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Predicting context-sensitive urban green space quality to support urban green infrastructure planning

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HIGHLIGHTS

- Study develops a model to predict perceived urban green space quality across the city.
- Urban green space quality was found to contribute significantly to explaining its use.
- Residential areas in the study area differed in their access to high-quality urban green space.
- Knowledge of green space quality is needed to support urban green infrastructure planning.

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ABSTRACT

Urban green spaces (UGSs) support human health and well-being in diverse ways. In addition to their availability and accessibility, also the quality of UGSs is relevant for understanding human-environment interactions between urban populations and their local UGS. However, data on UGS quality are rarely available with the geographic coverage required for spatial decision making and urban green infrastructure (UGI) planning and management.

This study uses data from a large-scale public participation GIS (PPGIS) survey to predict perceived UGS quality across the city of Espoo, Finland. The respondents (*n* 3,132) mapped over 8,500 frequently visited sites situated in UGSs. Generalized linear mixed models were used to study associations between the perceived place quality of the respondent-mapped sites and diverse objectively measured UGS characteristics. The presence of blue elements, high forest biodiversity, level of UGS maintenance, and low daytime noise exposure contributed to positive perceptions of UGS quality, while daytime noise exposure and decreasing UGS size were associated with negative perceptions.

The model was extrapolated spatially to predict perceived UGS quality across the entire city, revealing local differences in the accessibility of high-quality UGS. The results exemplify how both UGS quantity and quality are relevant for understanding the mechanisms leading to UGS visitation and the health and well-being benefits gained from UGS use and exposure. Moreover, the study demonstrates how UGS characteristics valued by the local population may be identified to support local UGI planning and management.

1. Introduction

Urban green spaces (UGSs) play a crucial role in facilitating human-environment interactions in urban contexts (Kabisch et al., 2015). Among multiple other societal and environmental benefits, UGSs support human health and well-being by providing opportunities for active recreation and play, building restorative capacities, supporting social and community well-being, and mitigating the negative health effects of noise, air pollution, and heat exposure (Lee & Maheswaran, 2011; Markevych et al., 2017). In addition, UGSs host a variety of

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ecosystem services with direct and indirect benefits for human well-being (van den Bosch & Ode, 2017).

In recent years, active efforts have been made to translate the growing evidence on the benefits of the blue-green infrastructure for human health and well-being into actionable planning guidelines. These include evidence-based recommendations for minimum standards on UGS provision and accessibility, such as the widely-adapted WHO recommendation of having a medium-sized UGS reachable within a 300-m walking distance (WHO, 2016). However, while quantitative metrics are well-available to support spatial decision-making, integrating knowledge of *green space quality* into these processes remains challenging. From an environmental health standpoint, the quality of UGSs encompasses diverse aspects of the environment that extend beyond the mere availability of these spaces and contribute to positive health and well-being effects (van Dillen et al., 2012).

The need for metrics capturing UGS quality has been repeatedly addressed in the environmental health literature, which has proposed that alongside quantity, the quality of the UGS is relevant for understanding the reasons for UGS use, its impact on human health and well-being (van den Berg et al., 2015; van Dillen et al., 2012; Lee & Maheswaran, 2011; Markevych et al., 2017; Nguyen et al., 2021; Vilcins et al., 2022; Akpinar, 2016; Francis et al., 2012), as well as for translating evidence into urban planning (Nieuwenhuijsen et al., 2017). Despite these calls, studies investigating the links between human health and exposure to green and blue spaces still predominantly operationalize UGS in quantitative terms by focusing on its provision and accessibility (van den Berg et al., 2015; Labib et al., 2020; Kimpton, 2017). Moreover, the need for understanding UGS quality is pronounced in cities that implement urban densification policies and, consequently, must balance diverse demands for UGSs with densification needs. Recent views regarding compact green cities have emphasized the provision of attractive and high-quality UGS over the mere amount or accessibility of green land use (Haaland & van den Bosch, 2015; Artmann et al., 2019; Littke, 2015). These views suggest that knowledge of the quality of UGSs is increasingly important in order to manage urban growth without losing quality green space as well as to promote equitable access to high-quality UGSs. Information on UGS quality is also needed to support urban green infrastructure (UGI) planning, i.e., strategic approaches to integrate the planning of green spaces and elements on different scales, from detailed infrastructure planning to planning of networks of green and blue infrastructure in local master planning (Davies & Lafortezza, 2017; Pauleit et al., 2019).

However, the inclusion of quality-based metrics in planning and research is complicated by the context-specificity of UGS quality (Bertram & Rehdanz, 2015) and the challenges in acquiring local place-based knowledge. Moreover, the definition of 'quality' varies across disciplines interested in green spaces (Taylor & Hochuli, 2017) and may refer to both subjective and objective views of quality (Vilcins et al., 2022; Fongar,et al., 2019). Subjective measures of UGS quality portray an individual's perception of the quality of an UGS or some of its aspects. These measures are typically obtained through resident and on-site surveys that focus on the perceived quality of a particular UGS or UGSs within a specific geographic area (e.g., Akpinar, 2016; Bertram & Rehdanz, 2015; Fongar, Aamodt, Randrup, & Solfjeld, 2019; Stessens, Canters, Huysmans, & Khan, 2020; Zhang, Tan, & Richards, 2021). While these data sources provide valuable local knowledge regarding UGS quality, they are resource-intensive to collect and typically have limited geographic coverage. Consequently, incorporating them into urban and regional-level spatial decision-making alongside other geospatial data sources with broader geographic coverage poses challenges.

By contrast, objective measures of UGS quality are typically derived from expert assessments of primary or secondary geospatial data (e.g., land cover data and vegetation indices based on active or passive remote sensing methods or data on the availability of diverse facilities and services) or in-situ audits for green space quality assessment (Knobel et al., 2019). These approaches provide extensive geographic coverage through diverse geospatial data sources and are commonly used in studies assessing the provision or accessibility of UGSs of varying quality in larger geographic areas. However, they are likely to overlook certain aspects of UGS quality valued by the local population, such as aesthetic or restorative value. This absence of context-specific measures may complicate the translation of research evidence into local UGI planning.

In recent years, diverse methodological approaches have been introduced for capturing context-specific correlates of UGS quality in a wider geographic context. Such methods include the extraction of UGS quality metrics from street view images (Li et al., 2015; Wang et al., 2021) and social media data (Brindley et al., 2019) as well as study designs combining both subjective and objective measures of UGS quality (Stessens et al., 2020). Moreover, the development of digital participatory mapping tools has expanded the use of place-based citizen knowledge in green space governance (Møller et al., 2019). Among such approaches, public participation GIS (PPGIS) tools (Brown & Kyttä, 2014, 2018) have provided a feasible way to collect local spatial knowledge produced by urban residents based on their expertise of their day-to-day environment. Typically used through online surveys, these tools enable the large-scale collection of participatory mapping data, such as diverse place-based experiences, values, and behaviors.

To date, PPGIS tools have been used in various fields for studying human interactions with green, blue, and natural environments. Applications include studies focusing on values attached to UGSs (Tyrväinen et al., 2007; Ives et al., 2017), patterns of UGS use (Brown et al., 2018; Ives et al., 2018; Bijker & Sijtsma, 2017; Korpilo et al., 2021; Pietrzyk-Kaszyńska et al., 2017; Fagerholm et al., 2022), and urban ecosystem services (Rall, Hansen, & Pauleit, 2019; Baumeister et al., 2020). From an analytical perspective, PPGIS data can be used to identify spatial trends, patterns, and dependencies in the mapped attributes. Moreover, the data may be extrapolated spatially to model and predict these trends in other places and contexts (Fagerholm et al., 2021). This approach has been notably explored by Samuelsson et al. (2018), who used PPGIS data to predict the probabilities of positive and negative environmental experiences in Stockholm.

1.1. Study aims

This study uses a large-scale, city-level PPGIS dataset to address the aforementioned methodological challenges in incorporating measures of perceived, locally valued UGS quality into UGI planning and environmental health research. The main aim of the study is to develop a city-level model for predicting perceived UGS quality by combining both subjective and objective measures. As a secondary aim, we will explore the useability of the predicted UGS quality measure from an environmental health perspective by testing its capability to explain UGS use.

These aims will be achieved by (1) using PPGIS data on UGS use and user perceptions to model the environmental correlates of perceived UGS quality in the study area, (2) employing the model results to predict UGS quality across the study area, and (3) testing if the predicted UGS quality in an individual's neighborhood contributes to explaining their UGS use in models accounting also for UGS provision. Last, we will discuss the applicability of city-wide metrics of perceived UGS quality in UGI planning.

2. Data and methods

2.1. Study area

The study area was limited to the City of Espoo located in South Finland (Fig. 1). With 297,000 inhabitants, Espoo is the second largest municipality in Finland and in the Helsinki Metropolitan Area (OSF, 2021). Espoo has a land area of 312 km^2 and a coastline with the Baltic Sea measuring 58 km (City of Espoo, 2023). Most of the population resides in the southern parts of the city (Fig. 1C), where the green–blue infrastructure is characterized by a mix of urban forests, maintained

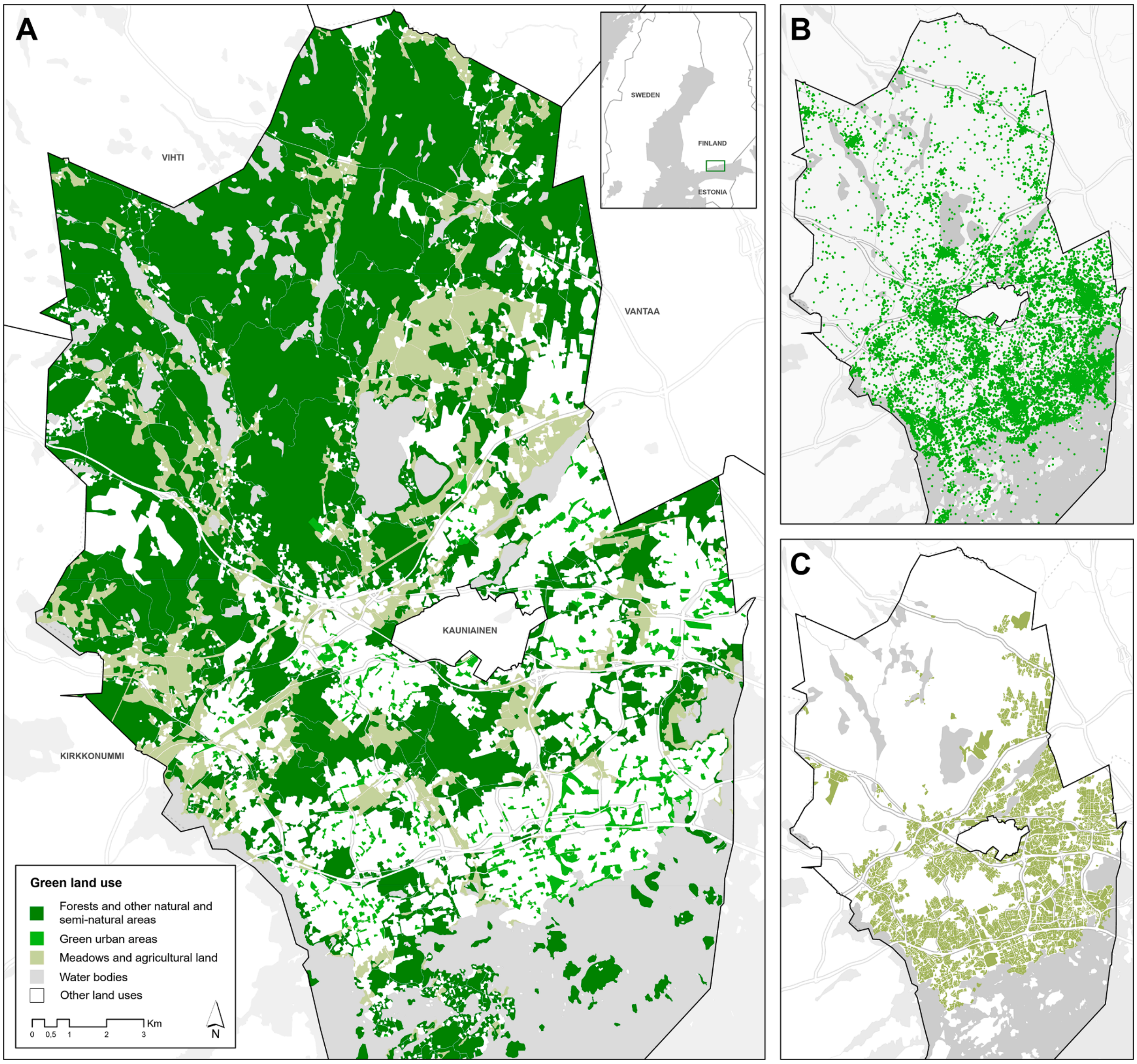

Fig. 1. A) Green land use in the study area. B) Distribution of respondent-mapped places. C) Residential land use in the study area. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

parks, and coastal areas (Fig. 1A). The city is facing population growth with the number of inhabitants expected to reach 340,000 by 2030 and 385,000 by 2040 (Greater Helsinki Open Statistical Databases, 2022). In 2019–2023, Espoo has committed to the aim of building 3,300 new dwellings per year (Ministry of the Environment, 2022).

2.2. Data collection

The data were collected with an online PPGIS survey directed for the adult inhabitants of Espoo. The data collection took place in September-October 2020 and was executed in collaboration with the City of Espoo. A random sample of 15,000 inhabitants aged 18 to 80 years and living permanently in Espoo was ordered from the Finnish Population Register Centre. These sample members received a letter of invitation to participate in the online survey, followed by a reminder postcard. The survey was also promoted as a municipal-level participatory planning process by the City of Espoo and was open to answer on the municipal website.

A total of 4,250 respondents participated in the survey. For the present study, the analysis was narrowed to the subset of 3,132 respondents who had mapped their residential location within the study area. The demographic and socio-economic characteristics of these respondents (Appendix A) were compared to corresponding data from the study population (OSF, 2020). Female participants and residents with higher levels of formal education were over-represented in the study sample. The geographic representativeness of the sample was satisfactory as the survey reached 1.2 to 3.4 percent of the adult population in all of Espoo postal code areas.

2.3. Mapping the use and perceived quality of urban green spaces

The respondents were requested to locate on a base map places that they visit in their day-to-day lives and places that they visit less often but that are otherwise meaningful to them. Each mapping task was accompanied by follow-up questions on the visiting frequency and the perceived quality of the place. Here, respondents were asked to indicate their overall perception of each mapped place ("how do you perceive this place?") on a scale from 0 (very negative) to 100 (very positive).

In this study, we defined an UGS as a publicly accessible open space characterized by green elements. Within these parameters, we considered spaces with both natural and more planned elements. Respondent-mapped places fitting these criteria were identified with the help of Urban Atlas land cover data (EEA, 2018) and land use data provided by the City of Espoo. Based on the recommendation of the World Health Organization (2016), Urban Atlas land cover data, particularly class 14100, "Green Urban Areas", provides a good basis for the identification of UGS. However, in the context of our study area, this category alone was not found sufficient to capture the recreational use of UGS. Following the typology of urban green infrastructure proposed by Pauleit et al. (2019), we extended the UGS typology to also include natural and agricultural land uses in the following Urban Atlas categories: meadows and agricultural land (classes 21000–25000) and natural and semi-natural environments (classes 31000–40000). Finally, these classes were supplemented with small-scale urban green space data from the City of Espoo to include smaller public UGSs classified in Urban Atlas data as residential or commercial areas.

Respondent-mapped points situated within the above land use categories were classified as points within UGS. Only points with valid information on perceived place quality were included in the analysis. Points situated in UGS but marked as indoor activities (e.g., shopping or childcare) were interpreted as potential mapping errors and were excluded from the analysis. Finally, distances between the mapped locations and respondent homes were calculated as network distance.

2.4. Measures

2.4.1. Perceived urban green space quality

In order to distinguish between UGS qualities that, on one hand, encourage their use and, on the other, act as deterring barriers for UGS use, we focus on the environmental correlates of positive and negative UGS quality separately. Moreover, as the values of respondent-mapped place quality were skewed towards the extremes of the scale and median (50) values, perceived UGS quality was examined as a categorical variable with the following values:

- *Positive perceived quality,* i.e., places with values of 51–100,
- *Neutral perceived quality,* i.e., places with a value of 50, and
- *Negative perceived quality,* i.e., places with values of 0–49.

2.4.2. Environmental variables

A range of environmental variables was tested to identify variables associated with perceived UGS quality in the study area. The included variables were chosen based on existing evidence on the diverse pathways between UGS exposure and human health and well-being (Markevych et al., 2017) and environmental correlates of perceived UGS quality identified in prior studies. Variables describing UGS size, shape, and service availability were included to represent UGS functionality and recreational opportunities. Drawing on evidence highlighting the positive effects of green space naturalness (Tyrväinen et al., 2014) and biodiversity (Cameron et al., 2020; Wood et al., 2018) on restorative benefits and positive emotional responses among UGS users, measures of forest biodiversity, tree volume and average age, and land cover type were included in the tested models. The influence of UGS cleanliness and maintenance on perceived quality (Bertram & Rehdanz, 2015; Stessens et al., 2020) was explored by including a variable representing UGS maintenance level. Following the evidence on the health and well-being benefits derived from exposure to blue spaces (Gascon et al., 2017; White et al., 2020; Foley & Kistemann, 2015), variables related to the proximity of the seashore and inland waters were tested. Last, variables describing the presence of diverse environmental stressors (e.g., exposure to noise, heavy traffic, or crowding) were included due to their expected detrimental influence on health and perceived UGS quality (Markevych et al., 2017; Stessens, et al., 2020). For continuous variables that did not conform to a normal distribution, logarithmic or exponential transformations were applied.

From these variables, those that contributed to the best model fits were selected for the final models. The complete list of tested variables is reported in Appendix B and the variables included in the final models are presented in Table 1.

2.5. Data analysis

2.5.1. Urban green space characteristics and perceived quality

Generalized linear mixed models were utilized to study associations between the environmental variables described in Section 2.4.2 and the categorical outcome variable of perceived UGS quality. To identify environmental features contributing to distinct positive and negative place experiences, category "neutral perceived quality" was treated as the reference category. As the unit of analysis was mapped places in UGSs, we expected the data to be clustered both on the spatial and individual levels (as the respondents could map multiple places). In order to account for spatial autocorrelation, spatial clusters of point data were identified and included as a categorical, clustering-level variable in the models. Spatial clusters were formed employing density-based clustering with a minimum of two points per cluster and a distance-band value of 124 m. This value was identified as a distance in which each point had at least one neighbor. Following these criteria, a total of 537 spatial clusters were identified. Points that did not belong to any spatial cluster (*n* 593) were treated as individual clusters. Clustering on the

Table 1
Environmental variables included in the final models.

Construct	Variable	Description	Data source
Expected positive association			
Functionality	UGS size	Size (m^2) of the green space the mapped place is located in (quartiles)	Urban Atlas 2018 (classes 14100, 21000–25000, 31000–40000) and City of Espoo (public green space within Urban Atlas 2018 classes 11100–11240 and 12100)
Proximity to blue spaces	Proximity to seashore	A four-class ordinal variable based on the shortest Euclidean distance (m) to the sea. Classes: ≥ 1,000 m; 300–1,000 m; 100–300 m; < 100 m	Shorelines 2020, The Finnish Environment Institute
	Proximity to inland water	Mapped place located within 50 m from a lake or river	Shorelines 2020, The Finnish Environment Institute
Naturalness	Forest biodiversity	Mean forest biodiversity value within a 100-m buffer. Based on species diversity, dead wood potential, and forestry operations. Exponential transformation	High biodiversity value forests 2018 (regional scale V4). The Finnish Environment Institute
Maintenance	Maintenance level	Mapped place is located in an actively maintained urban green space	City of Espoo 2020, RAMS-classification (R1-R3; A1-A3)
Expected negative association			
Exposure to environmental stressors	Daytime noise exposure	A three-class ordinal variable based on daytime road and rail traffic noise (LAeq 7am–10 pm). Classes: < 55 dB; 55–60 dB; > 60 dB	Traffic noise zones 2012, City of Espoo Environment Department
	Usage pressure (residential population)	Residential population living within a 300-m Euclidean distance from the mapped place (square-root transformed)	Population data 2021, Helsinki Region Environmental Services HSY

individual level did not significantly influence the model results but weakened the model fits. Thus, it was omitted from the final models (model results including clustering on individual level and covariates for gender, age, and education level are reported in Appendix C). All statistical analyses were performed with IBM Statistics SPSS v28 and spatial analyses with ESRI ArcGIS Pro 2.9.1.

Akaike Information Criterion (AIC) and multicollinearity diagnosis were employed to compare models and choose the ones that best fit the data. Environmental variables included in the final models are listed in Table 1 and their descriptive statistics in Appendix D. As prior studies have observed that green space values and perceptions differ on different spatial scales (e.g., Ives et al., 2018; Bijker & Sijtsma, 2017), we tested two separate models on the city and neighborhood levels. The full city-level model included all the mapped points regardless of their distance to respondent homes. By contrast, the neighborhood-level model included only points mapped within a 2-km network distance from the respondent's home. The choice of this threshold distance was motivated by prior results on the usual travel distances to UGSs in European cities (Schindler et al., 2022) and the travel distances observed in our data (see Section 3.1.).

2.5.2. Predicting perceived urban green space quality

Following a similar analytical approach as the one introduced by Samuelsson et al. (2018), the results of the city-level model were extrapolated over the entire study area. The environmental variables included in the final models were calculated for each cell of a 50 m x 50 m grid spanning the study area. Distances were calculated from the grid cell centroids. At the time of modeling, five percent of the original data (425 points) were left out of the analysis to be later used in model validation. The validation resulted in a 64 % match between the predicted and observed value suggesting a satisfactory accuracy (Moriasi et al., 2007). Subsequently, the model was applied on the grid cells to estimate the probabilities of positive and negative perceptions of UGS quality and predict the perceived UGS quality in each cell. This was done by calculating the predicted log odds from the regression model and then measuring the probabilities (P) of the target events (positive, negative, and neutral) as follows:

$$P = \frac{1}{1 + e^{-z}}$$

where Z is the predicted log odd which is the output of the model for the independent variables $x_1, \ldots x_n$.

2.5.3. Urban green space use

Finally, we examined if the predicted UGS quality near an individual's residential location contributed to explaining their actual use of neighborhood UGS. To achieve this, we conducted a series of binomial logistic regression models with variables calculated on varying neighborhood threshold distances (500-m, 1-km, and 2-km buffers around the respondent homes). The outcome variables were dichotomic variables indicating if the respondent had marked at least one UGS location within the respective neighborhood distance. The independent variables included a variable representing UGS availability (m^2) and variables describing the average probabilities of negative and positive UGS quality within the buffer. These probability variables were derived from the city-level model and were entered into the models converted to a scale ranging from 0 to 100. All models were controlled for respondent age, gender, and educational level.

3. Results

3.1. Descriptive results

The respondents mapped altogether 31,336 places (Fig. 1B) of which 8,517 were located within UGSs. The majority (64 %) of these places were perceived to have positive place quality (Table 2).

Respondent-mapped places in UGSs were most often located within a two-kilometer road and path network distance from home; after which, the number of mapped locations gradually declined (Fig. 2A). Over 50 percent of UGS visits (i.e., mapped places adjusted for the number of monthly visits) were located within two kilometers and 80 percent within five kilometers from respondent homes (Fig. 2B). Places with negatively perceived quality were located significantly closer to home than places with neutral (H = -3.82, $p < .001$) or positive perceived quality (H = -3.76, p = .001).

3.2. Associations between urban green space characteristics and perceived quality

Table 3 presents the associations between the studied environmental variables and the perceived quality of respondent-mapped places situated in UGSs. In the neighborhood-level model, the best model fit was achieved by including variables on noise exposure, forest biodiversity, and the number of people residing within 300-m buffer distance from the mapped location. No significant associations were observed between positive perceived quality and the studied environmental variables. However, negative perceived quality was associated with daytime noise exposure (OR 2.04, $p < .001$) and an increase in the number of people living within 300 m from the mapped location (OR 1.02, p = .034).

In the city-level model, the best model fit was found for a model including variables of noise exposure, distance to blue spaces, UGS maintenance level, UGS size, and forest biodiversity. In this model, significant associations were observed between the environmental variables and both positive and negative perceptions of UGS quality. Compared to the reference category of places with neutral perceived quality, places with positive perceived quality were more likely to be positively associated with proximity to the sea (OR 1.09, p = .004) or inland waters (OR 1.46, $p < .001$), forest biodiversity score (OR 1.22, p = .002), and UGS maintenance level (OR 1.20, p = .035), and negatively with daytime noise exposure (OR 0.89, p = .016). By contrast, the likelihood of negative place quality significantly increased with an increase in daytime noise exposure (OR 1.63, $p < .001$) and decrease in UGS size (OR 0.77, p = .002).

3.3. Predicted urban green space quality in the study area

Fig. 3A and 3B portray the predicted probabilities of positive and negative perceptions of UGS quality across the study area. Fig. 3C combines these values for an overall measure of predicted quality. The distribution of UGSs with predicted positive quality varies across the study area, with the highest probabilities of positive quality observed outside the main urban areas. In the more populated areas of south-east Espoo, high probabilities of positive UGS quality are found in UGSs

Table 2
Perceived quality and visiting frequency of places mapped in UGSs.

Perceived quality	n	%	Visits per month (mean)
City level [a]	8,517	100.0	5.82
Positive	5,455	64.0	5.61
Neutral	2,747	32.3	6.03
Negative	315	3.7	7.41
Neighborhood level [b]	2,440	100.0	11.50
Positive	1,555	63.7	11.13
Neutral	759	31.1	12.18
Negative	126	5.2	11.87

Note: The following estimates were used in calculating visiting frequency: "Daily or almost daily" = 25, "Once a week or more often = 7, "A few times a month" = 3, "Once a month" = 1, "Several times a year" = 0.25, "Once a year" = 0.08.
[a] Including all mapped points.
[b] Including points mapped within a 2-km network distance from the respondent's home.

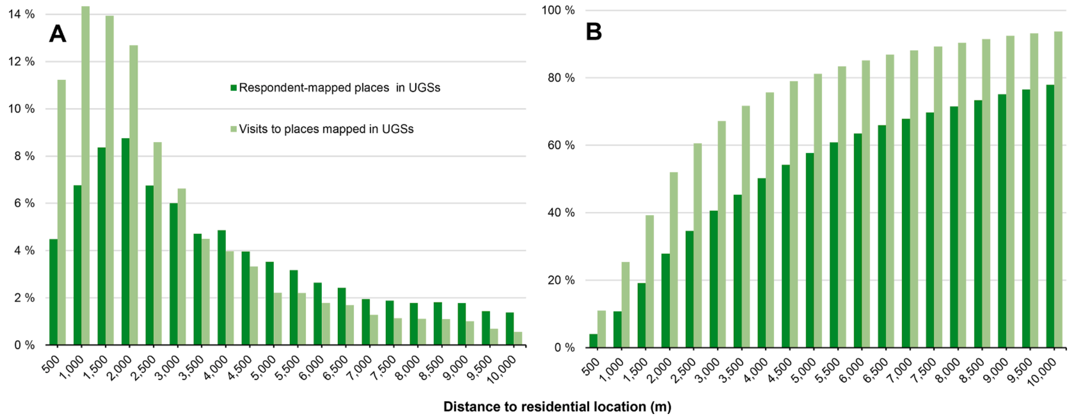

Fig. 2. Network distances between respondent homes and the mapped places. Distances by A) the share of visits to places mapped in UGSs, and B) the cumulative percentage of visits to places mapped in UGSs.

Table 3
City and neighborhood-level models on the associations between environmental variables and the perceived quality of respondent-mapped places located in UGSs. In both models, "neutral perceived quality" is used as the reference category.

Environmental variable	City level (*n* 8,517)						Neighborhood level (*n* 2,440)					
	Positive perceived quality			Negative perceived quality			Positive perceived quality			Negative perceived quality		
	OR	95 % CI	*p*-value	OR	95 % CI	*p*-value	OR	95 % CI	*p*-value	OR	95 % CI	*p*-value
Daytime noise exposure	**0.89**	**0.80–0.98**	0.016	**1.63**	**1.32–2.03**	<0.001	0.92	0.78–1.10	0.369	**2.04**	**1.42–2.92**	<0.001
Proximity to seashore	**1.09**	**1.03–1.16**	0.004	0.89	0.76–1.04	0.144	N/A			N/A		
Proximity to inland water	**1.46**	**1.21–1.76**	< 0.001	1.06	0.65–1.75	0.814	N/A			N/A		
Maintenance level	**1.20**	**1.01–1.42**	0.035	1.00	0.67–1.50	0.987	N/A			N/A		
UGS size	1.06	0.99–1.13	0.085	**0.77**	**0.65–0.91**	0.002	N/A			N/A		
Forest biodiversity	**1.22**	**1.08–1.37**	0.002	0.85	0.62–1.16	0.306	1.06	0.87–1.31	0.554	0.61	0.36–1.06	0.079
Usage pressure (residential population)	N/A			N/A			1.00	0.99–1.01	0.950	**1.02**	**1.01–1.05**	**0.034**

Note: CI Confidence interval. *p*-values below 0.05 have been bolded. Variables that were not included in the model have been marked as "not applicable" (N/A).

located near the sea and inland water bodies as well as in larger continuous UGSs.

Fig. 4 presents four maps that illustrate the availability of UGS in the residential areas of south-east Espoo. A comparison of distances to the nearest UGS ($\geq$0.5 ha) in residential areas shows that UGSs are generally well-accessible throughout the study area (Fig. 4A). However, residential areas differ in their access to UGSs with predicted positive quality (Fig. 4B). The longest distances to UGS with predicted positive quality are found in residential areas located in the immediate vicinity of highways or lacking close access to mid-sized or large UGSs. Fig. 4C and 4D show the average probabilities of positively and negatively perceived UGS within a 1-km buffer.

3.4. Associations between predicted urban green space quality and use

The inclusion of predicted UGS quality significantly improved the fit of regression models explaining the use of UGS within 500 m and one kilometer from respondent homes (Table 4). The fit of the model considering UGS availability within 500 m from home and the personal-level covariates significantly improved ($\chi2$ = 8.89, p =.003) when a variable representing negative UGS quality was added. This variable significantly decreased the likelihood of frequenting an UGS within a 500-m distance from home (OR 0.97, p =.003). Within the 1-km buffer distance, both the variables representing negative and positive UGS quality significantly improved the model fits ($\chi2$ = 6.45, p =.011 and $\chi2$ = 4.69, p =.032, respectively). Negative UGS quality reduced the likelihood of visiting an UGS within a 1-kilometer distance from home (OR 0.96, p =.011), while positive UGS quality increased the likelihood of such visits (OR 1.06, p =.032). Associations measured on the other threshold distances were not significant (reported in Appendix E).

4. Discussion

While indicators of ecological quality are often well available to support spatial decision making, information about the UGS qualities valued by the local populations are rarely available with the geographic coverage required for spatial decision making. This study has approached UGS quality from the perspective of local residents and identified the UGS characteristics valued by the study population. By combining geospatial and statistical analyses, we have inferred the environmental correlates of perceived green space quality from a large-scale participatory mapping dataset and extrapolated the results locally to assess the availability of high-quality UGS in the study area. Overall, our results show that understanding UGS quality may both explain UGS use and help to assess equity in access to high-quality UGS.

4.1. Environmental correlates of perceived urban green space quality

We tested diverse environmental variables to understand which UGS characteristics contributed to the perceived UGS quality among the local population. We found that different environmental features explained the likelihoods of positive and negative place experiences, suggesting that the relationships between UGS characteristics and its perceived quality are rarely linear. The only variable that shared a significant association with both positive and negative perceptions of UGS quality was daytime noise exposure. This finding suggests that noise not only increases the likelihood of negative perceived quality but also actively diminishes the likelihood of positive perceived quality. These results are consistent with existing evidence on the restorative benefits provided by undisturbed natural environments (Hartig et al., 2014) and the overall negative effects of noise exposure on health and well-being (Basner et al., 2014).

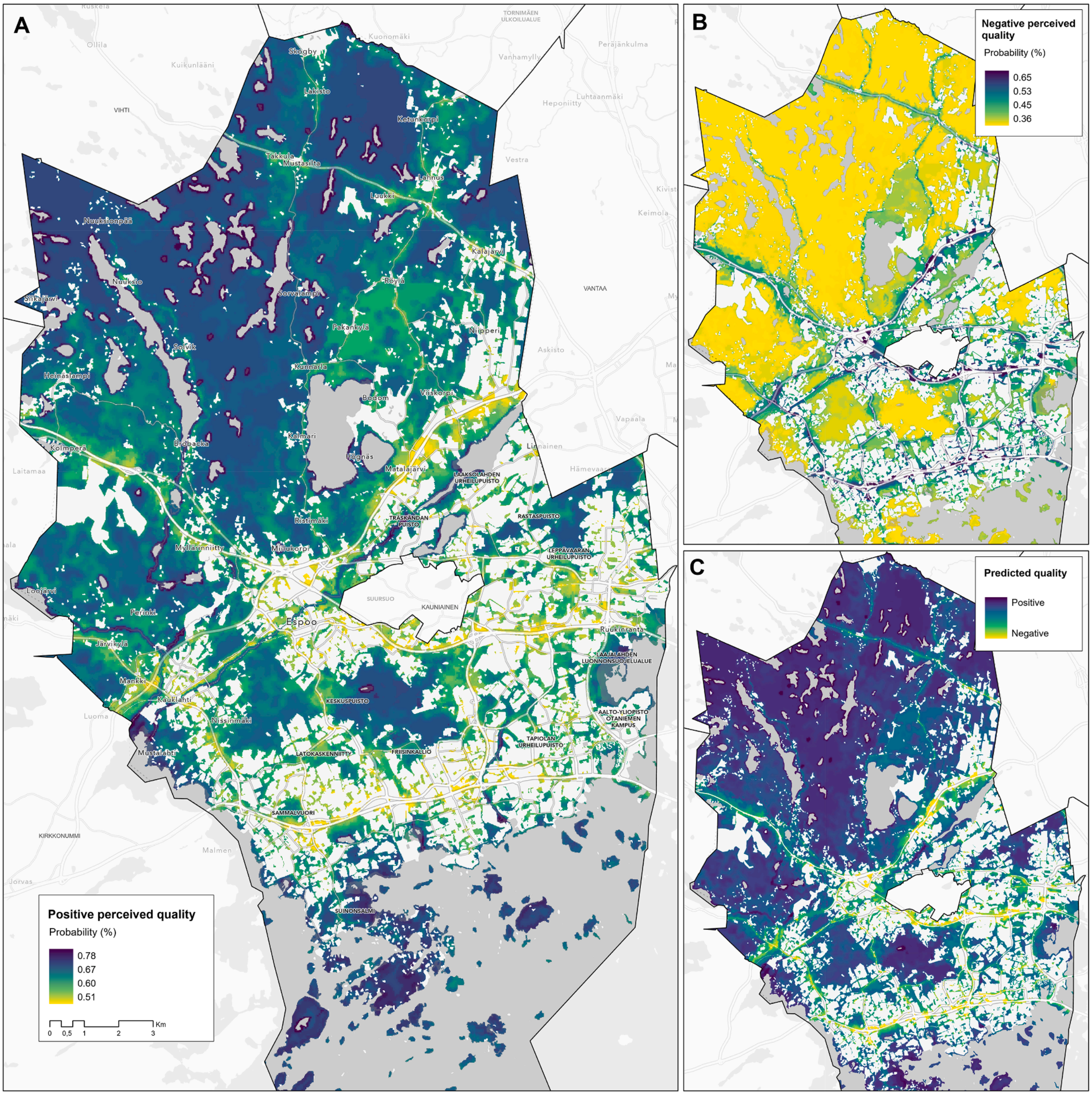

Fig. 3. Probabilities of positive perceptions of UGS quality (A), probabilities of negative perceptions of UGS quality (B), and a combined measure of predicted UGS quality (C) in the study area. For visualization, the maps have been interpolated with a 15-m cell size.

Moreover, the presence of several environmental features increased the likelihood of positive perceptions of UGS quality, yet their absence did not increase the likelihood of negative perceptions. Among such variables, the presence of blue elements and the level of forest biodiversity had a significant positive impact on perceived UGS quality. These connections are supported by the evidence on the beneficial impacts of exposure to blue spaces (Gascon et al., 2017; White et al., 2020) and natural green spaces (Hartig et al., 2014; Ode Sang et al., 2016; Wood et al., 2018) for mental and physical well-being. The positive influence of these variables on perceived UGS quality also persisted in the final models including UGS size, thus suggesting that natural elements can contribute to the quality of UGSs of all sizes.

However, the identified environmental correlates of UGS quality also extended to functional characteristics. Our results, which connect UGS maintenance level with positive perceptions of UGS quality, align with previous studies that have reported UGS cleanliness and maintenance to increase both the perceived quality of UGSs and their use (Bertram & Rehdanz, 2015; Stessens et al., 2020). Moreover, UGS size was associated with negatively perceived quality, and the direction of this relationship suggests that smaller UGSs are more susceptible to negative qualities than larger ones. From a functional perspective, larger UGSs may offer a higher diversity of activities (Brown et al., 2018; Giles-Corti et al., 2005) and more extensive trail and path networks. Larger UGS may also support higher biodiversity and contribute to the restorative benefits of UGS by offering a sense of being away, tranquility, and the feeling of being in nature (Wood et al., 2018). By contrast, smaller UGSs may offer specific statutory services and support social and community well-being especially in densely built urban environments (Peschardt et al., 2012). However, they are also susceptible to external disturbances such as noise, traffic, and crowding (Nordh & Østby, 2013), the presence of which may also explain the negative experiences associated with smaller UGSs in this study.

As prior studies have observed that green space values and perceptions vary on different spatial scales (Ives et al., 2018; Bijker & Sijtsma, 2017), we also tested a neighborhood-level model that included only respondent-mapped UGSs visited within a 2-km distance from their

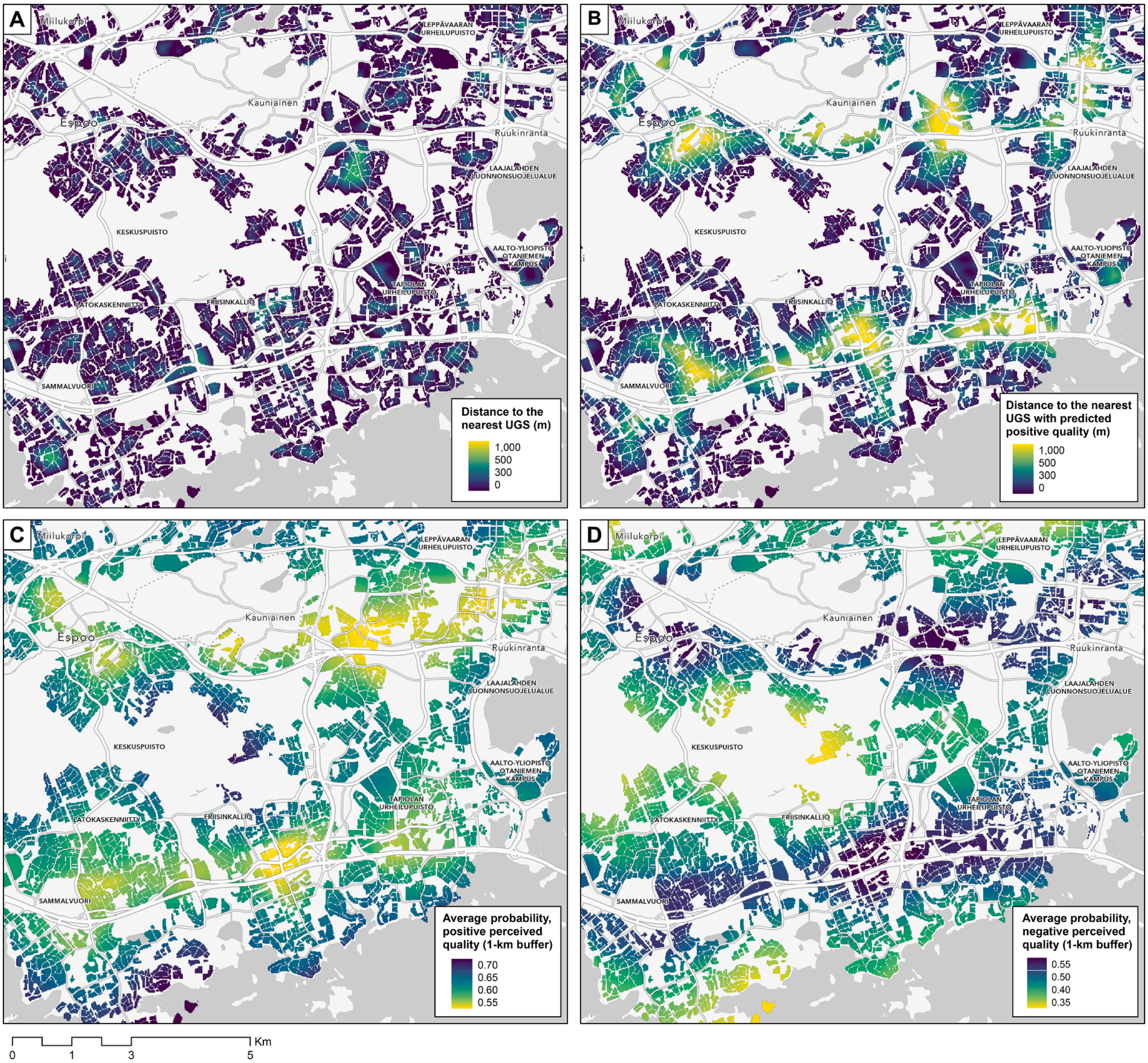

Fig. 4. UGS availability and quality in the residential areas of south-east Espoo. A) Distance (Euclidean) to the closest UGS (>0.5 ha). B) Distance (Euclidean) to the closest UGS (>0.5 ha) grid cell with predicted positive UGS quality. C) Average probability of positive UGS quality within a 1-km buffer. D) Average probability of negative UGS quality within a 1-km buffer. Maps covering the entire municipality are available as supplementary materials. All spatial analyses are based on the cell centroids of a 50 m x 50 m grid, thus excluding small UGSs that are not captured with a grid of this resolution. For visualization, the maps have been interpolated with a 15 m x 15 m cell size.

homes. However, while noise exposure and usage pressure were related to negative UGS quality, we identified no significant relationships between positive UGS quality and the neighborhood environment. We see two potential explanations for this observation. First, the environmental variables used in this study might not be sufficiently detailed to capture microscale UGS features (e.g., availability of walking paths or benches, presence of tree canopy, or other human-scale design elements) that contribute positively to the functionality and aesthetic value of a UGS and that may facilitate more statutory activities in the neighborhood environment. Second, based on the observed scale effects, it seems likely that place attachment, i.e., how strongly people feel a sense of connection to a particular place (Lewicka, 2011), may serve as a moderating factor between UGS characteristics and perceived UGS quality. While we did not measure the respondents' attachment to their residential environment, this hypothesis could be supported by the respondents' tendency to rate local UGS with varied environmental characteristics positively, regardless of whether they possessed qualities associated with positively perceived UGS quality in the city-level model.

4.2. Urban green space quality and use

The environmental health literature has consistently suggested that UGS quality plays an important role in understanding UGS use and, consequently, the health and well-being benefits derived from exposure to these environments (Lee & Maheswaran, 2011; Markevych et al., 2017; Nguyen et al., 2021). However, the empirical evidence on the health and well-being impacts of UGS quality remains inconclusive due to the low number of empirical studies (van den Berg et al., 2015; Labib et al., 2020). Addressing this knowledge gap, our study examined how perceived UGS quality influences UGS use.

In our study area, UGSs were visited most actively within two kilometers from respondents' homes, a distance aligning with threshold distances reported in previous European studies on UGS use (Schindler et al., 2022). However, positively perceived UGSs were, on average, visited further from home than negatively perceived ones, indicating a potential link between perceived quality and UGS use. Regression models exploring this relationship showed that models including a measure of predicted UGS quality explained the neighborhood use of

Table 4
Logistic regression models on the associations between UGS availability, perceived quality (city-level model), and use. In each model, the independent variables have been calculated within the corresponding buffer distance.

	An UGS visited within 500-m from home			An UGS visited within 1-km from home		
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
UGS availability (m^2)	1.00*** (1.00–1.01)	1.00*** (1.00–1.01)	1.00*** (1.00–1.01)	1.00*** (1.00–1.00)	1.00*** (1.00–1.00)	1.00*** (1.00–1.00)
Positive perceived quality (mean prob.)		1.03 (0.99–1.06)			1.06* (1.01–1.12)	
Negative perceived quality (mean prob.)			0.97** (0.95–0.99)			0.96* (0.93–0.99)
R-square (Nagelkerke)	0.026	0.028	0.031	0.071	0.074	0.075

Note: All models were controlled for gender (female / other vs. male), age (in years), and educational level (tertiary education vs. lower).
*** p <.001, ** p <.01, *p <.05. OR = Odds ratio. CI = Confidence interval.

UGSs significantly better than those considering only the amount of green land use. As expected, predicted negative quality lowered, while predicted positive quality increased the likelihoods of using neighborhood UGSs.

Overall, these results suggest that UGS quality both encourages UGS use within the neighborhood as well as provides a reason for travelling to UGSs located further from home. According to our results, high-quality UGS may facilitate the neighborhood use of UGSs, while negatively perceived UGS may act as a barrier for UGS use. These findings align with prior empirical studies suggesting that proximity alone does not explain UGS use (Schipperijn et al., 2010; Kaczynski et al., 2014) and that UGS quality plays a significant role in explaining spatial patterns of UGS visitation (Phillips et al., 2022; Schindler et al., 2022; Bijker & Sijtsma, 2017).

4.3. Implications for policy and practice

We identify three key implications for UGI planning and management. First, this study has proposed a novel analytical approach for incorporating knowledge of locally important UGS into UGI planning and management. As conflicting valuations of UGS can create tensions in land use planning and green space governance, approaches integrating citizens' experiential knowledge can help balance conflicts between locally important green space, densification needs, and ecological perspectives (Brown & Raymond, 2014; Kahila-Tani et al., 2016; Faehnle et al., 2014). The analytical approach of this study offers a potential method for integrating local citizen knowledge into municipal-level UGI planning alongside expert knowledge and objective geospatial data.

Second, based on the identified relationships between UGS quality and use, we recommend considering both UGS provision and quality when assessing spatial equity in UGS access. The analytical framework introduced here presents a potential approach for inferring local UGS quality from resident surveys (see also Stessens et al., 2020; Samuelsson et al., 2018) and assessing how UGS characteristics that are valued highly by the local population are distributed within the study area. In UGI planning, such context-sensitive metrics of perceived UGS quality could serve as planning support tools (Stessens et al., 2017; Stessens et al., 2020) or be incorporated into planning support systems. These metrics can be used to identify areas of high and low perceived UGS quality as well as to assess equitable access to these areas within the local population. This study has briefly exemplified such uses with a visual analysis of the availability of high-quality UGS within the study area. The results of this analysis show that, while the area meets the WHO recommendation of having a medium-sized (>0.5 ha) UGS reachable within a 300-m walking distance (WHO, 2016), neighborhoods within the study area differ in their access to high-quality UGS.

Finally, since different environmental correlates were identified for positively and negatively perceived UGSs, we suggest that these two quality aspects have partially separate implications for UGI planning and policy. While certain features of negatively perceived UGSs, such as their proximity to heavily trafficked roads and the resulting noise, are difficult to change, it is crucial to monitor their spatial distribution to prevent their concentration in specific residential areas. At the same time, identifying UGS characteristics linked to high perceived quality in the local context provides actionable information for UGI planning and management. Understanding the characteristics of locally valued UGSs can be used to improve their equitable accessibility and inform urban densification plans and policies. However, while indicators of UGS quality are needed to understand the city-wide distribution of UGS of varied quality, they alone are not sufficient to motivate specific UGI planning solutions. For instance, trade-offs between diverse environmental features that contribute to UGS quality, such as biodiversity levels and UGS maintenance, need to be addressed on a case-by-case basis. Additionally, further investigation is required to identify which environmental features influencing UGS quality can be realistically targeted on different levels of UGI planning.

4.4. Study strengths and limitations

The present study has certain strengths and limitations. A key strength of the study was the use of a large participatory mapping data set that adequately represented the study population and provided good geographic coverage of the study area. Moreover, the use of a digital participatory mapping method allowed us to collect place-based experiential data and thus to examine the perceived UGS quality in the actual UGS visited by residents in their day-to-day lives.

An evident limitation of the study is the adoption of a one-item indicator of perceived place quality. Other studies examining perceived UGS quality have used diverse approaches for measuring different aspects of UGS quality, such as employing multi-dimensional quality assessment tools (Knobel et al., 2019), focusing on multiple aspects of user preferences (Stessens et al., 2020), or measuring perceived sensory dimensions (Grahn & Stigsdotter, 2010). Incorporating such measures into participatory mapping approaches could provide a more nuanced understanding of UGS quality. Moreover, although this study explored a wide range of environmental variables, the measures used here were unable to capture certain aspects of UGS quality identified in prior qualitative studies. For example, negative aspects of the social environment (e.g., concerns for safety) or aesthetic quality of the green environment were not included. However, if available through expert audits or other sources of citizen-produced geoinformation, variables capturing these aspects could be incorporated into the models. Finally, our data focused on UGSs visited on purpose, thus excluding more incidental visits to green spaces, which may form a considerable portion of an individual's exposure to green environments (Beery et al., 2017; Mears et al., 2021) and should not be overlooked in attempting to understand UGS quality.

5. Conclusions

This study has introduced an analytical approach to predict perceived UGS quality across an urban area and discussed the potential use of such metrics to support UGI planning. In addition, the study provides two key empirical contributions. First, we have identified UGS characteristics that contribute to explaining perceived UGS quality. We found that proximity to blue spaces, high forest biodiversity, active UGS maintenance, and low daytime noise exposure contributed to positive experiences of UGS quality, while high daytime noise exposure and small UGS size increased the likelihood of negative experiences. As a second contribution, we have demonstrated that UGS quality contributes to explaining UGS use. This result suggests that knowledge of UGS quality, not only quantity, is needed to understand the pathways between UGS and human health and well-being. Based on these findings, we encourage the active development and utilization of UGS quality metrics in both UGI planning and environmental health research.

CRediT authorship contribution statement

Anna Kajosaari: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing - original draft. **Kamyar Hasanzadeh:** Formal analysis, Methodology, Writing - review & editing. **Nora Fagerholm:** Writing - review & editing. **Pilvi Nummi:** Writing - review & editing. **Paula Kuusisto-Hjort:** Writing - review & editing. **Marketta Kyttä:** Funding acquisition, Supervision, Writing - review & editing.

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.

Data availability

Data will be made available on request.

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Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2023.104952.

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