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Assessing the internal quality of PPGIS data: development and testing of a quality assessment framework

Anni Simola[a], Nora Fagerholm[a], Carolin Klonner[a] and Anna Kajosaari[b]

[a]Department of Geography and Geology, University of Turku, Finland; [b]Institute for Urban and Regional Research, Austrian Academy of Sciences, Vienna, Austria

ABSTRACT
Participatory mapping allows citizens to share place-based values with researchers and planning authorities. Public participation GIS (PPGIS), a common approach of participatory mapping, is used in land use planning to engage citizens via online map-based surveys. Despite known quality issues, the quality of PPGIS data is rarely systematically assessed. Since no guideline exists for assessing PPGIS data quality, we produced a quality assessment framework based on a review of academic literature, focusing on internal data quality. We propose key data quality criteria and measures for spatial PPGIS data. We tested the framework with three PPGIS datasets, finding that some criteria, such as geometric precision and spatial autocorrelation, are straightforward to assess, while others, for example thematic accuracy, could not be assessed due to the subjective nature of PPGIS data. Additionally, the selected PPGIS datasets lacked required information for assessing some criteria, for example mapping effort. Conventional geospatial data quality criteria were particularly challenging to assess, highlighting the need for PPGIS-specific alternative criteria. The proposed framework provides an important basis for establishing systematic quality assessment practices in the PPGIS field and increasing trust in PPGIS data. However, further testing of the framework with diverse PPGIS data is needed.

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1. Introduction

Geospatial data and maps are valuable for understanding the world and sparking discussion about the past, present and future of places. An enormous amount of data is produced in today's society, the majority of which is place-based due to advancing geospatial technologies. Data actively produced by the lay public is a growing source of information (Grêt-Regamey et al., 2021). Approaches by which citizens generate place-based data either digitally or with analogue methods, both individually and collectively, are referred to as "participatory mapping" (Brown & Kyttä, 2014). Participatory mapping is seen as a bridge between expert and citizen knowledge. It can help understand the world in ways that are not possible with traditional geospatial methods (Miller, 2020). In the field of participatory mapping, volunteered geographic information (VGI) refers to citizens collecting data based on contribution and communication of information, whereas public participation GIS (PPGIS) and participatory GIS (PGIS) are based on participation and refer to actively engaging citizens in research and spatial planning (Fagerholm et al., 2021). In this paper, we focus on PPGIS and define it according to Fagerholm et al. (2021) as an approach to understand place-based values, perceptions, behavior, and preferences for land use development, with online map-based surveys being the most common data collection method.

PPGIS methodologies have raised interest widely over the past two decades among research community and spatial planners interested in people's values and experiences linked to their everyday environments, as well as in mapping land use preferences in diverse contexts from urban to rural (Mohamed, 2025). To name a few examples, studies have investigated nature conservation values as input for land use planning (Brown & Reed, 2009; Solé et al., 2025), cultural ecosystem services (Rall et al., 2017; Ridding et al., 2018), and perceived accessibility and safety in the city (Laatikainen et al., 2017; Pánek et al., 2017). Additionally, researchers have developed ways to

CONTACT Anni Simola anni.i.simola@utu.fi
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analyze PPGIS data by exploring, explaining, and predicting (Fagerholm et al., 2021). Online map-based surveys are a widely used platform for PPGIS, as online surveys are easy to implement and can reach a large audience relatively quickly (Afzalan & Muller, 2018). Furthermore, a benefit of PPGIS is that citizens do not have to be in a certain place at a certain time to participate (Kantola et al., 2023). Popularity of digital participation platforms has increased, advancing the digitalization of participatory research and planning (Arku & Buttazzoni, 2025; Staffans et al., 2020). For example, a survey conducted in 2023 studied the use of digital participatory tools among Finnish municipalities (Kaskela, 2024). Two-thirds of the respondents reported having implemented online surveys for spatial planning, and PPGIS surveys are used in 43% of the responding municipalities. Recently, research has addressed the effective utilization of PPGIS methods, such as the usability of PPGIS tools (Ballatore et al., 2020), requirements for implementing PPGIS methods (Babelon et al., 2017), as well as the quality of participation processes (Hofmann et al., 2020). However, to date there are no established ways of systematically assessing the quality of PPGIS data mapped by participants to ensure that the data is a good fit for the intended use. This is a considerable restriction in the field.

PPGIS data typically consists of both spatial and non-spatial data collected through self-administered online surveys (Fagerholm et al., 2021). Spatial features may represent participants' place-based values, perceptions, behavior, or preferences. Non-spatial data is collected via open or structured survey questions and can include, for example, socio-economic-demographic characteristics or statements about well-being, value orientations or everyday life. Although digital tools allow effective data collection, sufficient data quality cannot be guaranteed, as the quality of the spatial features is often dependent on the skills, knowledge, and motivation of participants, as well as the survey design (e.g. Brown, 2012; Fagerholm et al., 2021; Ramírez Aranda et al., 2021). Traditional bio-physical geospatial data objectively representing the physical environment also contains uncertainties, but shortcomings in quality are often more obvious in citizen-based data and can weaken its reliability (Brown, 2012).

Geospatial data quality assessment is often anything but straightforward. According to Veregin (2005), quality assessment is conducted by evaluating the data against quality criteria; the most common criteria being accuracy, precision, consistency, and completeness. However, traditional quality criteria cannot always be applied to PPGIS data (Ramírez Aranda et al., 2021). Still, quality assessment is a key step in analyzing PPGIS data (Fagerholm et al., 2021). As the digitalization of participatory planning progresses and PPGIS methods have become more established, there is a need for a more effective utilization of PPGIS data, which can be promoted by systematic quality assessment. Assessing the quality of the spatial component of PPGIS data would help understand the uncertainties and characteristics of collected PPGIS datasets and thus increase trust in their use.

Currently, no comprehensive understanding exists of suitable criteria for the quality assessment of PPGIS data. A systematic guideline of quality assessment has been developed for crowdsourced geospatial data (Degrossi et al., 2018), but such a framework does not yet exist for PPGIS data. Some quality-related issues and quality indicators have been identified in the literature (e.g. Hosseini et al., 2024; Mohamed, 2025; Salminen et al., 2025), but the practices of quality assessment are still fragmented and lack standardized quality criteria, including established definitions and measures for them. To fill this knowledge gap, the main objective of this study is to produce a quality assessment framework, based on a literature review, which can be applied to assessing the internal quality of diverse PPGIS datasets after data collection and before data analysis. Internal quality refers to quality aspects independent of the context where data is used (Devillers et al., 2005). The main objective is divided into two sub-objectives:

(1) to identify key criteria defining the internal quality of PPGIS data and measures for assessing these criteria, and
(2) to test the applicability of the produced quality assessment framework with selected PPGIS datasets.

Based on the results, we discuss the applicability of the criteria as well as the potential and challenges of the framework, and consider how it can be further improved in future research.

2. Geospatial data quality

Quality of geospatial data refers to characteristics that describe the state of the dataset and allow users to evaluate its suitability for the desired purpose (Veregin, 2005). It also describes compliance with certain quality requirements. Imperfect representation of the real world is inherent to all geospatial data (Lush et al., 2012), so data quality assessment focuses on supporting data utilization despite uncertainties and shortcomings in quality (Devillers et al., 2007).

Data quality consists of internal and external quality. Internal quality refers to quality aspects independent of the use context of the data and is a result of data production methods (Devillers et al., 2005). The most common internal quality criteria applied to geospatial data include accuracy, precision, consistency, and completeness (de Smith et al., 2024; Veregin, 2005). According to Veregin (2005), accuracy denotes the lack of discrepancy between features in the data and the features' true values, and precision represents the level of detail that can be discerned in the data. Consistency represents the absence of contradictions, and completeness measures how well the data corresponds with all true features in terms of errors of omission (missing features) and commission (redundant features). Each can be assessed through the geometric, temporal, and thematic dimension, which refer to the location, recorded time, and attribute data, respectively. In the context of PPGIS data, we focus on assessing the internal quality based on how well the spatial data has been produced, that is, how well the spatial features have been mapped by participants. External quality refers to how well data meets user's needs in its specific context of use, referred to as fitness for use (Devillers et al., 2005). Understanding internal quality is necessary to examine external quality, so that users can evaluate if data quality is sufficient for desired use. Therefore, the concepts of internal and external quality are strongly interlinked, and external quality is considered broader than the internal one in terms of its scope.

To ensure the quality of geospatial data, international standards like the ISO 19157 have been developed by ISO, the International Organization for Standardization (ISO, 2013). The ISO 19157 standard defines six quality components: completeness, thematic accuracy, positional accuracy, logical consistency and temporal quality (internal quality) as well as usability (external quality). Internal quality components include measures for quality assessment, usually by comparison to ground truth (Mocnik et al., 2018). For example, completeness can be measured as the number of missing features and thematic accuracy as the number of incorrectly classified features (ISO, 2013). Usability does not have specific measures, as this component depends on the intended use of the data (Vullings et al., 2015).

As geospatial datasets are increasingly shared and repurposed, criteria included in the quality standards can help compare datasets and determine which one best meets quality requirements (ISO, 2013). Using high-quality input data makes geospatial analyses more reliable. In evidence-based decision-making, low-quality data can have negative impacts and even lead to unwanted social or economic consequences (Devillers et al., 2005). Awareness of shortcomings in data quality is therefore essential.

Some quality indicators have been applied to PPGIS data, although no quality standards have been adopted. One external quality aspect of PPGIS data that is often assessed is representativeness compared to target population (Brown & Kyttä, 2014). The population engaged in a PPGIS process can also affect internal data quality, specifically accuracy. A study by Brown (2012) showed a relationship between representativeness and geometric accuracy, where knowledgeable, voluntary participants map PPGIS features more accurately than the randomly selected public. This trade-off should be considered when choosing the sampling method for PPGIS data collection.

Another consideration before collecting PPGIS data is the type of information primarily needed, a large quantity of mapped features or qualitative descriptions of mapped places, since participants are often willing to provide one or the other (Fagerholm et al., 2021). Thus, the survey can be designed accordingly. Further, clear and intuitive survey structure and content are essential, as the mapping experience influences the mapping outcome and data quality. Mapping experience is also affected by choices related to scale, such as technical settings and cartographic representations in the survey (Kajosaari, 2024). Scale-related issues are reflected in internal data quality, especially accuracy and precision. Data quality and analysis possibilities can therefore be controlled already before data collection.

The most significant difference between PPGIS data and bio-physical geospatial data that affects quality assessment is the nature of the phenomena being mapped. Most PPGIS datasets represent subjective phenomena based on people's values and experiences. Due to the subjective nature of such data, internal quality criteria of bio-physical geospatial data cannot always be applied (Ramírez Aranda et al., 2021). Assessing the internal quality of intangible PPGIS features is particularly difficult. For example, determining the exact location of a peaceful landscape and the correctness of its placement may not be possible.

High-quality PPGIS data requires adequate participant knowledge of the mapped area (Brown & Kyttä, 2014). Additionally, map literacy and digital skills are found to influence internal quality (Brown & Kyttä, 2018; Ramírez Aranda et al., 2021). Low-quality PPGIS data consists of features mapped without enough time and effort, reflecting participants' low motivation (Brown & Kyttä, 2014). Generally, participants are more willing to put effort into mapping if they have a personal connection to the study area (Brown, 2012) or a strong opinion on the survey topic.

Although several factors affecting PPGIS data quality have been identified, as showcased above, quality assessment has not been systematic or followed specific criteria, similar to those of ISO standards. A framework of quality criteria and measures would assist in evaluating collected PPGIS datasets and support their use and analysis.

3. Data and methods

3.1. Literature review for the quality assessment framework

A literature review was conducted to identify key quality criteria, their dimensions when applicable, and their measures to represent internal quality of PPGIS data. For a comprehensive view of the research topic, three databases – Web of Science, Scopus and Google Scholar – were reviewed. Search terms were chosen to cover five key themes: sub-terms of participatory mapping, participatory processes, map surveys, geospatial data quality, and digitality (Table S1). The selection of these themes was based on the theoretical-methodological background of the topic, and the themes were decided among the authors. Alternative search terms were identified from keywords of participatory mapping literature. Although the focus was on PPGIS data, other sub-terms of participatory mapping were included, as different terms are occasionally associated with online map surveys.

Search queries were formed using Boolean operators (Table S2). The first query was used in all databases without specifying a temporal range. All results were reviewed, as they were few. The query was then extended with more keywords, yielding more results. A temporal range of 2010–2024 was applied for this search in Scopus and Google Scholar to identify the most relevant publications, as the number of results was large in these databases. No temporal range was applied in Web of Science, and all results were reviewed. In Scopus the first 100 and in Google Scholar the first 350 results were reviewed, after which no relevant results were found. Web of Science returned fewer but more relevant results, so one more search was conducted in this database, but only previously reviewed or irrelevant publications were found. All queries were conducted as All fields searches in April and May 2024.

The literature screening was done by the corresponding author. Screening began by reviewing titles and keywords and skimming through more ambiguous publications (Figure 1). The review was partly guided by the four previously introduced quality criteria – accuracy, precision, consistency and completeness.

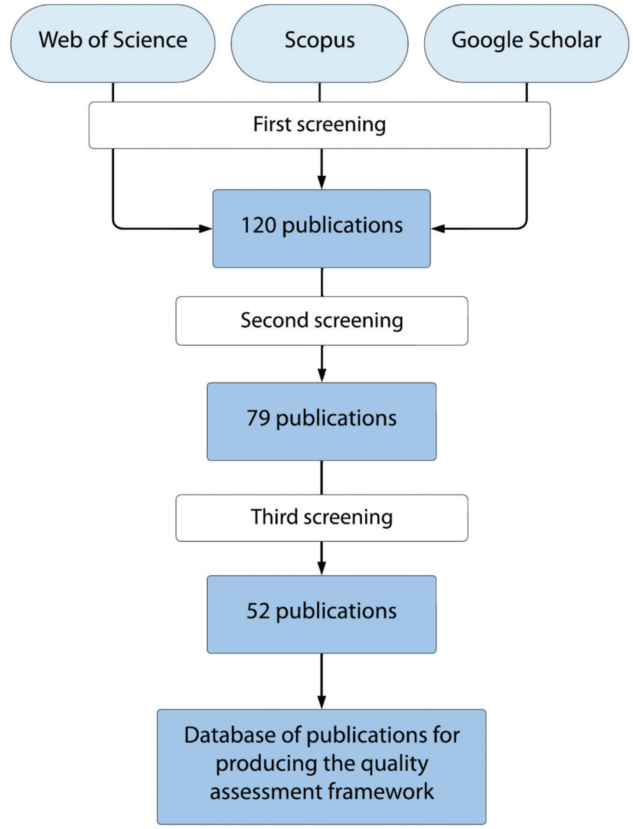

Figure 1. Flow chart of the literature review.

Publications addressing these criteria, including their dimensions, were broadly searched from participatory mapping literature. Further, criteria specific for PPGIS data were searched to make the framework better suited for PPGIS data. In the first screening, publications were selected if they addressed the internal quality of any participatory mapping data to some extent. Research on participatory mapping data quality is relatively limited, so publications were selected inclusively. Only English-language publications that had open access or could be accessed through the University of Turku library were included. Although Google Scholar also contains gray literature, the reviewed publications only include peer-reviewed literature.

In the first screening, 120 publications were selected and reviewed again in the second screening. Abstracts were read and full texts were examined, focusing on data and methods, results, and discussions. First, mentions of the four previously introduced quality criteria and their dimensions were searched. Second, other criteria describing the internal quality of PPGIS data were identified. In addition to the criteria and dimensions, publications were reviewed to identify measures for the addressed criteria and dimensions. Publications were selected if they focused on internal data quality, describing factors affecting it or conducting quality assessment.

Publications that only briefly mentioned data quality and did not allow for specific quality criteria to be deduced were excluded.

After the second screening, 79 publications remained. These were reviewed a third time to form a clear picture of the quality criteria and dimensions as well as their definitions and measures. Sections addressing data quality were read more thoroughly with the help of notes taken during the previous screening. Publications were selected if they clearly expressed internal data quality criteria and dimensions applicable for PPGIS data. Information was systematically recorded about the addressed quality criteria, dimensions, and measures. After the screenings, 52 publications remained.

Based on the reviewed publications, quality criteria and dimensions for the framework were identified. The framework includes mainly one quality measure per criterion or dimension, but the number of measures was not restricted, in case a criterion or its dimension has several equally important measures. Quality measures were primarily identified from the publications. In case a measure could not be identified from the publications, the measure was chosen based on well-known GIS methodology (e.g. de Smith et al., 2024) and applied for PPGIS data. While 52 publications were selected, 44 were used to compile the framework, as some did not ultimately add to the framework.

3.2. Testing the quality assessment framework

The framework was tested with selected existing PPGIS datasets to evaluate the suitability of the identified criteria for internal quality assessment of PPGIS data. Three datasets were chosen, and one geospatial data layer was selected from each (Table 1). All datasets have been collected in recent research projects applying PPGIS methods. The datasets were selected based on their geometry type (point, line, and polygon), as we aimed to test the applicability of the framework with diverse datasets with different types of features. Another criterion for selecting the datasets was that they cover different

Table 1. Background information on the selected datasets.

	Dataset 1 (Laatikainen & Kyttä, 2020)	Dataset 2 (Fagerholm, 2020)	Dataset 3 (Ramírez Aranda et al., 2020)
Survey name	Me and my everyday environment	Outdoor recreation in Turku	My Green Place
Research project	ActiveAge	GreenPlace	RECOMS
University and department	Aalto University, Department of Built Environment	University of Turku, Department of Geography and Geology	Ghent University, Department of Geography
Year of collection	2015	2020	2019–2020
Number of participants	1139	730	449
Phenomenon represented in the selected layer	Places frequently visited by older adults living in the Helsinki metropolitan area	Outdoor recreation routes of Turku residents and associated values and activities	Ghent residents' favorite green spaces and associated activities
Classification of the phenomenon	• Leisure and recreational places • Offices, bureaus, businesses • Outdoor and sports facilities • Shopping	• Beautiful place or scenery • Being outside • Biodiversity • Closeness to nature or nature itself • Closeness to water • Cultural or historical significance • Emotions, ideas and experiences triggered by the route • Enjoyable sounds or silence • Everyday connection • Hiking • Observing nature • Playing with children • Pleasant smells • Possibility to relax or freshen up • Religious or spiritual experience • Spending time with family or other people • Sports/Exercising • Walking • Walking a pet • Other	• Biking • Camping • Fishing • Gardening • Listening • Meditation • Meeting with friends • Paddling • Painting/drawing • Photography • Picnic/BBQ • Running • Sitting • Sporting • Swimming • Walking • Walking the dog • Other
Geometry of the selected layer	Point	Line	Polygon
Number of mapped features in the selected layer	5005	417	449
Geographical area	Helsinki metropolitan area, Finland (cities of Helsinki, Espoo and Vantaa)	City of Turku, Finland	City of Ghent, Belgium
Survey platform	Maptionnaire	Maptionnaire	PPGIS platform developed by Ghent University
Availability	Open access (Zenodo)	Open access (University of Turku Geospatial Data Service)	Open access (Zenodo)

thematic topics and geographical contexts. We aimed to assess typical PPGIS datasets collected to support planning, so a common trait of the datasets is that they represent subjective phenomena. All datasets have been published with open access.

The first dataset was collected in 2015 in the Helsinki metropolitan area, Finland, with a map survey called "Me and my everyday environment" (Laatikainen & Kyttä, 2020). It contains three point-data layers representing places that participants frequently visit, places where they feel happy, and locations of their residence. The layer of frequently visited places was selected for the quality assessment, since it has enough attribute data for evaluating the thematic quality dimension. The second dataset was collected in 2020 with a map survey called "Outdoor recreation in Turku" (Fagerholm, 2020). This survey gathered information on where and how residents of Turku, Finland, engaged in outdoor activities during and before the COVID-19 pandemic and how they perceive nature to impact their well-being. The two layers of the dataset represent participants' outdoor recreation places as points and routes as lines, along with values and activities associated with them. For the quality assessment, the linear layer was selected. The third dataset was collected in 2019–2020 in the city of Ghent, Belgium, with a map survey called "My Green Place" (Ramírez Aranda et al., 2020). This survey studied the favorite green spaces of Ghent residents as well as characteristics and cultural ecosystem services associated with them. The study produced point, line and polygon data, and the polygon layer was selected.

Quality assessment was conducted using QGIS and ArcGIS software as well as Excel spreadsheet program. In addition to the three PPGIS datasets, other geospatial data was used as reference data (Table S3). The exact assessment methods were selected case by case according to the criterion and data (see Tables S4-S6).

4. Results

4.1. The quality assessment framework and assessment workflow

The quality assessment framework was developed by identifying the quality criteria, some of which include quality dimensions, as well as the quality measures from literature. These form the core components of the framework. Additionally, we included example questions for each quality criterion or its dimension to guide the assessment. Example methods for assessing the criteria were also included. The terminology of the framework is explained in Table 2. In this section, we describe the identified quality criteria and dimensions and introduce a quality assessment workflow we propose for applying the framework.

Eleven criteria for internal quality of PPGIS data were identified from the literature to form the basis of the framework (Table 3). These include accuracy, precision, consistency and completeness and their dimensions. The definitions of these four criteria used in the framework were formulated based on common definitions used in GIScience (Veregin, 2005), and we ensured, based on the reviewed literature, that they align with how these terms have been used in the context of PPGIS and participatory mapping. One additional criterion was incorporated after reviewing the identified criteria among the authors, namely self-efficacy. This criterion was not identified from the literature, but authors have considered it important in their own empirical research, and therefore considered it a necessary addition to the framework. Three of the identified criteria – mapping effort, extreme mappers, and self-efficacy – are connected to participants' behavior during the mapping, so these were grouped as quality dimensions under one criterion, referred to as variation in mapping behavior. Ultimately, the framework includes 10 criteria, but 18 different quality aspects, meaning either criteria or their dimensions, can be assessed (Figure 2).

The framework includes a total of 20 quality measures, as geometric accuracy has three alternative measures (Table 3). When no quality measure was presented for a criterion in the publications found, the selected measure is based on common GIS methodology (e.g. de Smith et al., 2024) and applied for PPGIS data. If a criterion does not have quality dimensions, a measure directly for that criterion is presented. If a criterion has quality dimensions, measures are only presented for each dimension, not for the criterion. Assessment methods are based on the quality measures, and should be selected case by case depending on the

Table 2. Definitions for the terms used in the PPGIS data quality assessment framework.

Term used in the framework	Definition
Quality criterion	A criterion by which the quality of a dataset is judged.
Quality dimension	A sub-component of a quality criterion; a component of geospatial data quality that is assessed against the criterion.
Quality measure	An indicator for judging how well a dataset meets the quality criterion or its dimension.
Assessment method	GIS tool, analysis, calculation, or other means of assessing how well a dataset meets the quality criterion or its dimension.

Table 3. Produced PPGIS quality assessment framework. Criteria are presented in rows as headings. Under each criterion, the columns describe the quality dimensions (if applicable), definitions and example questions, quality measures, and example assessment methods.

Quality dimension	Definition with references + example of a question to be answered in the assessment	Quality measure(s) with references	Example assessment method
Accuracy			
Geometric	Discrepancy between the PPGIS feature and the true location of the feature being mapped (Brown & Pullar, 2012; Jankowski et al., 2016; Ramírez Aranda et al., 2021; Veregin, 2005) *How closely are the mapped places/routes/areas placed in relation to their true location?*	• Distance between the PPGIS feature and the true feature based on the place name given to the PPGIS feature (Aminpour et al., 2023; Bressan, 2021; Escobedo et al., 2022; Fatehian et al., 2018; Huck et al., 2014; Jankowski et al., 2016; Mahmoody-Vanolya & Jelokhani-Niaraki, 2023; Ricker et al., 2013) • Overlap with reference data (Brown, 2012; Cox et al., 2014; Haklay, 2010; Kulawiak et al., 2023) • Difference between PPGIS points and randomly placed points with statistical tests (Brown, 2012; Brown et al., 2015)	Calculating the average distance from vertices of a linear PPGIS feature to a reference feature
Temporal	Discrepancy between temporal information of the PPGIS feature and the true temporal value (Senaratne et al., 2017; Veregin, 2005) *Do the mapped land use changes have correct information of their time of occurrence?*	Difference between the recorded occurrence time for a PPGIS feature and the true occurrence time of the phenomenon	Calculating the time lag between the recorded time of the PPGIS feature and the true time
Thematic	Discrepancy between the PPGIS feature's attribute data and the feature's true attributes (Brown et al., 2015; Jankowski et al., 2016; McCall, 2006; Veregin, 2005) *Have participants given correct thematic attributes to the places/routes/areas they mapped?*	Proportion of PPGIS features with correct attribute values (Antoniou & Skopeliti, 2015)	Calculating agreement rate between the thematic attributes of PPGIS features and their true thematic attributes
Precision			
Geometric	Level of detail in placing a PPGIS feature (Brown & Pullar, 2012; Veregin, 2005) *Have participants zoomed in close enough when mapping the places/routes/areas for the features to be placed correctly?*	Proportion of PPGIS features with a sufficient zoom level, i.e. a sufficiently precise mapping scale (Brown et al., 2018; Brown, Kelly, et al., 2014; Brown, Schebella, et al., 2014; Brown & Brabyn, 2012; Brown & Fagerholm, 2015; Garcia-Martin et al., 2017; Pietilä & Fagerholm, 2016)	Calculating the proportion of PPGIS features in the data with a sufficient zoom level
Thematic	Level of detail in the categories of the PPGIS features (Brown & Fagerholm, 2015; Veregin, 2005) *How comprehensive and distinct are the thematic categories in the data?*	Difference between the classification of the PPGIS features and the true classification of the phenomenon in the study area	Identifying missing categories based on open responses of the PPGIS data
Consistency			
Geometric	Absence of contradictions between mutually exclusive PPGIS features (e.g. land use classes) (Antoniou & Skopeliti, 2015; Brown, 2013; Czepkiewicz et al., 2017; Veregin, 2005) *Do the mapped land use types contradictorily overlap with each other or real-world land use?*	Proportion of PPGIS features that do not conflict with each other or with reference data (Czepkiewicz et al., 2017; Jankowski et al., 2016)	Overlay analysis to identify PPGIS features that overlap with the real-world features
Temporal	Absence of contradictions in the recorded temporal data of PPGIS features (Brown et al., 2018; Veregin, 2005) *Does the time of occurrence of the mapped land use change contradict with the temporal range of the land use changes being studied?*	Difference between recorded temporal data and the true temporal range of the phenomenon according to reference data or expert knowledge	Calculating the proportion of features that fall within the valid temporal range
Thematic	Absence of contradictions and similarity in the attributes between PPGIS features (Antoniou & Skopeliti, 2015; Veregin, 2005) *Are the places/routes/areas mapped closely together similar in terms of their thematic attributes?*	Inconsistently classified PPGIS features compared to other features (Antoniou & Skopeliti, 2015)	Hot spot analysis + identifying PPGIS features that are classified differently than most features in clusters

(*Continued*)

Table 3. (Continued).

Quality dimension	Definition with references + example of a question to be answered in the assessment	Quality measure(s) with references	Example assessment method
Completeness			
Geometric	Relationship between PPGIS features and all true features, including both errors of omission (missing features) and errors of commission (redundant features) (Brown et al., 2015; Jackson et al., 2013; Senaratne et al., 2017; Veregin, 2005) *Are there any existing real-world green spaces missing from the PPGIS data, or any mapped green spaces that should not be in the data?*	Number of PPGIS features (Bayazidy et al., 2024; Brown et al., 2015; Levin et al., 2017; Rohrbach et al., 2016) or geometric properties, such as length or area (Antoniou & Skopeliti, 2015; Haklay, 2010), compared to reference data	Overlay analysis to compare the area covered by PPGIS features to the area covered by the real-world features
Thematic	Degree to which all required attributes are included in the data (Bijker & Sijtsma, 2017; Laatikainen et al., 2017; Veregin, 2005) *Has the participant answered to all questions in the survey regarding the mapped place/ route/area?*	Proportion of PPGIS features that include all attribute data	Calculating the proportion of PPGIS features that do not have any missing attribute values
Construct validity			
–	How well the PPGIS features represent the phenomenon that is studied (Czepkiewicz et al., 2017, 2018; Jankowski et al., 2016) *Has the desired green space been mapped in a place where it can truly be located?*	Proportion of PPGIS features that meet the needs of the study, e.g. a mapped future land use is not in an area where it already exists (Czepkiewicz et al., 2017; Jankowski et al., 2016)	Overlay analysis to identify PPGIS features that overlap with the real-world features
Variation in mapping behavior			
Mapping effort	The amount of physical and mental effort used for mapping, which is connected to mapping errors (Brown & Fagerholm, 2015; Brown et al., 2012) *Have participants spent enough time in mapping to produce reliable data?*	Elapsed time between placing the first and last PPGIS feature for each participant to determine the proportion of participants with enough time spent on mapping (Brown, 2017; Brown et al., 2012; Rzeszewski & Kotus, 2019; Wolf et al., 2018; Zolkafli et al., 2017)	Calculating the difference in time between placing the first and last PPGIS feature, and calculating the proportion of participants who spent enough time on mapping
Extreme mappers	One participant has mapped the same feature multiple times (Griffin & Jiao, 2019) *Are there multiple mapped parks in the data that represent the same real-world park and have been mapped by the same participant?*	Subjective evaluation of features mapped by potentially extreme mappers to detect outliers, based on features' placement and attribute data (Griffin & Jiao, 2019)	Reviewing the attribute data and placement of multiple features mapped by one participant to determine whether they overrepresent the same real-world feature
Self-efficacy	The participant's self-assessed probability that the PPGIS feature is mapped in the correct location *How reliable are the mapped places/routes/ areas in terms of the correctness of their location?*	Proportion of PPGIS features that are likely mapped correctly	Calculating the proportion of PPGIS features for which the probability of being mapped in the correct location is sufficiently high
Spatial autocorrelation			
–	Spatial distribution of the PPGIS features (Garcia-Martin et al., 2017; Pietilä & Fagerholm, 2016; Van Riper & Kyle, 2014) *Are the mapped outdoor recreation places clustered to identify patterns of outdoor recreation, or is their distribution random?*	Nearest neighbor index: if value is less than 1, the features are clustered, if value is more than 1, the features are randomly dispersed; clustering indicates good quality, as the features are not mapped randomly and patterns can be identified in the data (Pietilä & Fagerholm, 2016; Van Riper & Kyle, 2014)	Average nearest neighbor tool
Data quantity			
–	Sufficient number of PPGIS features to ensure the reliability of findings (Aminpour et al., 2023; Brown & Pullar, 2012; Brown et al., 2020) *Are there enough mapped green spaces to make reliable conclusions about which green spaces are important to residents?*	Number of PPGIS features in relation to the study area size	Calculating the density of PPGIS features in the study area
Mapped features in the study area			
–	Placement of PPGIS features in relation to the study area (Brown et al., 2012; Brown, Kelly, et al., 2014) *Are the mapped places/routes/areas located within the study area, so that they can be used for data analysis?*	Proportion of PPGIS features located within the study area (Brown et al., 2012; Brown, Kelly, et al., 2014; Johnson et al., 2024)	Overlay analysis with reference data representing the study area
Uniformity			
–	Similarity of geometry of linear or polygonal PPGIS features (Johnson et al., 2024) *Are there illogically mapped routes or areas in the data that are possibly erroneous?*	Proportion of linear or polygonal PPGIS features with abnormal geometric shapes (Hansen et al., 2021; Johnson et al., 2024)	Visual assessment of abnormal geometric shape or position of PPGIS features and calculating the proportion of abnormal features

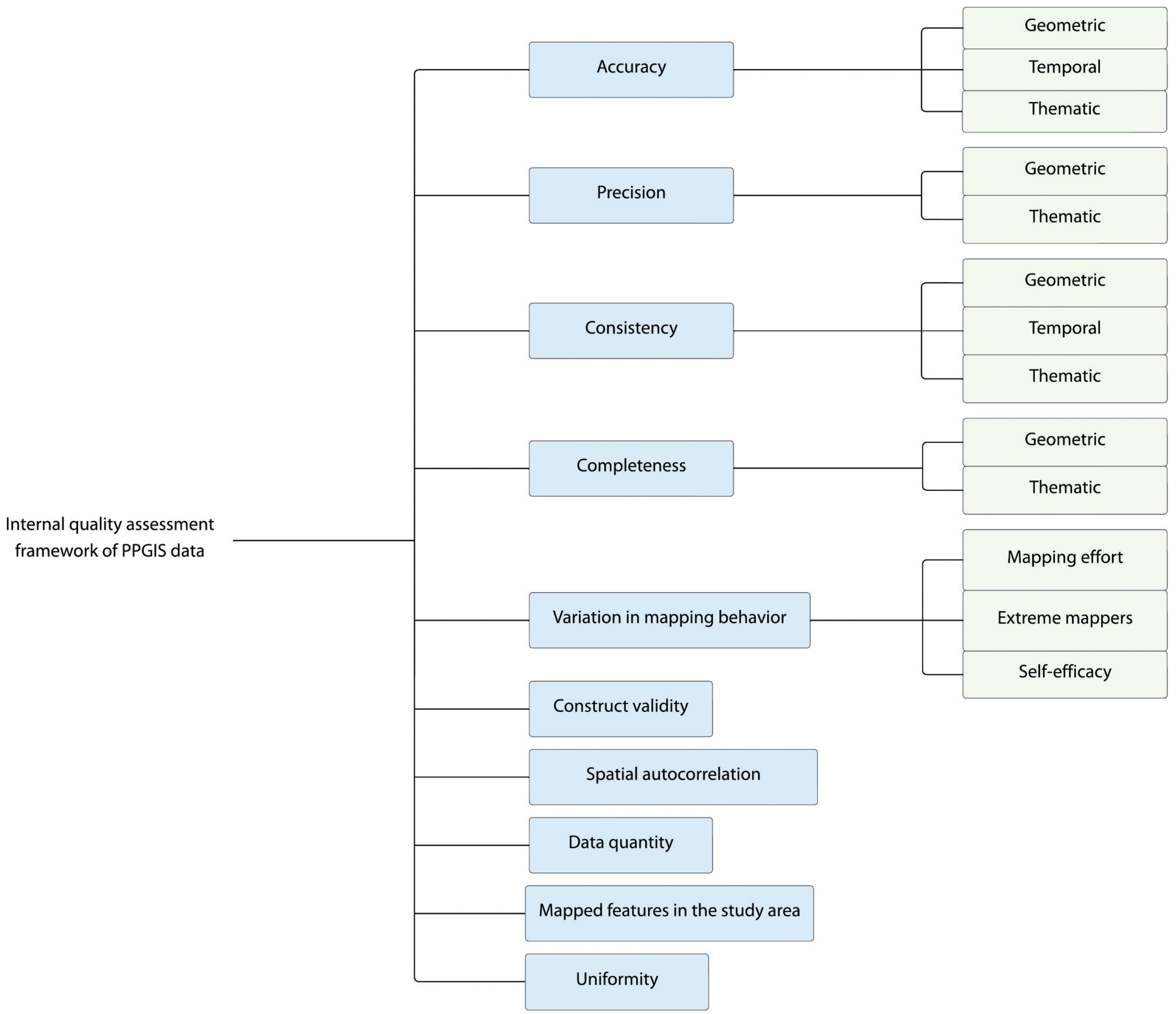

Figure 2. Internal quality criteria for PPGIS data and their dimensions, if applicable.

data type. The methods we applied when testing the framework are included in Table 3 as examples of ways to assess the criteria. Assessment methods are either quantitative or subjective, the latter applying when no quantitative measure exists.

Some criteria appeared more frequently in the literature than others, the most common being geometric accuracy, which is mentioned in 52% of the identified publications. Less frequently mentioned criteria include temporal accuracy, thematic precision, and temporal and thematic consistency, each appearing in one identified publication. Assessing accuracy, precision, consistency, and completeness through different dimensions was not always directly implied, but the assessed dimension could be inferred from the context of the study, definition of the criterion, or the quality measure. In our review, we did not identify studies addressing precision and completeness in the temporal dimension, and thus the temporal dimension of these criteria is not included in the framework.

Accuracy and **precision** are terms that are close to one another. In the context of PPGIS, mapping scale has occasionally been used as a measure for both. In the framework, these are separated so that accuracy assesses the correctness of location, attribute, and temporal data, while geometric precision refers to the exactness of feature placement, indicated by mapping scale. Thematic precision refers to the exactness of the thematic classification. Comparing the thematic classification to another known classification of the phenomenon helps identify themes that might be missing from the data to understand its potential thematic limitations.

Two other criteria that are similar to one another are **consistency** and **construct validity**, as both describe the absence of contradictions or illogicalities. Geometric consistency can be assessed either internally within the data or externally using reference data. When internal assessment is not possible, meaning when features of the dataset can overlap and would not contradict with each other, for example outdoor recreation routes of different participants, reference data might be the same as for construct validity.

For **completeness**, similar definitions and measures have been used for PPGIS as for other geospatial data. However, finding appropriate reference data for subjective PPGIS data is not always possible. Criteria assessing the **variation in mapping behavior** can be an alternative for such data. **Mapping effort**, assessed as time spent in mapping, indicates the carefulness of mapping, since features mapped quickly are more likely to contain errors. **Extreme mappers** refer to participants who have mapped the same feature multiple times to emphasize that feature, which can distort the data analysis as outliers. Such behavior may be related to participants' strong motivation to influence the planning outcome. Mapping multiple features in the same location but with different thematic attributes would not be interpreted as an extreme mapper, as one place may have multiple subjective meanings that the participant wants to express. **Self-efficacy** refers to the participants' self-estimated probability of the correctness of features they mapped. It indicates the participants' mapping skills as well as knowledge of the phenomenon and area being mapped.

PPGIS-specific quality criteria also include **data quantity** and **uniformity**. Data should contain enough mapped features to make reliable conclusions about the phenomenon being studied. This can be assessed in relation to the size of the study area. However, no reference value for a sufficient number or density of features was presented in the literature. This can complicate the interpretation of the assessment result, as there is no benchmark to compare the result to. In future studies, further testing of the framework would allow developing such assessment benchmarks. Uniformity indicates the similarity in the geometry of mapped features and helps identify features that notably differ from other features and may have been mapped incorrectly.

Quality of PPGIS data can be assessed based on feature placement. Identifying **mapped features located in the study area** is a quick way to point out features that are suitable for analysis. **Spatial autocorrelation** describes the spatial distribution of features in relation to each other. It is a common spatial statistic in GIS assessed with indices such as Moran's I (de Smith et al., 2024). In PPGIS studies, mapped features are often found to form clusters, because many phenomena studied with PPGIS surveys concentrate in certain areas. Thus, the nearest neighbor index can be used to determine whether clustering is observed or if the placement of features is randomly dispersed. A random dispersion would suggest that more PPGIS features are needed to identify patterns of the phenomenon being mapped. However, data users should be aware that clustering of features can also be connected to the applied sampling method and might reflect a bias toward a certain area or a group of respondents. Information on the study context and data collection would help users interpret this criterion.

We propose a quality assessment workflow for performing PPGIS data quality assessment with the quality aspects outlined above (Figure 3). The workflow consists of seven consecutive steps, all of which are applied after data collection and before its analysis. Quality assessment starts by identifying knowledge needs to guide the assessment, for example how the user wants to analyze the data. Second, the user identifies what kind of data is being assessed, such as the geometry type and the type of phenomenon represented in the data. Third, the user selects the relevant quality criteria and dimensions for their study context. Fourth, reference data needs to be

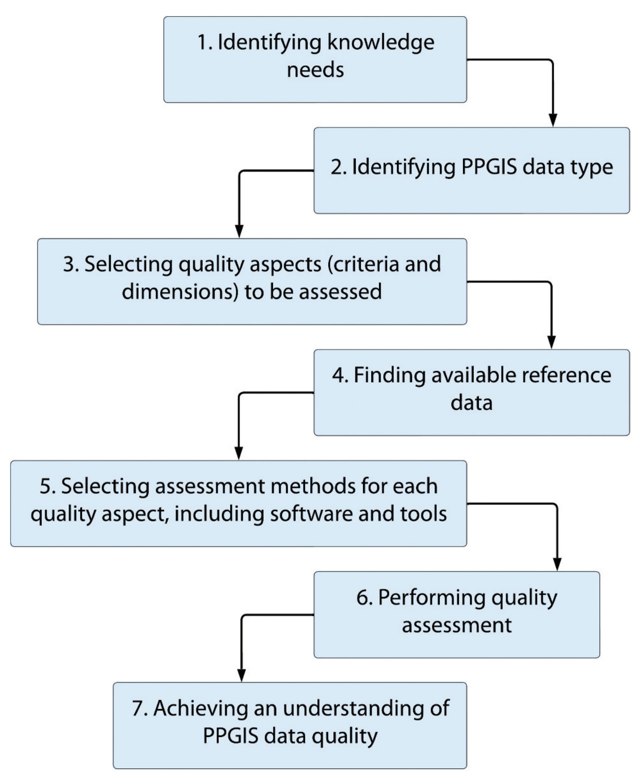

Figure 3. Quality assessment workflow for PPGIS data.

identified for those criteria that require it. Fifth, specific assessment methods and tools are selected, depending on the characteristics of the data. Sixth, quality assessment is performed using the selected methods, and finally, an understanding of data quality is obtained by examining and reporting the assessment results.

4.2. Quality assessment of selected PPGIS data

4.2.1. "Me and my everyday environment" point data

In the quality assessment of the "Me and my everyday environment" point data, 9 out of 18 quality aspects were assessed (Table S4). The geometric dimension of quality was only assessed with consistency, through overlay analysis with reference data representing buildings and market squares. The same method indicated construct validity, showing overlap on 83–84% of the features. However, not all types of mapped points could be assessed due to the lack of suitable reference data. Geometric accuracy and precision could not be assessed due to the ambiguity of features and the lack of required information. Assessing geometric completeness was not possible, as no appropriate reference data exists for the corresponding real-world features. Uniformity could not be assessed as points are always geometrically uniform.

Thematically, a rather large share of features (87%) is complete, containing all attribute data, considering that additional questions regarding the mapped features were not mandatory in the survey. Thematic precision was assessed by examining how the studied phenomenon is classified, that is, what types of everyday places the data represents. Based on a subjective evaluation, the categories of the data (presented in Table 1) are broad, so more precise categories might clarify the classification and help specify the mapped places.

Spatial autocorrelation showed clustering of features, indicating that features are not placed randomly. When visually examining the most notable clusters, it was found that features are thematically consistent in many areas, meaning that features of the same category are often mapped in a clustered manner (Figure 4), which is expected in a dataset that represents places inherently connected to the physical environment. Most features (97%) are placed within the study area, with a density of 3.4 features per square kilometer.

Quality related to mapping behavior was assessed with extreme mappers. 36 participants were identified to have mapped one or two same features more than once, usually two or three times. However, assessing this criterion was somewhat ambiguous, as it was difficult to determine whether the mapped features represent the same real-world features. Considering the total number

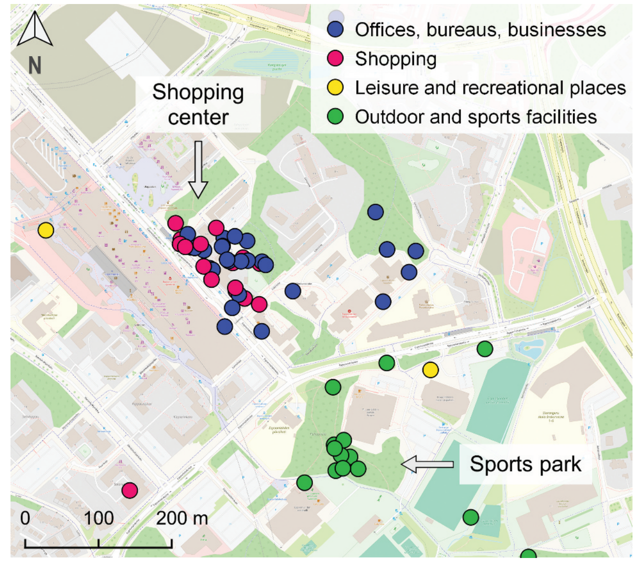

Figure 4. Example of thematic consistency in the "Me and my everyday environment" data: features categorized as "Offices, bureaus, businesses" and "Shopping" are clustered near a shopping center, and features categorized as "Outdoor and sports facilities" are clustered near a park. Background map: OpenStreetMap.

of participants ($n = 1139$), this number of extreme mappers is unlikely to create a bias.

To summarize the assessment results, no clear errors were observed in the "Me and my everyday environment" data, and features do not appear to be mapped randomly, so analysis results of the data could be considered rather reliable. There is no notable lack in the attribute data, and the features are well located within the study area. On the other hand, interpreting the data was challenging due to the broad thematic classification and the lack of required information, which may introduce uncertainty into data analysis, when it is not known how accurate and precise the data is, for example.

4.2.2. "Outdoor recreation in Turku" line data

Quality of the "Outdoor recreation in Turku" line data was assessed using 11 out of 18 quality aspects (Table S5). Geometric accuracy was assessed with proximity analysis based on place names or descriptions written by participants to the mapped features (Figure 5), with accuracy varying between two and 860 meters, which indicates considerable variation in quality with this criterion. However, only 8% of features had adequate descriptions for assessing geometric accuracy. Geometric precision was assessed based on mapping scale, with 48% of features mapped at a sufficient zoom level, which indicates that only half of the features have been mapped precisely enough. Sufficient zoom

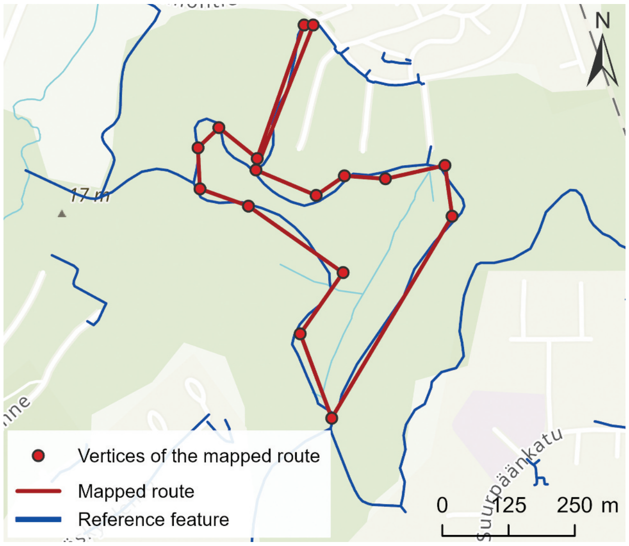

Figure 5. Example of assessing geometric accuracy with the "Outdoor recreation in Turku" data: a mapped route and its vertices, and a reference feature (OpenStreetMap) to which the distance from the vertices was calculated. Background map: World Topographic Map, Esri.

level was defined based on commonly used mapping scales in previous studies (e.g. Brown & Brabyn, 2012; Brown & Fagerholm, 2015; Brown et al., 2018) and by visually evaluating the data. Sufficient zoom level indicates that the feature has been mapped with enough detail, in relation to the studied phenomenon, to ensure that the placement of the feature is correct. In this data, features mapped at higher zoom levels appear more natural and resemble routes, whereas features mapped at lower zoom levels have sharp edges and seem to be mapped with less effort (Figure 6). Geometric consistency and construct validity were assessed similarly as with the previous data, with 21% of features aligned with reference data, which suggests poor quality. Geometric completeness could not be assessed due to the lack of reference data.

Thematically, 27% of features are complete, which also is a low result. Thematic precision was evaluated based on responses to two open-ended questions regarding other meanings of the mapped places than those listed in the survey to identify themes missing from the thematic classification of the data, revealing seven themes of outdoor recreation activities and values that could complement the used classification, for example unique natural environment, picnicking, and proximity to home. Spatial autocorrelation showed clustering of features. However, examining the thematic consistency in clusters was not reasonable with this data. Although there are thematically different features in clusters, deviant features do not indicate low data quality, as the features of different categories can be located in the same cluster. For example, a feature classified as "observing nature" located in a cluster of features classified as "walking" cannot be interpreted as an error, as features of both classes can realistically be located in the same place.

Most features (94%) are placed at least partially within the study area, with a density of 1.4 features per

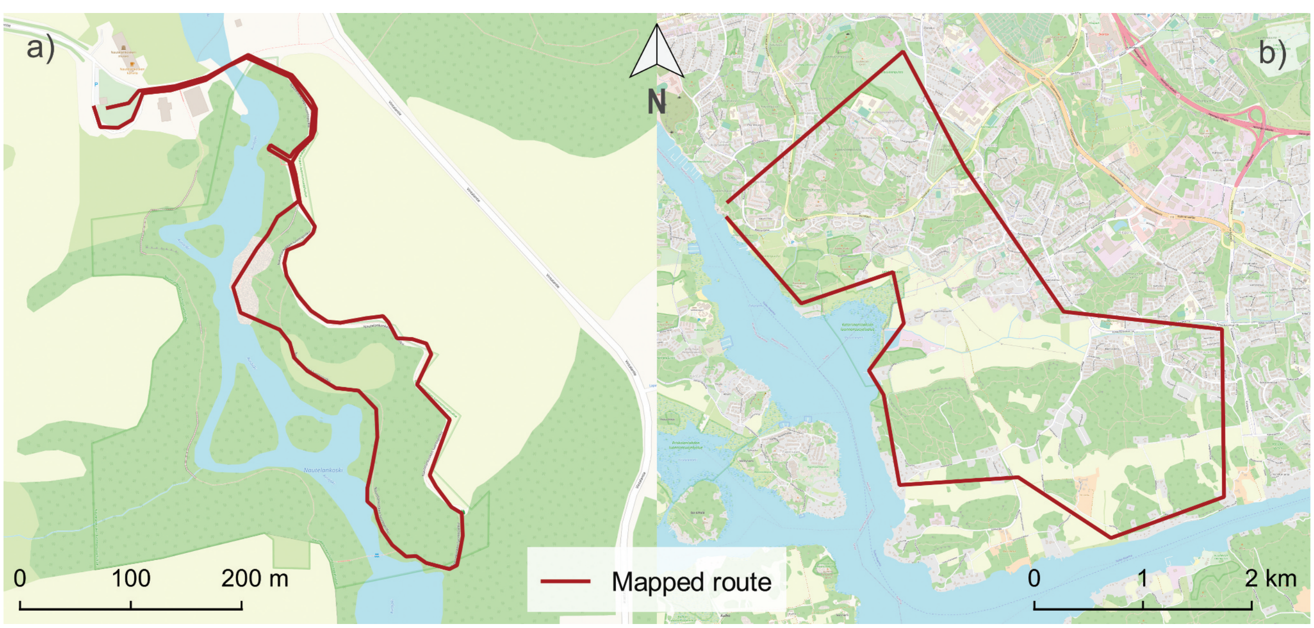

Figure 6. Example of geometric precision in the "Outdoor recreation in Turku" data: a) a route mapped at zoom level 19, allowing a detailed mapping scale, and b) a route mapped at zoom level 12, allowing a coarse mapping scale. Background map: OpenStreetMap.

square kilometer. 21 participants mapped five or more features, which was considered unusual based on the average and standard deviation of the number of features per participant, but none of them were identified to have mapped the same feature multiple times. Therefore, the data does not contain extreme mappers. Uniformity was assessed by visually comparing particularly long routes to other mapped routes as well as the base map. A route was interpreted as abnormal if it has illogical geometric shapes and is not in line with other routes. 87% of routes are mapped uniformly. The least uniform features, such as long straight lines and features with sharp angles, were clearly identifiable (Figure 7).

In conclusion, precision of mapping and geometric accuracy of features vary in the "Outdoor recreation in Turku" data, and some illogical routes were identified. According to overlay analysis, a lot of routes were mapped partly in areas where routes cannot realistically be located. There is also room for improvement in the completeness of attribute data. However, according to the assessment of spatial autocorrelation, routes were not mapped randomly, and some of the most common recreational places can clearly be identified in the data.

4.2.3. "My Green Place" polygon data

Quality of the "My Green Place" polygon data was assessed with 12 out of 18 quality aspects (Table S6). Geometric accuracy could be assessed with overlay analysis, showing sufficient overlap with green spaces of the reference data on 88% of the features. Geometric precision indicated that 53% of features were mapped at a sufficient zoom level, while almost half of the features were not mapped precisely enough. Geometric completeness could be assessed by examining redundant features, indicating that 57% of the mapped area is outside the green spaces of the reference data. Assessing geometric consistency and construct validity showed 46% of features entirely overlapping with reference data (Figure 8), which suggests that there are many errors where features have been completely or partly mapped outside the real-world green spaces.

Thematically, approximately 100% of features are complete, as the data does not contain optional survey questions. Thematic precision was assessed by comparing the thematic classification to that of the "Outdoor recreation in Turku" data, revealing five themes that could complement the used classification, such as observing nature and playing with children. Spatial autocorrelation indicated clustering of features. Again, examining thematic consistency in clusters was not reasonable for the same reason as with the previous data.

Most features (99%) are mapped at least partly within the study area, with a density of 2.9 features per square kilometer. In the survey, participants were asked to map only one feature. However, 17 participants mapped two or three features. One was identified to have mapped the same feature twice, but the data does not seem to contain extreme mappers that would affect data analysis. Uniformity was assessed by examining particularly large polygons and comparing them to other mapped polygons and the base map. This revealed that 98% of the features are mapped uniformly.

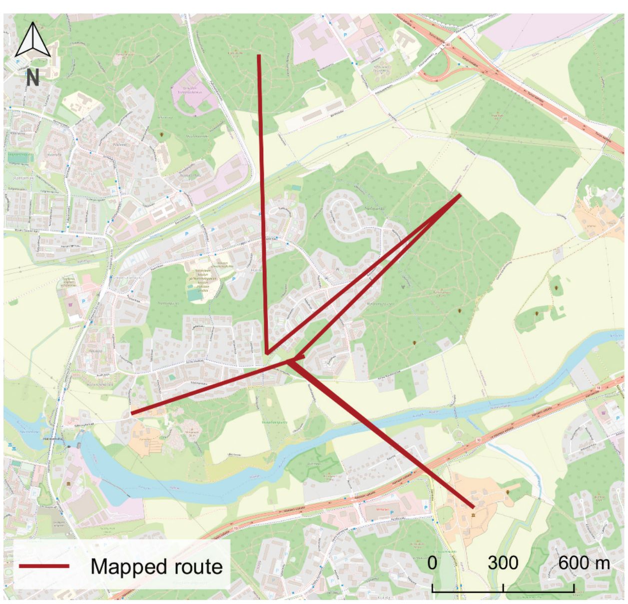

Figure 7. Example of an abnormal and illogical feature in the "Outdoor recreation in Turku" data. Background map: OpenStreetMap.

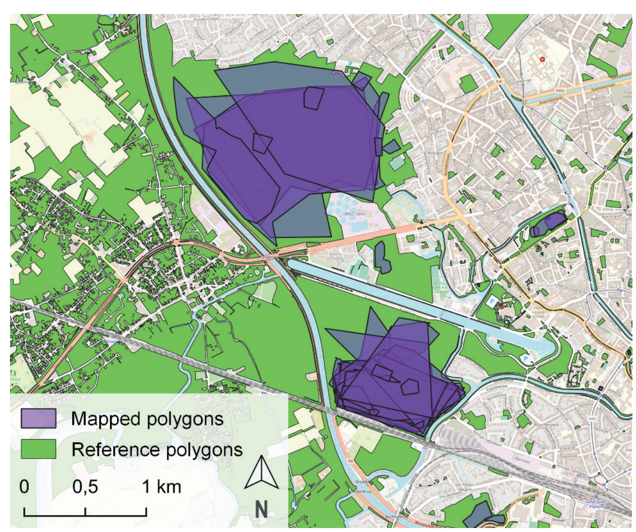

Figure 8. Example of geometric consistency in the "My Green Place" data: mapped polygons that overlap entirely with the reference data. Background map: OpenStreetMap.

To summarize, the mapped green spaces of the "My Green Place" data do not completely match real-world green spaces, but the mapped features are still clustered near the green spaces of the city. There is variation in the precision of mapping, and the data contains some clearly illogical features. In terms of attribute data, however, the data is of high quality, with minimal missing attribute information.

4.2.4. Suitability of the criteria for assessing PPGIS data quality

Based on testing the framework, a subjective evaluation of the suitability of each criterion and dimension for PPGIS data was made among the authors. Well-suited criteria and dimensions include geometric accuracy, geometric precision, thematic completeness, spatial autocorrelation, mapped features in the study area, and uniformity (Table 4). Spatial autocorrelation and mapped features in the study area are good criteria for examining the distribution of features, and thematic completeness is useful for identifying possible deficiencies in attribute data. These could be assessed with all of the selected datasets. Although geometric accuracy and precision were only partially assessable, their assessment provided insight into the carefulness of mapping and possible errors, revealing for example that in the "Outdoor recreation in Turku" data, participants mapped the routes two meters away from true routes at best. Assessing uniformity, though somewhat interpretative and only partially assessable, helps identify abnormal and possibly erroneous features, such as illogical routes in the "Outdoor recreation in Turku" data. Of these well-suited criteria, thematic completeness, spatial autocorrelation, and mapped features in the study area are the most straightforward to assess, making them good starting points for quality assessment.

Moderately suitable criteria and dimensions include thematic precision, geometric and thematic consistency, geometric completeness, construct validity, extreme mappers, and data quantity (Table 4). Geometric consistency

Table 4. Summary of empirical PPGIS data quality assessment based on sections 4.2.1–4.2.3: results across three assessed datasets and authors' subjective evaluation of the suitability of each quality criterion and dimension for assessing PPGIS data quality. See more detailed results concerning each dataset in Tables S4-S6.

Quality dimension	"Me and my everyday environment" point data	"Outdoor recreation in Turku" line data	"My Green Place" polygon data	Evaluation of suitability for PPGIS across assessed datasets
Accuracy				
Geometric	–	2–860 m	88%	Good
Temporal	–	–	–	Not suitable
Thematic	–	–	–	Not suitable
Precision				
Geometric	–	48%	53%	Good
Thematic	More precise categories would clarify the classification.	Seven themes were identified to complement the classification.	Five themes were identified to complement the classification.	Moderate
Consistency				
Geometric	83–84%	21%	46%	Moderate
Temporal	–	–	–	Not suitable
Thematic	PPGIS features of notable clusters are thematically consistent.	–	–	Moderate
Completeness				
Geometric	–	–	57% of the mapped area is redundant.	Moderate
Thematic	87%	27%	100%	Good
Construct validity				
–	83–84%	21%	46%	Moderate
Variation in mapping behavior				
Mapping effort	–	–	–	Not assessed
Extreme mappers	No extreme mappers.	No extreme mappers.	No extreme mappers.	Moderate
Self-efficacy	–	–	–	Not assessed
Spatial autocorrelation				
–	0.1 = Features are clustered.	0.4 = Features are clustered.	0.4 = Features are clustered.	Good
Data quantity				
–	3.4 features/km^2	1.4 features/km^2	2.9 features/km^2	Moderate
Mapped features in the study area				
–	97%	94%	99%	Good
Uniformity				
–	–	87%	98%	Good

and construct validity could be assessed with all datasets, but selecting suitable reference data especially for the "Me and my everyday environment" data was challenging, making these less applicable to all PPGIS data. Assessing data quantity was possible for all datasets but did not directly demonstrate data quality with the selected method. Extreme mappers could be assessed with all datasets and can reveal potential outliers, but the assessment included uncertainty. Assessing thematic precision and thematic consistency was partially assessable and more interpretative, but can help evaluate thematic properties of the data. Assessing geometric completeness was also partially assessable, as only the features of "My Green Place" data could be compared to all true features. However, geometric completeness, along with geometric consistency and construct validity, can indicate correctness of mapping if their assessment is feasible.

Five quality aspects could not be assessed at all in our study. Temporal accuracy and temporal consistency could not be assessed because the selected datasets represent phenomena that do not have a specific time of occurrence. Thematic accuracy could not be assessed due to the nature of the represented phenomena, as the thematic values of subjective features are considered their true values. These three quality aspects were evaluated as not suitable (Table 4). Mapping effort and self-efficacy were not assessed due to the lack of required information that was either not collected in the surveys or was removed from the data. However, these quality aspects could be suitable if the required information was available.

5. Discussion

5.1. Developing the internal quality assessment framework for PPGIS data

In this study, a quality assessment framework was produced for performing systematic internal quality assessment of spatial PPGIS data mapped by participants, with several criteria identified from participatory mapping literature. Testing the quality assessment framework revealed differences in the assessment process and applicability of criteria across selected datasets. Some criteria were easier to assess, while others required more effort or could not be assessed at all. Our assessment results provide an understanding of the quality of selected datasets, but more importantly, they offer insight into the suitability of the criteria and measures for internal quality assessment of PPGIS data.

Criteria that were found most suitable allow identifying possibly erroneous features (geometric accuracy, geometric precision, uniformity), evaluating the distribution of features (spatial autocorrelation, mapped features in the study area), and recognizing the shortcomings in attribute data (thematic completeness). These can provide a good basis for internal quality assessment. Some of the well-suited criteria have already been widely applied in PPGIS studies, especially geometric precision and spatial autocorrelation (e.g. Garcia-Martin et al., 2017; Van Riper & Kyle, 2014). Criteria that were considered moderately suitable were more challenging to assess unequivocally, but can reveal potential outliers (extreme mappers), indicate correctness of mapping (geometric consistency, geometric completeness, construct validity), reveal whether there are enough mapped features (data quantity), and help evaluate thematic properties of the data (thematic precision, thematic consistency).

Three key reasons were identified for why assessing some criteria was not suitable as limitations of the framework's applicability. The first reason was the subjective nature of the phenomenon represented in the data. "Outdoor recreation in Turku" and "My Green Place" are exemplary cases of subjective PPGIS data, as they represent place-based values and activities (Fagerholm et al., 2021). Such data cannot be thematically compared to reference data, as we noted in the assessment of thematic accuracy of all datasets. PPGIS features can also be very abstract (Ramírez Aranda et al., 2021), with no correspondence to the physical environment, which makes assessing the geometric dimension challenging too. Reference data representing the physical environment can be used in PPGIS quality assessment (Fagerholm et al., 2021), but some PPGIS features might not align with authoritative datasets. For example, routes in the "Outdoor recreation in Turku" data might not necessarily correspond to official roads or paths and may not be represented in official datasets. This means that a ground truth may not exist for PPGIS features that are based on human perceptions, and thus, assessing especially accuracy by comparison to a reference data may not be possible nor relevant. Godfrey and Mackaness (2017) argue that recognition and meaning can be more important for the effectiveness of spatial representations than truth and accuracy. This particularly applies to mapping human perceptions with PPGIS. If accuracy is considered a priority, other methods may be more suitable for producing the data (Brown & Kyttä, 2014).

The second reason was the lack of required information. This affected especially the assessment of geometric precision, mapping effort and self-efficacy. These can act as alternative criteria when the subjective nature or the lack of correspondence to physical environment prevents assessing some criteria. Especially mapping scale and mapping effort were mentioned in the reviewed publications as important criteria for PPGIS data quality (e.g. Brown et al., 2012; Brown, Kelly, et al., 2014). When testing the framework, we noted that some attribute data had been removed from the "Me and my everyday environment" data, including mapping scale and time spent on mapping. These are important data, and we recommend that they are available for data users if such information is acquired on the PPGIS platform during data collection. Self-efficacy would indicate the reliability of the data, so in future studies we recommend asking participants to estimate the correctness of the features they map. Based on testing the framework, it would also be useful to ask the participants to name the mapped features for assessing geometric accuracy. When such survey questions are mandatory, the correctness of features can be assessed more reliably. This would also lead to higher thematic completeness.

The third reason for unsuccessful assessment of a criterion was related to the geometry type of the data. Naturally, assessing uniformity of point data is not possible as points are always geometrically similar. Otherwise, geometry type of the data did not affect the applicability of criteria. Geometric similarity of points also made it difficult to identify potentially erroneous features in this data, whereas abnormal features in polygon and line data were easier to detect. Mapping polygons is often more challenging or laborious than mapping points (Brown & Pullar, 2012), so participants might want to map such features with as little effort as possible. This was evident in the "My Green Place" data containing polygons with illogical, large, and angular shapes. Similar illogicalities were present in the linear data. The assessment of such features could have been complemented by evaluating the mapping effort, and we suggest to collect this data in future PPGIS surveys.

Based on the reviewed literature, temporal accuracy and thematic consistency have been more commonly applied for VGI data (Antoniou & Skopeliti, 2015; Senaratne et al., 2017) than for PPGIS data. These quality dimensions were still included in the framework, as they could potentially be applied for some PPGIS datasets. However, temporal accuracy could not be assessed when testing the framework, and thematic consistency was only partially assessable. In fact, data quality could not be assessed through the temporal dimension at all across the datasets, which links to the fact that PPGIS studies rarely focus on collecting temporal information and assessing temporal quality. Most phenomena studied with PPGIS, such as values and preferences, are not tied to a specific time or even a time period. In the "Me and my everyday environment" survey, participants were asked how often they visit the places they mapped, but accuracy or consistency of such temporal information cannot be assessed either. Furthermore, GPS-based data collection is still found to outdo PPGIS methods in the temporal dimension (Heikinheimo et al., 2020).

5.2. Potential and challenges of the quality assessment framework

Based on the literature review, research on PPGIS data quality has been heterogeneous, and the application of most of the quality criteria we identified is yet to become established in the field. The produced quality assessment framework responds to this knowledge gap and can promote the standardization of PPGIS data quality assessment by providing a collection of quality criteria and measures as well as guidance for their application with the proposed quality assessment workflow. Standardization of quality assessment would support understanding the nature of PPGIS data, as we demonstrated in the empirical quality assessment, and drawing reliable conclusions from the data. The framework can also serve as a tool for understanding the multidimensionality of PPGIS data quality. Most importantly, quality assessment can increase trust in PPGIS data (Bressan, 2021), and the framework introduced here is an important step towards that.

Although there has been concern about the quality and reliability of PPGIS data (Brown et al., 2015), a comprehensive understanding of PPGIS data quality assessment has not been formed, and quality assessment is easily overlooked. Data collected with participatory methods may not always be systematically utilized in planning processes (Rossi et al., 2025; Staffans et al., 2020), especially with no clear guideline for its assessment and analysis. PPGIS data collectors can typically access collected data easily, but often quality assessment remains minimal (Afzalan & Muller, 2018). Quality assessment can help examine data characteristics and select appropriate analysis methods accordingly. We identified from literature that spatial autocorrelation, uniformity of features, and extreme mappers, for example, are quality aspects that affect data processing and analysis (Fagerholm et al., 2021; Solé et al., 2025). The impact of PPGIS data has been studied in Finnish municipalities, and it was concluded that one prerequisite for the impact of PPGIS is indeed appropriate data analysis (Nurminen, 2022), which the framework supports.

The framework can provide a solution for understanding the uncertainties of PPGIS data and utilizing the data despite them, since data quality assessment is also about recognizing the possibilities of data despite its imperfections (Devillers et al., 2007). Uncertainties and imperfections are inherent to all geospatial data, because it always represents the real world in a simplified manner (Lush et al., 2012). With PPGIS data, the adequacy of participants' knowledge and skills adds further uncertainty to data quality (Ramírez Aranda et al., 2021). Quality assessment with the produced framework can indicate whether data quality is sufficient or if there are shortcomings. However, for effective quality assessment, quality thresholds should be defined for the criteria (Brown et al., 2015). We found that the results of data quantity and geometric accuracy for example cannot directly define whether data quality is high enough, and results should often be interpreted according to the user's requirements. For example, in land use planning, some variation in geometric accuracy of features representing pleasant places can be allowed, but in research dealing with the risk of natural hazards, participatory geospatial data should be accurate and reliable, or data quality must be at least known (Klonner et al., 2021).

The produced quality assessment framework is the first collection of criteria and measures for internal quality assessment of PPGIS data. Understanding of PPGIS data quality is likely to grow as PPGIS research progresses, so there are possibilities for refining the framework in the future, for example by defining some quality thresholds mentioned above. More testing of the framework with different types of PPGIS data is needed to more reliably determine which criteria are most suitable. PPGIS data can also be collected using other geometric entities than those assessed here, such as airbrush-style tools to capture vague spatial concepts (Huck et al., 2014). These can offer a solution for representing inherently imprecise spatial features, such as landscape values, but usefulness and applicability of the criteria might be different if the framework would be tested with such geometric entities, and for example accuracy and precision may not be relevant in such cases (Godfrey & Mackaness, 2017). Additionally, our selected datasets are similar in their temporal and geographic scope, and we recommend that the framework is tested with datasets collected in more diverse contexts.

One limitation of this study is that our suitability evaluation is connected to the assessment methods used. The framework and data quality assessment could be refined with the selection of reference data and assessment methods. We recognize that more precise reference data could be used, for example with geometric consistency of the "Me and my everyday environment" data by assessing overlap with the correct types of buildings. Reference features for geometric accuracy of the "Outdoor recreation in Turku" data may also not perfectly correspond with mapped routes, as routes mapped by participants might intentionally include paths deviating from official routes. Alternative assessment methods could also be tested. For example, uniformity could be assessed based on a node density ratio, calculating the average number of nodes within an area to identify abnormally mapped features. With the selected PPGIS datasets, construct validity was assessed similarly as geometric consistency. However, construct validity could also be linked to survey characteristics and the participants' understanding of the purpose of the survey (Jankowski et al., 2016).

A key issue in developing the quality assessment framework further is its applicability in different PPGIS contexts, including both research and planning. The framework and how we applied it might not be replicable for all PPGIS datasets and different use contexts as such, because different data types require different assessment methods, and different use cases have different knowledge needs. Our hope is that the framework would be further tested in different kinds of PPGIS processes and that the results would be shared, so that new insights and development suggestions could emerge. Testing the framework more would reveal typical results for the criteria, such as for data quantity, which does not currently have a benchmark value. This would help interpret quality assessment results, making the process more approachable for all users. Developing the framework into an automatic quality assessment tool in the future could also make assessing PPGIS data quality easier and applicable for anyone.

6. Conclusions

Like all geospatial data, PPGIS data has its shortcomings in quality that users need to be aware of. More and more PPGIS datasets are being collected, but their internal quality assessment is still heterogenous and often minimal. Unknown data quality can undermine trust in PPGIS data, hindering its effective use and the establishment of PPGIS methods in planning processes. We identified key quality criteria and measures for assessing the internal quality of PPGIS data and compiled them into a quality assessment framework and proposed a quality assessment workflow to facilitate the implementation of systematic PPGIS data quality assessment. The produced framework helps to understand uncertainties and characteristics of collected PPGIS datasets, increasing trust in PPGIS data.

We tested the applicability of the produced framework with selected PPGIS datasets and evaluated the suitability of the criteria for PPGIS data. An understanding was gained of why certain criteria were challenging to assess or could not be assessed. Main reasons for this were the nature of the phenomenon in the data and the lack of required information. Assessing some traditional geospatial data quality criteria, such as thematic accuracy and geometric consistency, was particularly challenging with PPGIS data. Therefore, internal quality assessment of subjective PPGIS data should focus more on using alternative criteria, such as mapping effort and self-efficacy, and we recommend PPGIS surveys to be designed so that assessing such criteria is possible.

In future studies, more testing of the framework is needed with diverse datasets from diverse use contexts to further explore the suitability and importance of the criteria. Testing the framework more would also help interpret the quality assessment results and advance the standardization of PPGIS data quality assessment. The framework is an important starting point for this standardization and ensuring good practice in data collection, which supports drawing reliable conclusions from PPGIS data and the realization of the goals of PPGIS processes.

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ORCID

Anni Simola http://orcid.org/0009-0004-4420-3990
Nora Fagerholm http://orcid.org/0000-0001-5020-0746
Carolin Klonner http://orcid.org/0000-0003-1981-2204
Anna Kajosaari http://orcid.org/0000-0001-8165-6770

Data availability statement

Data sharing does not apply to this article as no new data nor codes were created in this study. The PPGIS datasets that were used to test the produced quality assessment framework are openly available in Zenodo ("Me and my everyday environment" data: https://doi.org/10.5281/zenodo.3621321, and "My Green Place" data: https://doi.org/10.5281/zenodo.3621321) and University of Turku Geospatial Data Service ("Outdoor recreation in Turku" data: https://doi.org/10.5281/zenodo.3621321). Links to used reference datasets are included in Table S3.

References

Afzalan, N., & Muller, B. (2018). Online participatory technologies: Opportunities and challenges for enriching participatory planning. *Journal of the American Planning Association*, *84*(2), 162–177. https://doi.org/10.1080/01944363.2018.1434010

Aminpour, F., Bishop, K., & Corkery, L. (2023). The methodological challenges of using public participation geographic information system for understanding micro-scale physical characteristics of streetscapes. *Cities and Health*, *7*(3), 480–491. https://doi.org/10.1080/23748834.2022.2161295

Antoniou, V., & Skopeliti, A. (2015). Measures and indicators of VGI quality: An overview. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *II-3*(W5), 345–351. https://doi.org/10.5194/isprsannals-II-3-W5-345-2015

Arku, R. N., & Buttazzoni, A. (2025). A framework to evaluate the effectiveness of web-based geo-participation tools as a public participation technique. *Cartography and Geographic Information Science*, *53*(1), 1–17. https://doi.org/10.1080/15230406.2025.2464661

Babelon, I., Ståhle, A., & Balfors, B. (2017). Toward cyborg PPGIS: Exploring socio-technical requirements for the use of web-based PPGIS in two municipal planning cases, Stockholm region, Sweden. *Journal of Environmental Planning and Management*, *60*(8), 1366–1390. https://doi.org/10.1080/09640568.2016.1221798

Ballatore, A., McClintock, W., Goldberg, G., & Kuhn, W. (2020). Towards a usability scale for participatory GIS. In P. Kyriakidis, D. Hadjimitsis, D. Skarlatos, & A. Mansourian (Eds.), *Geospatial Technologies for local and regional development: Proceedings of the 22nd AGILE conference on geographic information science* (pp. 327–348). Springer. https://doi.org/10.1007/978-3-030-14745-7_18

Bayazidy, M., Maleki, M., Khosravi, A., Shadjou, A. M., Wang, J., Rustum, R., & Morovati, R. (2024). Assessing riverbank change caused by sand mining and waste disposal using web-based volunteered geographic information. *Water*, *16*(5), 734. https://doi.org/10.3390/w16050734

Bijker, R. A., & Sijtsma, F. J. (2017). A portfolio of natural places: Using a participatory GIS tool to compare the appreciation and use of green spaces inside and outside urban areas by urban residents. *Landscape and Urban Planning*, *158*, 155–165. https://doi.org/10.1016/j.landurbplan.2016.10.004

Bressan, G. (2021). Assessing the positional accuracy of perceptual landscape data: A study from Friuli Venezia Giulia, Italy. *Transactions in GIS*, *25*(2), 642–671. https://doi.org/10.1111/tgis.12752

Brown, G. (2012). An empirical evaluation of the spatial accuracy of public participation GIS (PPGIS) data. *Applied Geography*, *34*, 289–294. https://doi.org/10.1016/j.apgeog.2011.12.004

Brown, G. (2013). Relationships between spatial and non-spatial preferences and place-based values in national forests. *Applied Geography*, *44*, 1–11. https://doi.org/10.1016/j.apgeog.2013.07.008

Brown, G. (2017). A review of sampling effects and response bias in internet participatory mapping (PPGIS/PGIS/VGI). *Transactions in GIS*, *21*(1), 39–56. https://doi.org/10.1111/tgis.12207

Brown, G., & Brabyn, L. (2012). An analysis of the relationships between multiple values and physical landscapes at a regional scale using public participation GIS and landscape character classification. *Landscape and Urban Planning*, *107*(3), 317–331. https://doi.org/10.1016/j.landurbplan.2012.06.007

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

Brown, G., Kelly, M., & Whitall, D. (2014). Which 'public'? Sampling effects in public participation GIS (PPGIS) and volunteered geographic information (VGI) systems for public lands management. *Journal of Environmental Planning and Management*, *57*(2), 190–214. https://doi.org/10.1080/09640568.2012.741045

Brown, G., & Kyttä, M. (2014). Key issues and research priorities for public participation GIS (PPGIS): A synthesis based on empirical research. *Applied Geography*, *46*, 122–136. https://doi.org/10.1016/j.apgeog.2013.11.004

Brown, G., & Kyttä, M. (2018). Key issues and priorities in participatory mapping: Toward integration or increased specialization? *Applied Geography*, *95*, 1–8. https://doi.org/10.1016/j.apgeog.2018.04.002

Brown, G., & Pullar, D. V. (2012). An evaluation of the use of points versus polygons in public participation geographic information systems using quasi-experimental design and Monte Carlo simulation. *International Journal of Geographical Information Science*, *26*(2), 231–246. https://doi.org/10.1080/13658816.2011.585139

Brown, G., & Reed, P. (2009). Public participation GIS: A new method for use in national forest planning. *Forest Science*, *55*(2), 166–182. https://doi.org/10.1093/forestscience/55.2.166

Brown, G., Reed, P., & Raymond, C. M. (2020). Mapping place values: 10 lessons from two decades of public participation GIS empirical research. *Applied Geography*, *116*, 102156. https://doi.org/10.1016/j.apgeog.2020.102156

Brown, G., Rhodes, J., & Dade, M. (2018). An evaluation of participatory mapping methods to assess urban park benefits. *Landscape and Urban Planning*, *178*, 18–31. https://doi.org/10.1016/j.landurbplan.2018.05.018

Brown, G., Schebella, M. F., & Weber, D. (2014). Using participatory GIS to measure physical activity and urban park benefits. *Landscape and Urban Planning*, *121*, 34–44. https://doi.org/10.1016/j.landurbplan.2013.09.006

Brown, G., Weber, D., & De Bie, K. (2015). Is PPGIS good enough? An empirical evaluation of the quality of PPGIS crowd-sourced spatial data for conservation planning. *Land Use Policy*, *43*, 228–238. https://doi.org/10.1016/j.landusepol.2014.11.014

Brown, G., Weber, D., Zanon, D., & De Bie, K. (2012). Evaluation of an online (opt-in) panel for public participation geographic information systems surveys. *International Journal of Public Opinion Research*, *24*(4), 534–545. https://doi.org/10.1093/ijpor/eds001

Cox, C., Morse, W., Anderson, C., & Marzen, L. (2014). Applying public participation geographic information systems to wildlife management. *Human Dimensions of Wildlife*, *19*(2), 200–214. https://doi.org/10.1080/10871209.2014.871663

Czepkiewicz, M., Jankowski, P., & Młodkowski, M. (2017). Geo-questionnaires in urban planning: Recruitment methods, participant engagement, and data quality. *Cartography and Geographic Information Science*, *44*(6), 551–567. https://doi.org/10.1080/15230406.2016.1230520

Czepkiewicz, M., Jankowski, P., & Zwoliński, Z. (2018). Geo-questionnaire: A spatially explicit method for eliciting public preferences, behavioural patterns, and local knowledge - an overview. *Quaestiones Geographicae*, *37*(3), 177–190. https://doi.org/10.2478/quageo-2018-0033

Degrossi, L. C., Porto De Albuquerque, J., Santos Rocha, R. D., & Zipf, A. (2018). A taxonomy of quality assessment methods for volunteered and crowdsourced geographic information. *Transactions in GIS*, *22*(2), 542–560. https://doi.org/10.1111/tgis.12329

de Smith, M. J., Goodchild, M. F., & Longley, P. A. (2024). *Geospatial analysis: A comprehensive guide to principles, techniques and software tools* (7th ed.). Winchelsea. https://www.spatialanalysisonline.com/HTML/index.html?introduction_and_terminology.htm

Devillers, R., Bédard, Y., Gervais, M., Jeansoulin, R., Pinet, F., Schneider, M., Bejaoui, L., Levesque, M.-A., Salehi, M., & Zargar, A. (2007). How to improve geospatial data usability: From metadata to quality-aware GIS community. *AGILE pre-conference workshop* (pp. 1–8). AGILE Conference.

Devillers, R., Bédard, Y., & Jeansoulin, R. (2005). Multidimensional management of geospatial data quality information for its dynamic use within GIS. *Photogrammetric Engineering & Remote Sensing*, *71*(2), 205–215. https://doi.org/10.14358/PERS.71.2.205

Escobedo, F. J., Bottin, M., Clerici, N., Camargo, S. G., & Feged-Rivadeneira, A. (2022). Evaluating the role of spatial landscape literacy in public participation processes and opinions on environmental issues and ecosystem services. *Environmental Management*, *69*(2), 244–257. https://doi.org/10.1007/s00267-021-01591-7

Fagerholm, N. (2020). *Outdoor activities in Turku (routes)* [Dataset]. University of Turku Geospatial Data Service. https://geonode.utu.fi/catalogue/#/dataset/165

Fagerholm, N., Raymond, C. M., Olafsson, A. S., Brown, G., Rinne, T., Hasanzadeh, K., Broberg, A., & Kyttä, M. (2021). A methodological framework for analysis of participatory mapping data in research, planning, and management. *International Journal of Geographical Information Science*, *35*(9), 1848–1875. https://doi.org/10.1080/13658816.2020.1869747

Fatehian, S., Jelokhani-Niaraki, M., Kakroodi, A. A., Dero, Q. Y., & Samany, N. N. (2018). A volunteered geographic information system for managing environmental pollution of coastal zones: A case study in Nowshahr, Iran. *Ocean & Coastal Management*, *163*, 54–65. https://doi.org/10.1016/j.ocecoaman.2018.06.008

Garcia-Martin, M., Fagerholm, N., Bieling, C., Gounaridis, D., Kizos, T., Printsmann, A., Müller, M., Lieskovský, J., &

Plieninger, T. (2017). Participatory mapping of landscape values in a pan-European perspective. *Landscape Ecology*, *32*(11), 2133–2150. https://doi.org/10.1007/s10980-017-0531-x

Godfrey, L., & Mackaness, W. (2017). The bounds of distortion: Truth, meaning and efficacy in digital geographic representation. *International Journal of Cartography*, *3*(1), 31–44. https://doi.org/10.1080/23729333.2017.1301348

Grêt-Regamey, A., Switalski, M., Fagerholm, N., Korpilo, S., Juhola, S., Kyttä, M., Käyhkö, N., McPhearson, T., Nollert, M., Rinne, T., Soininen, N., Toivonen, T., Räsänen, A., Willberg, E., & Raymond, C. M. (2021). Harnessing sensing systems towards urban sustainability transformation. *NPJ Urban Sustainability*, *1*(1), 40. https://doi.org/10.1038/s42949-021-00042-w

Griffin, G. P., & Jiao, J. (2019). Crowdsourcing bike share station locations: Evaluating participation and placement. *Journal of the American Planning Association*, *85*(1), 35–48. https://doi.org/10.1080/01944363.2018.1476174

Haklay, M. (2010). How good is volunteered geographical information? A comparative study of OpenStreetMap and Ordnance Survey datasets. *Environment and Planning B: Planning and Design*, *37*(4), 682–703. https://doi.org/10.1068/b35097

Hansen, A. S., Glette, V., & Arce, J. F. (2021). Mapping recreational activities in coastal and marine areas - PPGIS findings from western Sweden. *Ocean & Coastal Management*, *205*, 105567. https://doi.org/10.1016/j.ocecoaman.2021.105567

Heikinheimo, V., Tenkanen, H., Bergroth, C., Järv, O., Hiippala, T., & Toivonen, T. (2020). Understanding the use of urban green spaces from user-generated geographic information. *Landscape and Urban Planning*, *201*, 103845. https://doi.org/10.1016/j.landurbplan.2020.103845

Hofmann, M., Münster, S., & Noennig, J. R. (2020). A theoretical framework for the evaluation of massive digital participation systems in urban planning. *Journal of Geovisualization and Spatial Analysis*, *4*(1), 3. https://doi.org/10.1007/s41651-019-0040-3

Hosseini, F. S., Jelokhani-Niaraki, M., & Sabokbar, H. F. (2024). A public participation GIS for infrastructure assessment in rural human settlements. *Applied Spatial Analysis and Policy*, *17*(4), 1521–1544. https://doi.org/10.1007/s12061-024-09594-7

Huck, J. J., Whyatt, J. D., & Coulton, P. (2014). Spraycan: A PPGIS for capturing imprecise notions of place. *Applied Geography*, *55*, 229–237. https://doi.org/10.1016/j.apgeog.2014.09.007

ISO. (2013). *ISO 19157: 2013: Geographic information-data quality* (1st ed.). International Organization for Standardization. https://www.iso.org/standard/32575.html

Jackson, S., Mullen, W., Agouris, P., Crooks, A., Croitoru, A., & Stefanidis, A. (2013). Assessing completeness and spatial error of features in volunteered geographic information. *ISPRS International Journal of Geo-Information*, *2*(2), 507–530. https://doi.org/10.3390/ijgi2020507

Jankowski, P., Czepkiewicz, M., Młodkowski, M., & Zwoliński, Z. (2016). Geo-questionnaire: A method and tool for public preference elicitation in land use planning. *Transactions in GIS*, *20*(6), 903–924. https://doi.org/10.1111/tgis.12191

Johnson, M. S., Adams, V. M., & Byrne, J. (2024). Addressing fraudulent responses in online surveys: Insights from a web-based participatory mapping study. *People and Nature*, *6*(1), 147–164. https://doi.org/10.1002/pan3.10557

Kajosaari, A. (2024). Scale dimensions in public participation GIS: An overview for planning and research. *Geojournal*, *89*(5), 197. https://doi.org/10.1007/s10708-024-11178-4

Kantola, S., Fagerholm, N., & Nikula, A. (2023). Utilization and implementation of PPGIS in land use planning and decision-making from the perspective of organizations. *Land Use Policy*, *127*, 106528. https://doi.org/10.1016/j.landusepol.2022.106528

Kaskela, E. (2024). *The current and future digital participation methods in urban planning in Finnish municipalities* [Master's thesis]. Aalto University. https://urn.fi/URN:NBN:fi:aalto-202401282082

Klonner, C., Hartmann, M., Dischl, R., Djami, L., Anderson, L., Raifer, M., Lima-Silva, F., Castro Degrossi, L., Zipf, A., & Porto De Albuquerque, J. (2021). The Sketch Map Tool facilitates the assessment of OpenStreetMap data for participatory mapping. *ISPRS International Journal of Geo-Information*, *10*(3), 130. https://doi.org/10.3390/ijgi10030130

Kulawiak, M., Krajnik, D., Czaplicka, M., & Dawidowicz, A. (2023). A web-GIS tool for diagnosing spatial orientation of young adults: Design and evaluation of Geo-Survey. *Scientific Reports*, *13*(1), 18621. https://doi.org/10.1038/s41598-023-45268-z

Laatikainen, T., & Kyttä, M. (2020). *Activeage data (AAGE-2015)* (Version v1) [Dataset]. Zenodo. https://doi.org/10.5281/zenodo.3621321

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

Levin, N., Lechner, A. M., & Brown, G. (2017). An evaluation of crowdsourced information for assessing the visitation and perceived importance of protected areas. *Applied Geography*, *79*, 115–126. https://doi.org/10.1016/j.apgeog.2016.12.009

Lush, V., Bastin, L., & Lumsden, J. (2012). Geospatial data quality indicators. In C. Vieira, V. Bogorny, & A. R. Aquino (Eds.), *Proceedings of the 10th international symposium on spatial accuracy assessment in natural resources and environmental sciences* (pp. 1–6). International Spatial Accuracy Research Association.

Mahmoody-Vanolya, N., & Jelokhani-Niaraki, M. R. (2023). Measuring the spatial similarities in volunteered geographic information. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *X-4*(W1–2022), 411–416. https://doi.org/10.5194/isprs-annals-X-4-W1-2022-411-2023

McCall, M. (2006). Precision for whom? Mapping ambiguity and certainty in (participatory) GIS. *Participatory Learning and Action*, *54*, 114–119. https://www.iied.org/g02958

Miller, H. J. (2020). Geographic information science III: GIScience, fast and slow - why faster geographic information is not always smarter. *Progress in Human Geography*, *44*(1), 129–138. https://doi.org/10.1177/0309132518799596

Mocnik, F.-B., Mobasheri, A., Griesbaum, L., Eckle, M., Jacobs, C., & Klonner, C. (2018). A grounding-based ontology of data quality measures. *Journal of Spatial Information Science*, *16*(16), 1–25. https://doi.org/10.5311/JOSIS.2018.16.360

Mohamed, A. A. (2025). Mapping the landscape of public participation GIS using natural language processing. *Annals of the American Association of Geographers*, 1–23. https://doi.org/10.1080/24694452.2025.2511944

Nurminen, V. (2022). *The influence of participatory mapping in urban planning* [Master's thesis]. Aalto University. https://urn.fi/URN:NBN:fi:aalto-202210165926

Pánek, J., Pászto, V., & Marek, L. (2017). Mapping emotions: Spatial distribution of safety perception in the city of Olomouc. In I. Ivan, A. Singleton, J. Horák, & T. Inspektor (Eds.), *The rise of big spatial data* (pp. 211–224). Springer. https://doi.org/10.1007/978-3-319-45123-7_16

Pietilä, M., & Fagerholm, N. (2016). Visitors' place-based evaluations of unacceptable tourism impacts in Oulanka National Park, Finland. *Tourism Geographies*, *18*(3), 258–279. https://doi.org/10.1080/14616688.2016.1169313

Rall, E., Bieling, C., Zytynska, S., & Haase, D. (2017). Exploring city-wide patterns of cultural ecosystem service perceptions and use. *Ecological Indicators*, *77*, 80–95. https://doi.org/10.1016/j.ecolind.2017.02.001

Ramírez Aranda, N., De Waegemaeker, J., Venhorst, V., Leendertse, W., Kerselaers, E., & Van De Weghe, N. (2020). *Point, polygon, or marker? In search of the best geographic entity for mapping cultural ecosystem services using the online PPGIS tool, "My Green Place."* (Version v1) [Dataset]. Zenodo. https://doi.org/10.5281/zenodo.4347404

Ramírez Aranda, N., De Waegemaeker, J., Venhorst, V., Leendertse, W., Kerselaers, E., & Van De Weghe, N. (2021). Point, polygon, or marker? In search of the best geographic entity for mapping cultural ecosystem services using the online public participation geographic information systems tool, "My Green Place". *Cartography and Geographic Information Science*, *48*(6), 491–511. https://doi.org/10.1080/15230406.2021.1949392

Ricker, B. A., Johnson, P. A., & Sieber, R. E. (2013). Tourism and environmental change in Barbados: Gathering citizen perspectives with volunteered geographic information (VGI). *Journal of Sustainable Tourism*, *21*(2), 212–228. https://doi.org/10.1080/09669582.2012.699059

Ridding, L. E., Redhead, J. W., Oliver, T. H., Schmucki, R., McGinlay, J., Graves, A. R., Morris, J., Bradbury, R. B., King, H., & Bullock, J. M. (2018). The importance of landscape characteristics for the delivery of cultural ecosystem services. *Journal of Environmental Management*, *206*, 1145–1154. https://doi.org/10.1016/j.jenvman.2017.11.066

Rohrbach, B., Anderson, S., & Laube, P. (2016). The effects of sample size on data quality in participatory mapping of past land use. *Environment and Planning B: Planning and Design*, *43*(4), 681–697. https://doi.org/10.1177/0265813515618578

Rossi, S., Harsia, E., Kajosaari, A., & Kyttä, M. (2025). The citizens have participated – what now? An action research study of factors impacting the use of participatory citizen knowledge in planning processes. *European Planning Studies*, *33*(1), 124–146. https://doi.org/10.1080/09654313.2024.2416001

Rzeszewski, M., & Kotus, J. (2019). Usability and usefulness of internet mapping platforms in participatory spatial planning. *Applied Geography*, *103*, 56–69. https://doi.org/10.1016/j.apgeog.2019.01.001

Salminen, E. A., Ancin Murguzur, F. J., Ollus, V. M. S., Engen, S., & Hausner, V. H. (2025). Using Public Participation GIS (PPGIS) to relate local concerns over growth in tourism and aquaculture to integrated coastal zone management in the Tromsø region, Norway. *Ocean & Coastal Management*, *261*, 107510. https://doi.org/10.1016/j.ocecoaman.2024.107510

Senaratne, H., Mobasheri, A., Ali, A. L., Capineri, C., & Haklay, M.. (2017). A review of volunteered geographic information quality assessment methods. *International Journal of Geographical Information Science*, *31*(1), 139–167. https://doi.org/10.1080/13658816.2016.1189556

Solé, L., Hearn, K. P., Witra, T., Lechner, A. M., & Fagerholm, N. (2025). Balancing landscape values and tourism choices: Integrating participatory mapping and the IPBES values typology. *Ambio*, *54*(5), 818–838. https://doi.org/10.1007/s13280-024-02112-6

Staffans, A., Kahila-Tani, M., & Kyttä, M. (2020). Participatory urban planning in the digital era. In S. Geertman & J. Stillwell (Eds.), *Handbook of planning support science* (pp. 307–322). Edward Elgar. https://doi.org/10.4337/9781788971089.00030

Van Riper, C. J., & Kyle, G. T. (2014). Capturing multiple values of ecosystem services shaped by environmental worldviews: A spatial analysis. *Journal of Environmental Management*, *145*, 374–384. https://doi.org/10.1016/j.jenvman.2014.06.014

Veregin, H. (2005). Data quality parameters. In P. A. Longley, M. F. Goodchild, D. J. Maguire, & D. W. Rhind (Eds.), *Geographical information systems: Principles, techniques, management and applications* (2nd ed., pp. 177–189). Wiley.

Vullings, W., Bulens, J., Rip, F. I., Boss, M., Meijer, M., Hazeu, G., & Storm, M. (2015). Spatial data quality: What do you mean? In F. Bacao, M. Y. Santos, & M. Painho (Eds.), *Proceedings of 18th AGILE International Conference on Geographic Information Science* (pp. 1–6). AGILE Conference.

Wolf, I. D., Brown, G., & Wohlfart, T. (2018). Applying public participation GIS (PPGIS) to inform and manage visitor conflict along multi-use trails. *Journal of Sustainable Tourism*, *26*(3), 470–495. https://doi.org/10.1080/09669582.2017.1360315

Zolkafli, A., Brown, G., & Liu, Y. (2017). An evaluation of participatory GIS (PGIS) for land use planning in Malaysia. *The Electronic Journal of Information Systems in Developing Countries*, *83*(1), 1–23. https://doi.org/10.1002/j.1681-4835.2017.tb00610.x