enhancement of urban green infrastructure (UGI) (Brears, 2023; Russo and Cirella, 2018).

UGI is defined as “a strategically planned network of natural and semi-natural areas with other environmental features, designed and managed to deliver a wide range of ecosystem services, while also enhancing biodiversity” (European Commission 2024). These green and blue spaces, which include public parks, forests, community gardens, green roofs, rivers, and lakes, significantly contribute to the environmental quality and human health in urban settings. Urban green spaces are essential not only for their ecological benefits but also for the numerous health and social benefits they provide. These spaces offer residents opportunities for physical activities, such as walking, jogging, and play, which are crucial for maintaining physical health (Akpinar, 2016). They also provide settings for relaxation, socialization, and experiencing nature, which contribute to mental well-being (Zijlema et al., 2024). Given the ongoing trend of urban densification, urban planners face the challenge of ensuring that green spaces meet the needs and preferences of urban residents (Kajosaari et al., 2024; Wolch, Byrne, and Newell, 2014). The role of UGI in promoting physical and mental health through recreation and social interaction is increasingly recognized (Dadvand et al., 2016), particularly as urban areas grow denser and access to natural environments becomes more constrained (Haaland and van den Bosch, 2015).

Understanding the specific green structures and elements that are preferred by people and offer significant well-being benefits is crucial for effective urban planning. This understanding is often achieved through participatory approaches such as Public Participation GIS (PPGIS). PPGIS combines surveys with mapping components to capture people’s place-based values and preferences, providing a valuable tool for incorporating public input into land use planning (Brown and Kytä 2018; Fagerholm et al., 2021). PPGIS has been extensively used to engage the public and stakeholders in mapping landscape values, activities, development preferences, and ecosystem services across various contexts globally, from national forests to urban landscapes (Fagerholm et al., 2012; Kahila-Tani et al., 2016; Kajosaari et al., 2024; Plieninger et al., 2013; Sherrouse et al., 2014).

The literature indicates that people’s perceptions of urban green areas are influenced by a variety of factors. These include the type and size of parks, the character of the landscape, the size and topography of open spaces, the diversity of vegetation, and the presence of blue spaces such as rivers and lakes (e.g., Baumeister et al., 2020; Brown et al., 2014; Ives et al., 2017; Kytä et al., 2015; Rall et al., 2017; Tyrväinen et al., 2007). For example, urban parks that are large, linear, and well-connected are often associated with higher levels of physical activity due to the accessibility and continuity they offer (Brown et al., 2014). Similarly, landscapes with diverse vegetation and complex structures are preferred for their aesthetic and recreational value (Rall et al., 2017).

Traditionally, spatial analysis of UGI characteristics has relied on 2D geospatial datasets derived from satellite imagery, such as land cover and land use data (Hasanzadeh et al., 2022; Hegetschweiler et al., 2017; Kabisch et al., 2015). These datasets provide valuable information about the type, shape and extent of green spaces but are limited in their ability to capture the detailed physical structure of these environments, which would be important to more thoroughly understand how landscape and vegetation structure is connected to their perceived importance by

people. Recent advancements in 3D geospatial data and analysis methods, particularly through airborne laser scanning (ALS), offer a more detailed and accurate representation of the physical structure of green areas. ALS techniques, initially developed for forest inventory, have proven useful in urban settings for maintaining urban tree databases and measuring tree characteristics with high spatial accuracy (Hyypä et al., 2012; Matasci et al., 2018; Tanhuanpää et al., 2019).

The application of 3D ALS data in urban studies allows analysis of canopy structures, including tree height, canopy density, and the spatial distribution of vegetation (Matasci et al., 2018). These detailed characteristics can help better understand the role of UGI in urban environments. For instance, canopy cover and tree height can influence microclimate, provide shade, and enhance the aesthetic and recreational value of urban spaces, or the proportion of open versus vegetation covered landscape connect to specific outdoor recreation activities. Despite the potential of 3D data, its application in studying the place-based perceptions of urban dwellers remains underexplored. In particular, little is known about how structural greenness characteristics derived from ALS—such as canopy height or density—compare with widely-used satellite-based greenness indices in explaining people’s spatial preferences. This comparison forms a key contribution of our work.

We hypothesize that the characteristics of urban green spaces, such as canopy cover, tree height, canopy density near the ground, and proximity to water elements, influence the preferred use of these areas. Specifically, we use the data from our study site Helsinki, Finland, to explore whether detailed 3D geospatial data can reveal insights that are not captured by traditional 2D satellite imagery.

Our research objectives are threefold. Firstly, we seek to identify the types of outdoor leisure-time physical activities that residents engage in across Helsinki and the spatial clusters these activities form. Secondly, we aim to determine the relative importance of various UGI characteristics, such as canopy cover, tree height, canopy density near the ground, and proximity to water elements, in influencing these perceived leisure-time activities. Thirdly, we compare UGI characteristics derived from ALS with those obtained from traditional satellite-based greenness categorization to assess their respective accuracies and insights.

2. Methods

2.1. Study area and data collection

The study was conducted in the Helsinki, Finland (Fig. 1). The Helsinki Metropolitan Area, which includes the municipalities of Espoo, Vantaa, and Kauniainen, has a population of approximately 1.2 million inhabitants (Statistics Finland, 2023). This region features a diverse urban landscape with a mix of dense and sparse urban fabric and extensive green and blue spaces, including parks, forests, community gardens, and coastal waterways. Helsinki, the capital city, is notable for its well-maintained UGI, integrating parks, forested areas, and coastal features.

The PPGIS data were collected through a map-based online survey between August and September 2018 in the Helsinki Metropolitan Area. A random sample of 10,000 inhabitants living permanently in this area and aged 18–65 years was obtained from the Finnish Population Register Centre. The participants received a letter of invitation to participate in the online survey, followed by a reminder postcard.

The survey included sections on personal characteristics, self-rated

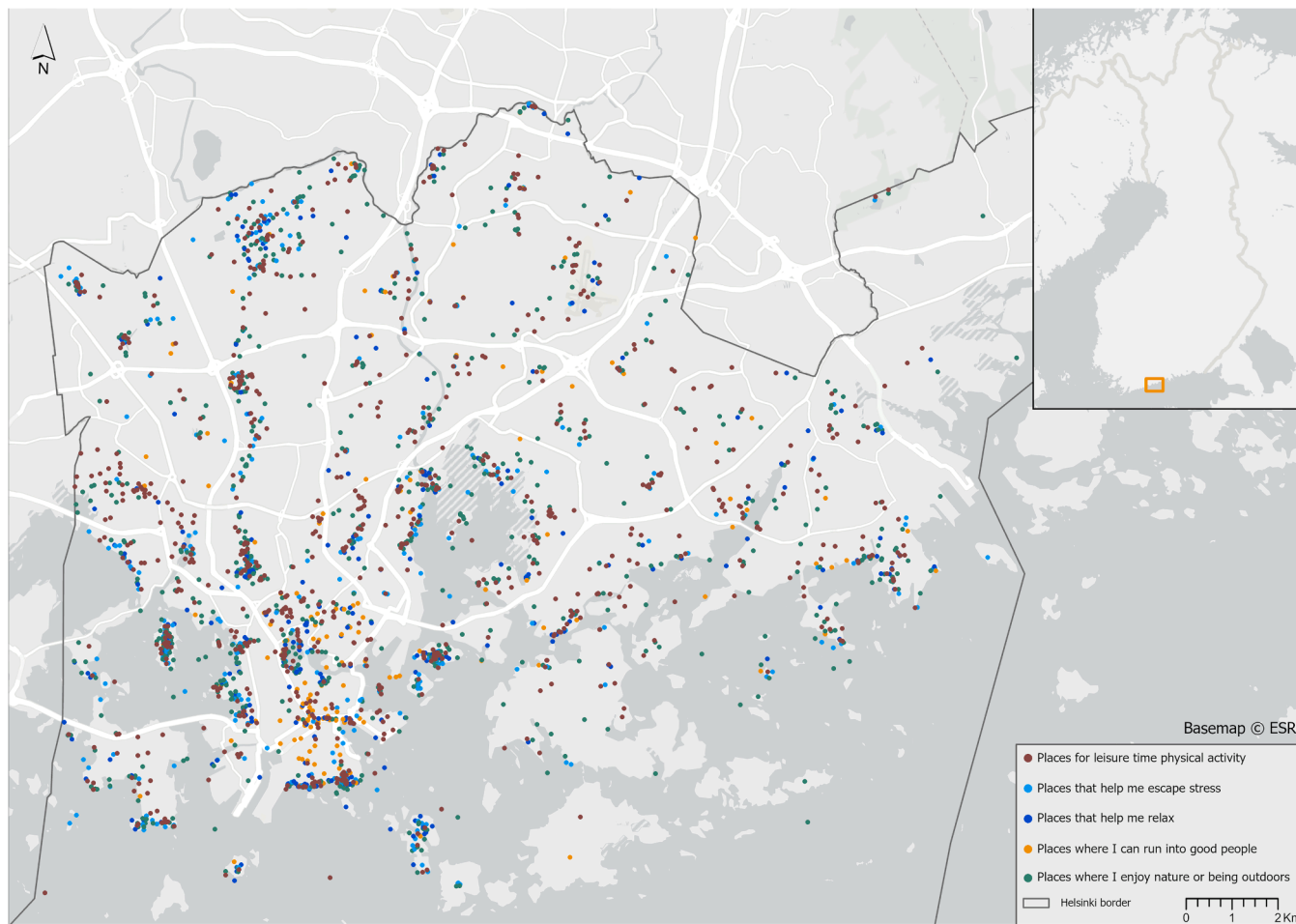


Fig. 1. 2470 locations mapped in the PPGIS survey for leisure-time physical activities in Helsinki area.

health, and physical activity behavior. This article focuses on analyzing the mapped leisure-time physical activities that respondents were asked to identify. Respondents were instructed to think of all the places that they frequently visit for leisure-time physical activity in the time of the year of the data collection and to locate them in the survey’s mapping view (Figure A.1). In addition, respondents were asked to map other leisure-time activities with social and restorative health benefits. These included six different activity types: places where I enjoy nature or being outdoors, places that help me escape stress, places where I spend time with family or friends, places where I enjoy urban life, places where I can run into good people, and places that help me relax. While overlaps exist among some activity types (e.g., nature enjoyment and stress relief), we retained all six categories to reflect the nuances in respondents’ self-reported motivations. These distinctions, though sometimes subtle,

align with prior PPGIS studies that emphasize capturing diverse experiential values even when they are conceptually related (Brown and Kyttä 2014; Kajosaari, 2024). After each mapped place followed additional questions asking further details about the place and whether it was an indoor or outdoor place.

The PPGIS data used in this study included leisure-time activities mapped by 838 respondents. Compared to the study population, female respondents (58 %, 50 % in the same age group in the study area) and respondents with higher levels of formal education (56 %, 37 % in the study area) were over-represented among the respondents. The respondents mapped on average 2.9 places for outdoor leisure-time activities, with the number of mappings placed by an individual respondent ranging from 1 to 18. Only the outdoor leisure-time activity places were considered in this study. Included data points are visualized

Table 1
PPGIS variables calculated for each outdoor leisure-time activity cluster (i.e., spatial cluster of PPGIS data).

Variable	Description	Interpretation
PointsM	Mean point density	Mean density of mapped places (number of points per 200 m x 200 m grid cell, i.e. per 4 ha)
Leisure_PA	Leisure time physical activity	Places for leisure time physical activity (% of all points in the cluster)
Esc_stress	Escape stress	Places that help me escape stress (% of all points in the cluster)
Relax	Relaxation	Places that help me relax (% of all points in the cluster)
Good_ppl	Run into good people	Places where I can run into good people (% of all points in the cluster)
Nature_Otd	Enjoy nature or being outdoors	Places where I enjoy nature or being outdoors (% of all points in the cluster)

in Fig. 1, and a more detailed overview of the background information of participants included in the study is provided as appendix in Table A.1.

2.2. Mapping outdoor leisure-time activity clusters

To identify clusters in the spatial pattern of mapped outdoor leisure-time physical activities, we performed a clustering analysis. Activities classified as ‘personal’ (e.g., shopping, running errands, visiting services) or ‘urban’ (e.g., going to cafés, museums, or cultural events) were excluded, as these are less likely to reflect interactions with natural environments or green infrastructure, which were the focus of this study, leaving 2470 points for analysis. Using Hot Spot Analysis in ArcGIS Pro, we employed a fixed distance band of 200 m and a pixel size of 50 × 50 m. The 200 m threshold was chosen to balance sensitivity in detecting clusters across both dense and more dispersed green areas, following earlier PPGIS clustering work (Bagstad et al., 2017; De Valck et al., 2016). To ensure representation of clusters in sparsely populated areas, we applied different confidence intervals based on surrounding population density: $p < .15$ for sparsely populated areas and $p < .05$ for highly populated areas. This adaptive thresholding approach improves the robustness of cluster identification across heterogeneous urban environments. A minimum bounding convex hull delineated each cluster’s cells. The clusters were validated against satellite images and OpenStreetMap layers through visual inspection. For each cluster, we calculated the mean density of mapped outdoor leisure-time activities and the percentage of mapped places for each of the five activity types (Table 1).

2.3. Determining UGI characteristics

The characteristics of UGI in this study include both green and blue space attributes. The green space characteristics were primarily assessed through the structure of the tree canopy within each study area. ALS point clouds with a minimum density of 20 points per square meter were utilized to derive these characteristics. The ALS data, collected in 2018 by the City of Helsinki, were made available through an open-access online repository for geographical datasets (Helsinki Map service: <https://kartta.hel.fi>).

To analyze the canopy structure, we first generated canopy height models (CHMs) with a 0.5-meter resolution from the ALS point clouds for each leisure-time activity cluster. These CHMs were then smoothed using a Gaussian filter in the R software package ‘raster’, with a σ -value of 0.5 to enhance the delineation of larger, older trees (Tanhuanpää et al., 2019). The tree crown segments were delineated from the smoothed CHMs using watershed segmentation in ArcGIS Pro software.

After delineating the tree crowns, ALS point clouds were clipped to each crown segment using TerraScan software. This allowed for the calculation of tree-specific canopy characteristics, known as individual tree detection (ITD) features. Five ITD features were computed for each crown segment (Table 2): tree height (h99), density and height of the foliage (h10 and h50), crown area (CA), and crown volume (CV). Heights h10, h50, and h99 correspond to the heights at 10 %, 50 %, and 99 % of point accumulation, respectively. Feature h10 was used as a surrogate for visibility near the ground (eye level), and h50 for visibility higher in the canopy, indicating the sense of openness. Crown area and

volume were calculated using 2D and 3D convex hulls, respectively.

These ITD features were then aggregated to the leisure-time activity cluster level by calculating the sum, mean, minimum, maximum, and standard deviation for each feature. Sums were also normalized by the cluster area, resulting in a total of 30 cluster specific ITD metrics (Table A.2). These metrics describe the presence and abundance of large trees, visibility within the cluster, and the prevalence of the canopy. To consider the blue space attributes, open GIS datasets from the Finnish Environment Institute (www.syke.fi) were used. We calculated the minimum, maximum, and mean distances from each cluster to the nearest water elements, such as the sea and rivers, resulting in six blue space features (Table A.3).

Finally, the performance of these ITD features was compared against a commonly used greenness index, calculated as the percentage of green area within each outdoor leisure-time activity cluster using Corine land cover data downloaded from the Finnish Environment Institute (<https://land.copernicus.eu/en/products/corine-land-cover>). This comparison helped interpret the ALS-derived data in the context of traditional satellite-based greenness measures. The greenness measure was calculated using Corine land cover data (2018). Corine classes 6 (green urban areas) and 8 (forests) were considered as green land covers.

2.4. Random Forest regression

To assess the relative importance of ITD features and distances to water elements on leisure-time physical activities, we employed Random Forest regression. This approach enables us to identify which UGI characteristics are most influential in predicting the mapped leisure-time activities. We utilized the randomForest package in R for this analysis.

We configured the Random Forest model with the following parameters: for each split, five features were randomly sampled (parameter mtry), and 3000 trees were generated (parameter ntree). The relative importance of each feature was determined using the mean decrease in mean squared error (%IncMSE). To ensure robust results, we averaged the feature importance values over 100 iterations of the Random Forest model. The model was run using default parameters for mtry and ntree based on prior benchmarking for medium-sized ecological datasets. No additional tuning was applied, as the focus was on relative feature importance rather than predictive optimization. Assumptions and limitations of the RF method were considered, and variable importance scores were averaged across 100 iterations to ensure robustness.

We classified the UGI characteristics based on their relative importance scores. Features with importance values more than 2.58 standard deviations above the mean were classified as highly significant (99th percentile), while those with importance values more than 1.98 standard deviations above the mean were classified as significant (95th percentile). All other features were placed in a lower significance category. Our further analysis primarily focused on the top two categories of UGI characteristics.

As the greenness index is widely used to describe the extent of UGI, it was included to find dependencies with ITD features. Because the spatial resolution of satellite-data-based Corine land cover data is coarse

Table 2

Description of crown-level individual tree detection (ITD) features calculated for each crown segment in the airborne laser scanning (ALS) point cloud data of Helsinki.

Crown-level ALS feature	Description	ITD
h10	The height of 10 % point accumulation, m	A surrogate for visibility at human level
h50	The height of 50 % point accumulation, m	A surrogate for the sense of openness and space under the canopy
h99	The height of 99 % point accumulation, m	Tree height
CA	Crown Area, m ²	Crown cover of a single tree
CV	Crown Volume, m ³	Crown volume of a single tree

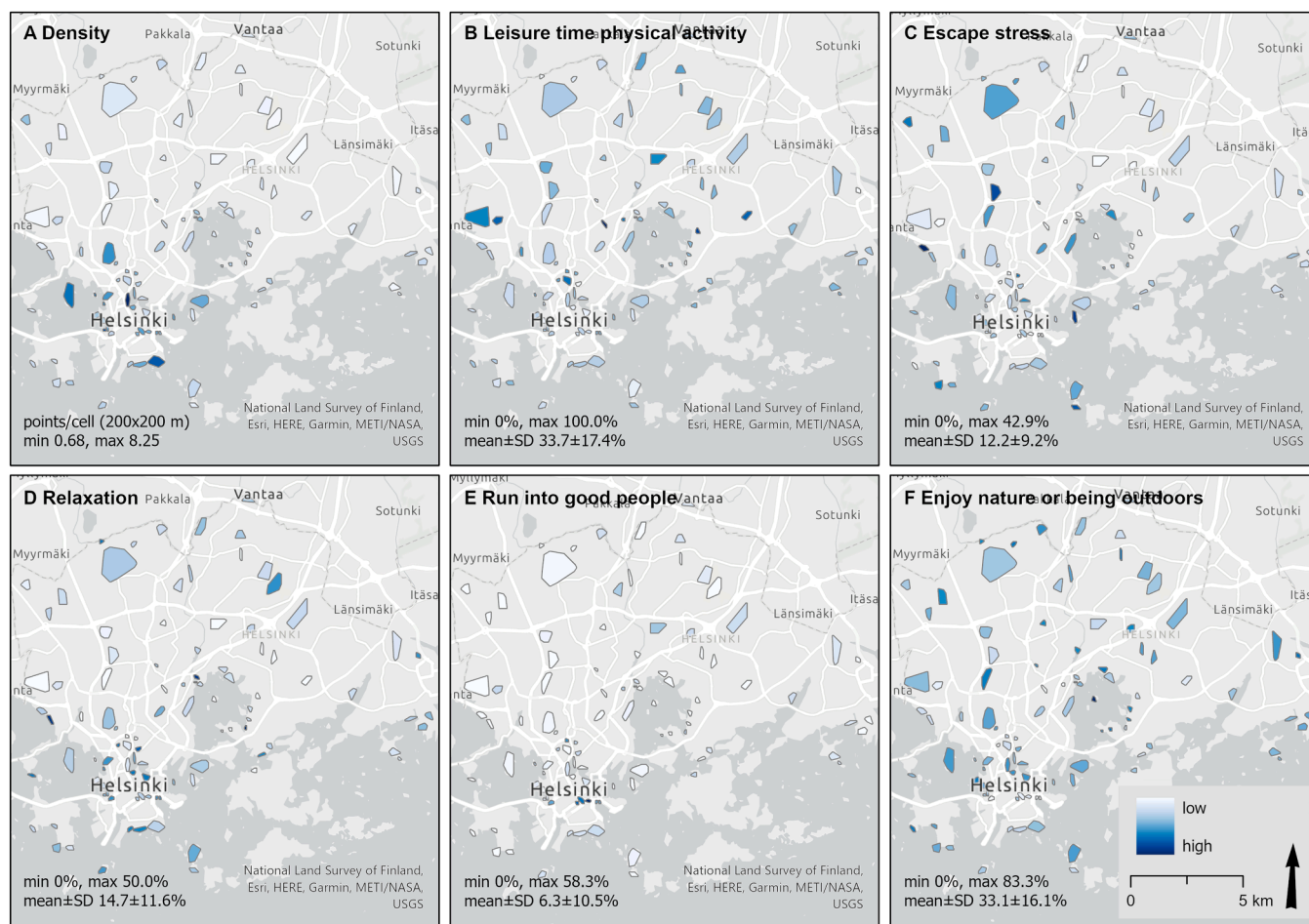


Fig. 2. Outdoor leisure-time activity clusters visualized with the mean density of mapped point locations (A) and the percentage of mapped places out of all mapped places in the cluster for each of the five activity types (B-F).

compared to ALS data, we did not expect high consistency but sought clear indications of which ALS-based ITD features best match the Corine data. The results of the Random Forest regression were also interpreted through visual inspection of the spatial data of the mapped outdoor leisure-time activities and their clusters against satellite images and OpenStreetMap layers.

In addition to feature-specific importances, we evaluated the overall goodness of fit for each Random Forest model using the pseudo R-squared value provided by the randomForest package. This metric estimates the proportion of variance explained by the model, offering insight into the predictive power of the UGI characteristics for each type of leisure-time physical activity.

3. Results

3.1. Leisure-time activities and their clusters in Helsinki

The PPGIS data covers the entire Helsinki area, with clear concentrations logically appearing around central areas characterized by higher population density and popular attractions. Notable examples include the forest park Keskuspuisto, the urban park by the sea in the city center named Kaivopuisto, and popular recreational islands such as Seurasaari and Mustikkamaa. Outdoor leisure-time activity clusters are also found close to or along rivers, although these areas show a lower density of mapped points. Our clustering analysis initially revealed 123 clusters. However, to ensure quality, clusters with fewer than five

mapped locations were removed or merged, resulting in a final count of 99 clusters (Fig. 2A).

Clusters for leisure-time physical activity (Leisure_PA) exhibit a dispersed pattern throughout the city (Fig. 2B). This activity type shows a high share of mapped sites within the clusters (mean ± SD: 33.7 ± 17.4 %) and is the only one among the six types to reach a 100 % relative share in any cluster. Notably, this occurs at a recreational forest in the city center that includes a children’s playground, community garden, and outdoor swimming pool.

Clusters that offer a high relative share of places for escaping stress (Esc_stress) are predominantly found in the large recreational forest

Table 3

Variance of PPGIS variables explained by UGI characteristics. Column rsq shows the pseudo-R-squared value for each PPGIS variable from the random forest models. Column mse shows the mean squared residuals, and mse_rel shows the mean squared error in relation to class mean value. Class mean shows the mean values for each PPGIS class.

PPGIS VARIABLE	RSQ	MSE	MSE_REL	CLASS_MEAN
PointsM	0.31	1.7	0.64	2.64
Leisure_PA	-0.11	334.4	9.92	33.69
Esc_stress	0.09	76.9	6.29	12.22
Relax	-0.01	135.9	9.25	14.70
Good_ppl	0.34	71.7	11.39	6.30
Nature_Otd	0.03	250.9	7.58	33.09

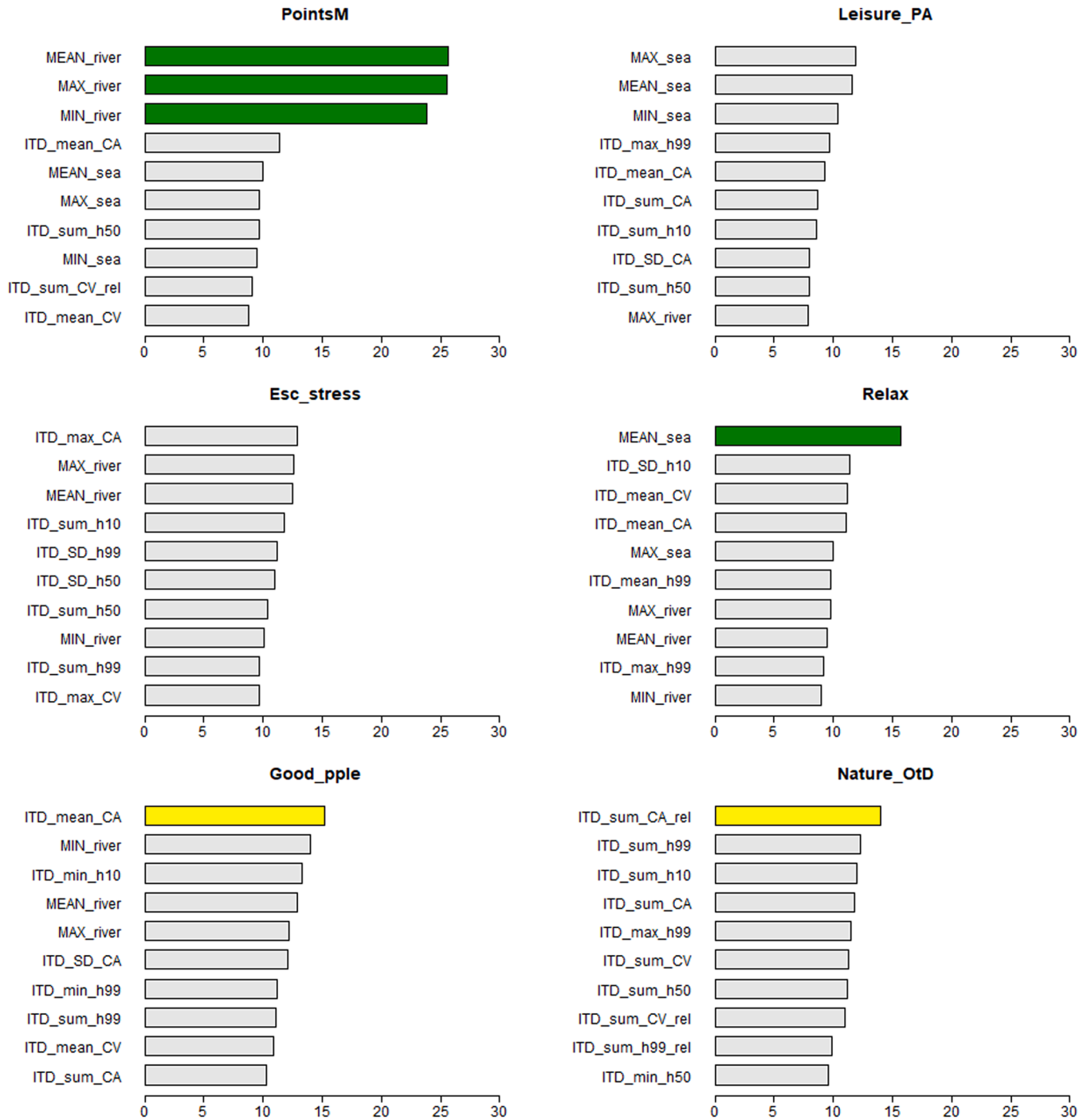


Fig. 3. Plots illustrating the relative importance of the ten most significant ITD and water features in the Random Forest analysis of PPGIS variables. The feature importances are presented on the X-axis, while the Y-axis defines the feature names. Green color indicates features with importance 2.58 SD above the class mean, yellow color indicates features with importance one SD above the class mean, and grey indicates all other features.

(Keskuspuisto) and in the expansive clusters in the northern parts of Helsinki, such as the largest cluster at Paloheinä (Fig. 2C). This area is the largest continuous forest in Helsinki, featuring a dense network of recreational routes. High-density clusters are also found by the sea or on the islands.

The highest relative share of mapped leisure-time activities related to relaxation (Relax) is located primarily along the seashore (Fig. 1D). These clusters are typically small and offer particular views towards the sea or over the city from high open cliffs.

Clusters related to running into good people (Good_pple) (Fig. 2E) have the lowest relative share of mapped places among all activity types (mean ± SD: 6.3 ± 10.5 %). These clusters are concentrated in downtown areas, which offer well-maintained green spaces, marketplaces, and proximity to the seashore.

Places used for leisure activities related to enjoying nature or being outdoors (Nature_Otd) show a dispersed pattern across Helsinki (Fig. 2F). Similar to physical activities (Fig. 2B), these sites have a high share of mapped locations in the clusters (mean ± SD: 33.1 ± 16.1 %), with a maximum of 83.3 % of points in a single cluster. Clusters with the highest share of mapped places are mostly unbuilt patches of nature.

3.2. Relative importance of UGI characteristics for clusters of leisure-time physical activities

The analysis of UGI characteristics revealed varying levels of importance across different leisure-time physical activities. Among the six variables calculated for each outdoor leisure-time activity cluster, only two, mean point density (PointsM) and places that offer encounters with good people (good_pple), showed a notable relationship with the ITD features and distances to water elements (Table 3). Specifically, 31 % and 34 % of the variance in these variables were explained, respectively.

Overall, six out of the 36 studied UGI characteristics stood out with statistical significance (Fig. 3, Table A.4). These included two ITD features: Average crown area (ITD_mean_CA) and Relative canopy cover (ITD_sum_CA_rel). Additionally, four features related to water bodies

were significant: minimum, maximum, and mean distances from river elements (MIN_river, MAX_river, and MEAN_river) and mean distance to the sea (MEAN_sea).

The variable mean point density (PointsM) demonstrated the second highest level of explained variance in the study. Unlike other PPGIS variables, it was influenced by three highly significant features, all related to distance to river elements (MEAN_river, MAX_river, MIN_river). These three ITD features had the highest significance levels within the study, with importance values all exceeding 23. Visual inspection confirmed that leisure-time activity clusters are often located close to or along rivers, despite these areas showing low mapped point density. The longitudinal shape of river features leads to several clusters forming along the rivers.

The variable denoting places related to running into good people (good_pple) showed the highest level of explained variance in the study, yet only one UGI characteristic, average crown area (ITD_mean_CA) reached the 95 % significance threshold. For this variable, ITD features outperformed those related to water elements. Visual interpretation indicated that high-density clusters often include single large trees and street trees, such as those along Helsinki’s main boulevard. However, the explained variance (34 %) was relatively low due to some high-density clusters lacking trees altogether, such as at the market square.

For the variable denoting relaxing places (Relax), the explained variance was minimal (1 %). While Mean distance to the sea (Mean_sea) reached the 95 % significance threshold in feature importance, this result should be interpreted with caution due to the model’s weak explanatory power.

Similarly, the variable for places to enjoy nature or being outdoors (Nature_Otd) had low explained variance (3 %), but one ITD feature, Relative canopy cover (ITD_sum_CA_rel), stood out. This feature describes canopy cover in relation to cluster area and reached the 95 % significance threshold. Visual analysis showed that clusters with a high share of nature enjoyment sites included areas with parks offering landscape views (e.g., Vuosaari) and dense urban forests (e.g., Tapanila sports center) or nature conservation areas (e.g., Lammasaari). Notably, in this class, ITD features were more significant than water

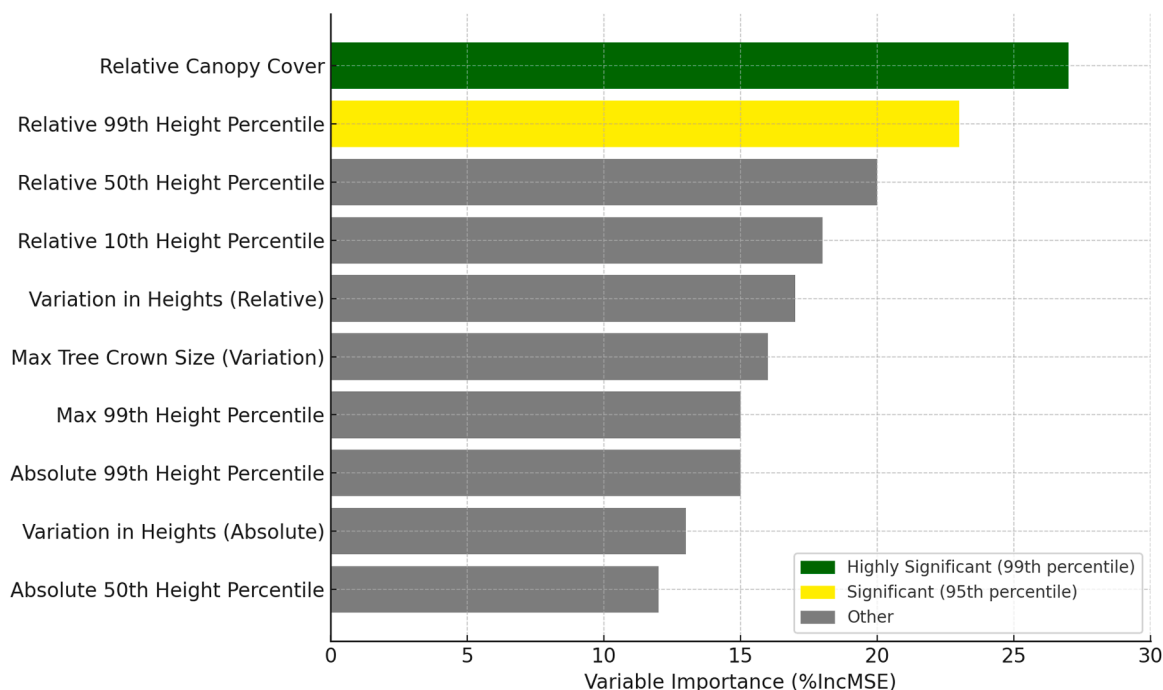


Fig. 4. Top 10 most important features from the Random Forest analysis of ALS-based structural greenness. Bars are colored by relative importance: green for highly significant predictors (≥ 2.58 SD above the mean), yellow for significant predictors (≥ 1.98 SD), and gray for all others.

features.

Variables representing places for leisure-time physical activity (Leisure_PA) and places for escaping stress (Esc_stress) showed low explained variance (-11 % and 9 %, respectively) and did not have any UGI characteristics that stood out statistically, as none of the features reached the 95 % significance threshold.

3.3. Relationship between ALS-based UGI and satellite-based greenness

The comparison between ALS-derived UGI characteristics and the satellite-based greenness index derived from land cover data revealed important insights into their relationship. The ALS-based ITD features explained 36 % of the variance in the greenness index, with a mean squared error of 594.5. The overall mean of the greenness index was 62.9. Although the explanatory power of the ITD features was relatively low, the analysis identified two features with a significant link to the greenness index: Relative canopy cover and the 99th height percentile. Relative canopy cover was the most significant feature, with an importance value of 27.96, followed by the 99th height percentile with an importance value of 24.67 (Fig. 4). Both features describe average values over the entire cluster, highlighting that the different sizes of clusters are treated equally, despite the high-resolution potential of ALS data. The maximum size of individual tree crowns was the most significant feature among tree-level attributes, with an importance value of 15.00. However, its significance was about half that of the best relative features, indicating that a detailed canopy structure plays a critical role in representing greenness.

4. Discussion

This study aimed to explore the potential of 3D geospatial data to explain the clustering of outdoor leisure-time activities of urban dwellers as mapped through PPGIS. The results indicate that while certain UGI characteristics have a significant association with these activities, the explanatory power of vegetation-related features alone is limited and lower than the water-related variables showed.

4.1. Significance of UGI characteristics

The analysis revealed that among the various UGI characteristics, only a few stood out with statistical significance. The ITD features, particularly Average crown area and Relative canopy cover, along with distances to water elements, showed notable importance. For instance, the mean point density of leisure-time activities in the clusters was significantly influenced by the proximity to river elements, highlighting the attractiveness of river-adjacent areas for leisure activities despite their low mapped point density. This finding is visually supported by the clustering of activities along rivers, which, due to their linear nature, naturally form multiple clusters. This result is consistent with a large body of literature highlighting the recreational significance of water bodies in urban settings (Völker and Kistemann, 2011).

The feature denoting places related to running into good people showed the highest explained variance (34 %), with average crown area being the most significant predictor. This suggests that large trees and well-maintained green spaces in downtown areas, such as those along Helsinki's main boulevard, are key social gathering points. However, the variance explained by this feature was lower due to some high-density clusters lacking trees entirely, like the market square, indicating the influence of other urban elements (Hasanzadeh et al., 2021). This

supports the findings from earlier studies, who noted the aesthetic and recreational value of diverse vegetation and complex structures (Brown et al., 2014; Hasanzadeh et al., 2021; Rall et al., 2017).

For relaxing places, although the explained variance was minimal (1 %), the mean distance to the sea was significant. This underscores the importance of coastal views and proximity to water for relaxation (Regan and Horn, 2005). Similarly, places to enjoy nature or being outdoors had low explained variance (3 %), but relative canopy cover was a key feature. Clusters with high shares of nature-related activities included both urban parks with expansive views and dense forested areas, as well as isolated nature conservation zones (Tyrväinen et al., 2007).

Conversely, variables representing places for leisure-time physical activity and places for escaping stress showed low explained variance and did not have any UGI characteristics that were statistically significant. This suggests that these activities might be influenced more by other factors UGI characteristics. For example, Korpilo (2018) shows that physical activities in UGI relate to multi-purpose behavior that comprises of both a goal-oriented behavior such as reaching a destination (e.g. commuting or using recreational facilities) and a leisure-oriented behavior. Similarly, Baumeister et al. (2020) point to walking paths, sport facilities, historical sites and buildings, and cafe's having a clear effect on where people tend to spend their time.

4.2. Comparison with satellite-based greenness

The comparison underscores a key novelty of our study: while land cover data, such as Corine, is based solely on spectral features, ALS-based UGI features provide a structurally detailed, three-dimensional view of urban greenery—capturing vertical complexity and canopy characteristics that are otherwise invisible in 2D remote sensing data. This difference could for example mean that green components with low height can result in high spectral greenness, but low structural greenness derived from ALS data. In other words, short trees may look very green in satellite images because they reflect a lot of green light, but they don't add much to the 3D structure of the forest as seen by ALS. This may introduce biases to the analysis of potential effects of green areas on behavioral and experiential patterns.

This distinction highlights the important contribution of ALS data in capturing detailed canopy structure that is not evident from satellite imagery alone. The comparison results from our study highlight the complementary nature of these data sources. The ALS-based ITD features explained 36 % of the variance in the greenness index, with relative canopy cover and the 99th height percentile being the most significant predictors. This finding underscores the value of potentially integrating both data types to achieve a broader understanding of urban green spaces. ALS data provides detailed insights into the vertical structure of urban greenery, which enhances our understanding of urban green spaces beyond what is captured by traditional satellite imagery (Laatikainen et al., 2017).

4.3. Methodological consideration

Several methodological considerations are relevant to this study. Firstly, the focus was on ITD features derived from ALS data, excluding other potential area-based features. The relatively low goodness-of-fit indicators for vegetation and water-related features reflect the complexity of human behavior in urban environments, influenced by a myriad of factors beyond UGI characteristics. However, in this

methodologically oriented paper our interest was to focus on interpreting the relevance of the explaining variables.

In addition, several limitations—commonly encountered in PPGIS approaches—should be acknowledged. Respondents may have been influenced by accessibility, often mapping locations that were close to home or easily reachable rather than their ideal or most preferred places. This may reduce the explanatory power of spatial-environmental variables. Moreover, interpersonal differences in place preferences introduce additional variability, contributing to noise in the models. Some conceptual overlap between activity categories (e.g., relaxation, escaping stress, and enjoying nature) may also blur distinctions in mapped responses and weaken associations with specific environmental features. These are some of the well-known limitations of participatory approaches which could be explored more in future work.

Future research should consider a holistic approach, integrating socio-demographic data, built environment features, blue space heterogeneity and seasonal variations of greenery to better understand the dynamics of urban recreational behavior. Furthermore, expanding the sample size and geographic scope could provide more robust insights and validate the findings across different urban contexts. The broader applicability and replicability of our approach are influenced by the availability and cost of ALS data. While Finland provides high-resolution ALS datasets through open-access platforms, this is not yet the norm globally. In many countries, such data remains limited, restricted, or expensive to access, posing barriers to the adoption of similar methods—particularly in low-resource settings. However, as open data initiatives and national geospatial strategies advance, the availability of ALS data is likely to improve. Expanding access to such high-quality 3D geospatial data holds significant potential for supporting urban planning, environmental research, and public health efforts worldwide.

5. Conclusions

This study demonstrates the potential of 3D geospatial data in understanding UGI characteristics and their association with outdoor leisure-time activities. Integrating ALS-derived data with traditional satellite-based land cover data provides complementary insights, with ALS data offering detailed views of the vertical structure of urban greenery. Our key findings indicate that features like relative canopy cover and average crown area are significant in explaining people's leisure-time activity distribution, particularly for social interactions and nature enjoyment. Proximity to rivers and the sea also plays a crucial role, highlighting the importance of blue spaces for relaxation and recreational activities.

Although high-resolution 3D data provide precise measurements essential for understanding UGI's ecological and social functions, the relatively low explained variance for some leisure-time activities suggests that urban recreational behavior is influenced by a complex mix of factors. This underscores the need for a holistic approach in urban planning, integrating various data sources and considering a wide range of variables, explanatory machine learning methods such as boosted

Appendix

regression trees can be useful for this as shown by [Lehto et al. \(2024\)](#).

Practically, these findings offer insights for urban planners and policymakers. Enhancing canopy cover and accessibility to blue spaces can promote social interactions, relaxation, and physical activities, contributing to overall well-being. Future research should incorporate larger datasets, explore seasonal variations, and examine additional environmental and social factors to better understand urban recreational behavior and inform sustainable urban development. Additionally, employing longitudinal data in future studies could help infer causality more reliably.

CRedit authorship contribution statement

Topi Tanhuanpää: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Kamyar Hasanzadeh:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Anna Kajosaari:** Writing – review & editing, Formal analysis, Data curation, Conceptualization. **Tiina Rinne:** Writing – review & editing, Conceptualization. **Markus Holpainen:** Writing – review & editing, Conceptualization. **Marketta Kyttä:** Writing – review & editing, Conceptualization. **Nora Fagerholm:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization.

Author contributions

Original idea: N.F.
 Conceptualization: all
 Data collection: A.K., T.R., M.K.
 Analysis: T.T., K.H., N.F. A.K.
 Interpretation of results: N.F., T.T., K.H.
 Writing first draft: N.F., K.H., T.T.
 Revising manuscript: all

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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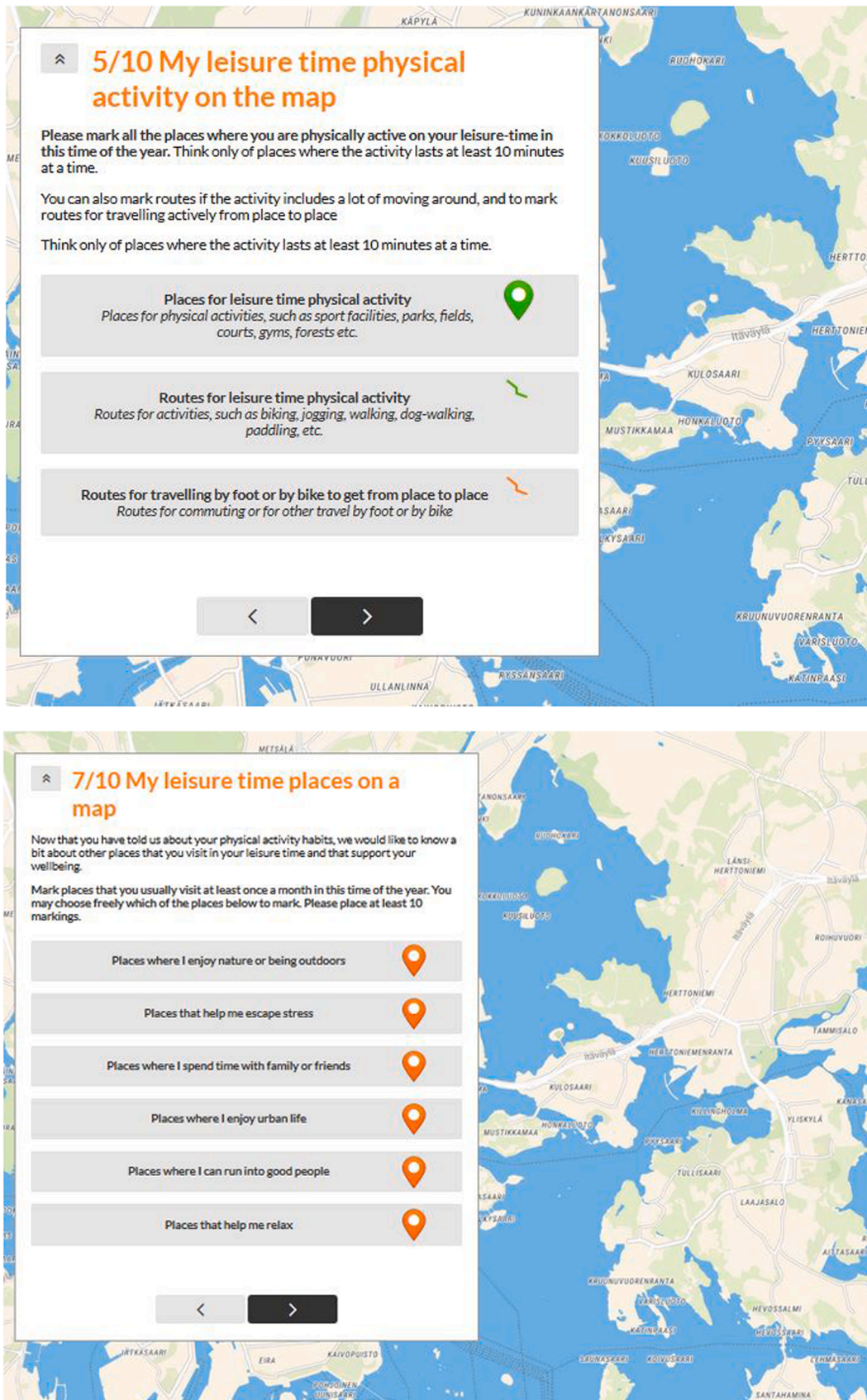


Figure A.1. Screen capture from the survey mapping pages for mapping leisure-time physical activities (survey page 5/10) and other leisure-time activities with social and restorative health benefits (survey page 7/10)

Table A1
 Socio-economic and demographic characteristics of the survey respondents (N 838)

	n	%
<i>Gender</i>		
Female	486	58.0
Male	339	40.4
Missing	13	1.6
<i>Age, in years</i>		
18–29	202	24.1
30–39	189	22.6
40–49	143	17.1
50–59	198	23.6
60–65	101	12.1
Missing	5	0.6
<i>Educational level</i>		
University degree ^a	465	55.5
Lower	301	35.9
Missing	72	8.6
<i>Employment status</i>		
Employed	534	63.7
Retired	48	5.7
Student	123	14.7
Unemployed	36	4.3
Other	28	3.3
Missing	69	8.2
<i>Household type</i>		
Household with children	237	28.3
Household without children	574	68.5
Missing	27	3.2

^a Including undergraduate, graduate and postgraduate degrees.

Table A.2
 Description and interpretation of crown-level ITD features calculated for each crown segment and generalized for each outdoor leisure-time activity cluster

Feature name	Feature description	Interpretation
ITD_sum_h10	Summed crown-level heights of 10 % ALS point accumulation, m	A general feature strongly related to free height in the canopy, i.e., visibility at ground level
ITD_sum_h10_rel	Summed crown-level heights of 10 % ALS point accumulation divided by the cluster area, m/ha	10 % visibility feature normalized with cluster size
ITD_mean_h10	Average height of 10 % ALS point accumulation at tree-level, m	Average height of good visibility at ground level
ITD_min_h10	Minimum height of 10 % ALS point accumulation at tree-level, m	Minimum height of good visibility at ground level
ITD_max_h10	Maximum height of 10 % ALS point accumulation at tree-level, m	Minimum height of good visibility at ground level
ITD_SD_h10	Standard deviation of heights of 10 % ALS point accumulation, m	Standard deviation of height of good visibility at ground level, i.e., visibility at ground level
ITD_sum_h50	Summed crown-level heights of 50 % ALS point accumulation, m	A general feature related to crown density in mid-canopy
ITD_sum_h50_rel	Summed crown-level heights of 50 % ALS point accumulation divided by the cluster area, m/ha	50 % visibility feature normalized with cluster size
ITD_mean_h50	Average height of 50 % ALS point accumulation at tree-level, m	Average height of good visibility in mid-canopy
ITD_min_h50	Minimum height of 50 % ALS point accumulation at tree-level, m	Minimum height of good visibility in mid-canopy
ITD_max_h50	Maximum height of 50 % ALS point accumulation at tree-level, m	Minimum height of good visibility in mid-canopy
ITD_SD_h50	Standard deviation of heights of 50 % ALS point accumulation, m	Standard deviation of height of good visibility in mid-canopy
ITD_sum_h99	Summed crown-level heights of 99 % ALS point accumulation, m	Total height of the trees, i.e., abundance of tall trees
ITD_sum_h99_rel	Summed crown-level heights of 99 % ALS point accumulation divided by the cluster area, m/ha	Total height of the trees per area, i.e., abundance of tall trees per area
ITD_mean_h99	Average height of 99 % ALS point accumulation at tree-level, m	Mean height of the trees within the cluster
ITD_min_h99	Minimum height of 99 % ALS point accumulation at tree-level, m	Height of the shortest tree within the cluster
ITD_max_h99	Maximum height of 99 % ALS point accumulation at tree-level, m	Height of the tallest tree within the cluster
ITD_SD_h99	Standard deviation of heights of 99 % ALS point accumulation, m	Variation in tree heights within the cluster
ITD_sum_CA	Summed crown-level crown areas within the cluster, m ²	Total canopy cover within the cluster
ITD_sum_CA_rel	Summed crown area within the cluster per area, m ² /ha	Canopy cover within the cluster per area
ITD_mean_CA	Average crown-level crown areas within the cluster, m ²	Crown area of an average tree within the cluster
ITD_min_CA	Minimum crown-level crown area within the cluster, m ²	Crown area of the smallest tree within the cluster
ITD_max_CA	Maximum crown-level crown area within the cluster, m ²	Crown area of the biggest tree within the cluster
ITD_SD_CA	Standard deviation of crown-level crown area within the cluster, m ²	Variation of crown areas within the cluster
ITD_sum_CV	Summed crown-level crown volume within the cluster, m ³	Total canopy volume within the cluster
ITD_min_CV	Summed crown-level crown volume within the cluster, m ³	Total canopy volume within the cluster
ITD_sum_CV_rel	Summed crown volume within the cluster per area, m ³ /ha	Canopy volume within the cluster per area
ITD_mean_CV	Average crown-level crown volume within the cluster, m ³	Crown volume of an average tree within the cluster
ITD_min_CV	Minimum crown-level crown volume within the cluster, m ³	Crown volume of the smallest tree within the cluster
ITD_max_CV	Maximum crown-level crown volume within the cluster, m ³	Crown volume of the biggest tree within the cluster
ITD_SD_CV	Standard deviation of crown-level crown volume within the cluster, m ³	Variation of crown volumes within the cluster

Table A.3

Blue space characteristics calculated from distances to sea and river elements for each leisure-time activity cluster

Feature name	Feature description
MIN_sea	Minimum distance from a cluster to the nearest sea element
MAX_sea	Maximum distance from a cluster to the nearest sea element
MEAN_sea	Mean distance within a cluster to the nearest sea element
MIN_river	Minimum distance from a cluster to the nearest river element
MAX_river	Maximum distance from a cluster to the nearest river element
MEAN_river	Mean distance within a cluster to the nearest river element

Table A.4

Class-specific importances of ITD and blue space features in RF analysis of PPGIS variables. Importance of ITD features against greenness index is presented in column Greenness

ITD-feature	PointsM	Leisure_PA	Esc_stress	Relax	Good_pple	Nature_Otd	Greenness
ITD_sum_h10	7.83	8.55	11.81	6.52	10.28	11.97	10.07
ITD_sum_h10_rel	5.29	6.19	7.92	6.17	3.90	7.84	17.73
ITD_min_h10	2.78	7.02	7.45	0.48	13.31	9.02	1.46
ITD_max_h10	1.24	7.17	8.61	8.47	3.63	7.88	4.5
ITD_mean_h10	6.93	3.71	7.38	4.79	7.08	9.07	4.19
ITD_SD_h10	2.83	4.35	6.58	11.38	5.06	6.79	6.63
ITD_sum_h50	9.67	7.96	10.38	7.96	10.31	11.19	12.45
ITD_sum_h50_rel	4.73	7.05	7.36	7.47	5.83	8.78	23.11
ITD_min_h50	1.84	7.12	5.69	1.01	7.51	9.57	6.61
ITD_max_h50	1.87	6.17	8.74	6.00	3.41	7.14	7.07
ITD_mean_h50	7.21	6.77	7.86	8.16	5.49	6.82	4.59
ITD_SD_h50	5.53	-0.46	10.97	3.66	6.68	3.81	8.24
ITD_sum_h99	8.47	7.91	9.69	7.38	11.04	12.28	13.53
ITD_sum_h99_rel	6.40	7.37	6.80	7.45	4.23	9.92	24.67
ITD_min_h99	0.30	4.64	5.65	1.98	11.19	7.04	5.18
ITD_max_h99	4.19	9.64	5.18	9.16	4.94	11.44	14.67
ITD_mean_h99	6.74	5.02	8.38	9.81	7.40	5.51	8.24
ITD_SD_h99	3.43	-0.31	11.20	4.15	4.35	1.98	5.17
ITD_sum_CA	5.67	8.69	8.44	5.67	10.33	11.74	11.84
ITD_sum_CA_rel	3.67	6.49	6.72	6.37	6.29	13.97	27.96
ITD_min_CA	6.30	3.91	4.24	2.68	6.15	4.79	7.94
ITD_max_CA	4.34	4.63	12.89	1.76	3.70	5.70	6.72
ITD_mean_CA	11.42	9.25	2.18	11.13	15.21	8.95	10.28
ITD_SD_CA	5.66	8.00	3.93	3.58	12.12	6.09	11.31
ITD_sum_CV	6.68	7.79	9.07	8.44	10.10	11.29	13.24
ITD_sum_CV	9.03	6.81	6.96	8.69	5.36	10.94	16.04
ITD_min_CV	5.13	3.39	1.43	5.27	5.30	4.21	8.67
ITD_max_CV	1.88	6.92	9.67	6.13	5.09	8.41	15
ITD_mean_CV	8.74	1.42	8.08	11.14	10.89	5.67	5.8
ITD_SD_CV	2.22	4.12	7.66	8.22	5.59	4.18	4.88
MIN_sea	9.44	10.35	2.91	5.37	8.94	2.67	—
MAX_sea	9.71	11.91	5.53	10.02	4.67	1.91	—
MEAN_sea	9.94	11.57	3.48	15.67	8.17	3.89	—
MIN_river	23.81	6.89	10.11	8.97	14.04	5.62	—
MAX_river	25.50	7.91	12.64	9.74	12.15	3.99	—
MEAN_river	25.59	7.80	12.45	9.52	12.91	4.38	—

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