



Integrating machine learning into public participation GIS: trends, challenges, and future directions for spatial information science

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Abstract

This paper presents an exploratory narrative review of machine learning (ML) applications in Public Participation Geographic Information Systems (PPGIS)-related studies. Based on a structured Scopus search and screening process, the review examines how ML techniques are used to process and interpret collaborative spatial data and identifies associated challenges. The findings show that supervised learning methods, including random forest, boosted regression trees, artificial neural networks, and deep learning, are most commonly applied, while unsupervised methods are used to detect spatial and perceptual patterns. These approaches can strengthen PPGIS by supporting the analysis of complex citizen-generated datasets and linking participatory inputs to spatial decision-support processes. However, concerns remain regarding data representativeness, participant bias, spatial uncertainty, privacy, and model interpretation. The paper highlights the need for more transparent, evidence-based, and explicable PPGIS frameworks, which would enable the use of ML to support participatory spatial decision-making.

Keywords Public participation GIS · Machine learning · Participatory mapping · Urban planning · Explainable AI

1 Introduction

Spatial information systems have become central to the collection, analysis, visualization, and communication of geospatial data across research, policy, and practice. As Geographic Information Systems (GIS) have become more accessible and operationally embedded in planning, environmental management, public administration, and urban

governance, attention has increasingly shifted from purely technical questions to the social, institutional, and participatory uses of geospatial technologies [1]. Within this development, PPGIS emerged as a significant field concerned with the use of GIS to support public involvement, citizen-generated spatial knowledge, and more inclusive forms of spatial decision-making [2].

PPGIS was formally articulated in the mid-1990s, including through discussions at the National Center for Geographic Information and Analysis (NCGIA), where the term was used to describe how GIS technologies could facilitate public participation and support the involvement of communities that are often underrepresented in formal planning processes [2]. Since then, PPGIS has developed into an important approach for collecting spatially explicit perceptions, local knowledge, landscape values, risk perceptions, mobility experiences, and place-based preferences. These data are increasingly relevant for urban planning, environmental management, public health, climate adaptation, and spatial policy.

At the same time, rapid developments in geospatial technologies and artificial intelligence (AI) are expanding the computational capacity of spatial information science. Improvements in remote sensing, Global Positioning

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System accuracy, mobile data collection, drones, and web-based mapping platforms have increased both the volume and complexity of geospatial data [3, 4]. In parallel, ML has become increasingly important for spatial analysis, enabling pattern detection, classification, clustering, prediction, and modeling across large and heterogeneous datasets [5]. ML methods are now widely used in urban and geographical studies, including land-use classification, environmental risk mapping, urban growth modeling, accessibility analysis, transport forecasting, and image-based spatial analysis.

Despite these advances, the relationship between ML and PPGIS remains underdeveloped. PPGIS generates rich forms of citizen-generated geospatial data, including mapped locations, survey responses, spatial perceptions, qualitative comments, and, at times, visual or multimedia inputs. These datasets offer significant opportunities for computational analysis, but they also raise specific methodological and ethical issues. Participatory spatial data are often unevenly distributed, socially biased, context-dependent, spatially uncertain, and difficult to translate into structured computational variables. As a result, the integration of ML into PPGIS cannot be treated simply as a technical extension of GIS analysis. It requires careful consideration of data quality, representativeness, interpretability, privacy, participatory legitimacy, and the operational use of model outputs in planning and decision-making.

Several reviews have examined ML in spatial analysis, urban studies, geospatial artificial intelligence, and spatial data science [5–9]. However, fewer studies have specifically examined how ML techniques are being applied to PPGIS-related data and what this means for spatial information science. In particular, there is limited understanding of which ML methods are currently used in PPGIS contexts, what types of participatory spatial data they process, how they support spatial decision-making, and what challenges arise when citizen-generated knowledge is transformed into computational outputs.

This study addresses this gap by examining the use of ML techniques in PPGIS research. The aim is to identify emerging trends in the use of ML for analyzing participatory spatial data and to discuss the methodological, computational, operational, and ethical implications of ML-enabled PPGIS. The study has three main objectives. First, it reviews the development of PPGIS as a method for collecting and analyzing citizen-generated geospatial data. Second, it examines relevant ML techniques used in urban, geographical, and spatial information research, with attention to their potential application to participatory datasets. Third, it analyses how ML is currently integrated into PPGIS-related studies and identifies future directions for more transparent, bias-aware, explainable, and operationally usable ML-enabled PPGIS.

The remainder of the paper is structured as follows. Section 2 describes the methodology of the review. Section 3 presents the reviewed studies and discusses the integration of ML and PPGIS. Section 4 discusses the main findings, the main challenges and constraints, and the prospects of ML-enabled PPGIS in the field of Spatial Information Science, and Section 5 concludes the paper.

2 Methods

2.1 Conceptual definitions

2.1.1 Public participation and PPGIS

The rise of public participation in urban studies and geography is evident in the writings of notable contributors such as Kurt Lewin, Patrick Geddes, and Lewis Mumford [10]. Arnstein [11], in *The Ladder of Citizen Participation* as a guide to increase citizen agencies, control, and power, provides a framework for evaluating the extent to which citizens are involved in decision-making. The idea of involving the citizens in decision-making began in the late 80s in Porto Alegre, Brazil, the first city in the world to increase citizen involvement in municipal management [12, 13].

The use of digital tools for citizen participation is widespread across all levels of government worldwide. It is common for public authorities to utilize digital tools to engage with the public, as they can appear more accessible and easier to use, and enable immediate and widespread participation.

Researchers and urban planners have been interested in the development and application of participatory methods since the 1970s. As Participatory Geographic Information Systems (PGIS) and PPGIS emerged in the mid-1990s, interest in methods grew.

PPGIS is an online public participation tool that utilizes GIS to facilitate the participatory discovery process. An example could be a GIS map attached to a survey or used to demonstrate the issue at stake during a public meeting. PPGIS may contain a large amount of data and help to visualize it, which helps the participant to understand complex planning processes [14]. As defined by Tulloch [15] (p.na), PPGIS is: “(...) a field within geographic information science that focuses on ways the public uses various forms of geospatial technologies to participate in public processes, such as mapping and decision making. Some members of the public participate in mapping activities simply to help inform the process.”

The PPGIS process involves designing a survey, recruiting participants, collecting data, and then analyzing the data [16]. In terms of survey design, PPGIS surveys may include

question types such as structured (closed-ended), open-ended, and multiple-choice [17]. In addition to traditional surveys, PPGIS surveys also include marking answers on the map by placing a point, drawing a line, or drawing a polygon. The respondent may provide additional information about the map labels, depending on the type of survey [17].

Online PPGIS surveys can recruit participants in several ways, including household registries, random samples of the country's population [18, 19], purposive sampling [20], crowd-sourced/volunteer sampling through traditional or social media [21, 22], and internet survey panels [23]. Online surveys for PPGIS data collection are often self-managed, allowing individuals to map relevant spatial attributes independently. In PPGIS, mapped spatial data can be represented as points, lines, or polygons, and simple points and lines are the most common mapping features [24].

Spatial analysis in PPGIS can be divided into three phases (Explore, Explain, and Predict/Model) [16]. First, the Explore phase involves exploratory and descriptive analysis methods. Secondly, the Explain phase aims to understand the relationship between PPGIS data and some other geospatial data sources that could serve as explanatory variables (e.g., soil coverage, road network data, plant and animal population data, or spatial plans) [25]. Third, the Predict and Model phase involves generalizing mapped attributes to other locations and contexts, and understanding future realities through the relationships that emerge from the Explain phase [25].

PPGIS approaches have been applied in various fields, including urban green spaces, protected area planning, and coastal zone management. In recent years, Platforms have emerged to meet the public's mapping needs, differing in the degree to which they integrate with and influence formal public planning and decision-making processes. Table 1 lists the latest platforms useful for PPGIS and participatory mapping.

The use of PPGIS has evolved from early studies on landscape and natural resources management to more recent research on urban equity, risk perceptions, public health, and climate change. In an early PPGIS study, Brown and Reed [10] asked participants to identify landscape values through selecting the location for the Chugach National Forest (U.S.) planning process.

Several studies on PPGIS have been conducted since 2020. Buendía et al. [26] used PPGIS to analyze how visitors and locals perceive the Ebro Delta Natural Park. Valánszki et al. [27] examined the use of PPGIS to investigate perceptions of cultural ecosystem services (CES) in Hungary, focusing on landscape features and accessibility. Jankowski et al. [28] investigated the effects of PPGIS on land use planning at the neighborhood and city scales in Finland and

Poland. Korpilo et al. [29] investigated procedural justice and perceived equity in the planning of the Urban Green and Blue Spaces (UGBS) area on Amager Island in Copenhagen using PPGIS. Gheitasi et al. [77] analyzed risk perception among the population using PPGIS in areas surrounded by petrochemical industries. Nurminen et al. [30] examined the impact of PPGIS on urban planning outcomes in Finland. Stoltz et al. [31] have investigated whether there is a relationship between outdoor recreation and health benefits, focusing on how landscape features respond to individuals' needs and preferences. Johnson et al. [32] explored how place-based risk perceptions and landscape values can inform climate change adaptation using a Q-method and PPGIS. Gheitasi et al. [77] examined the relationship between perceived technological risk and the emotional value of landscapes in petrochemical areas. Mansournia et al. [33] examined the use of PPGIS to assess the quality of outdoor spaces in Mariwan, Iran, by mapping children's favorite outdoor spaces. Mansournia et al. [34] employed a PPGIS approach to investigate urban child-friendliness among children in Mariwan and Sanandaj, Iran. Anderson et al. [35] employed a PPGIS survey to evaluate the equity of cooling-related visitor visits and to investigate the role of public green areas in mitigating urban heating in Bochum, Germany. Gheitasi et al. [77] examined the impact of the Oil Refinery on landscape perception values and mental health, using PPGIS and manipulated photographs in the Tehran Oil refinery area and surroundings.

2.1.2 ML

ML refers to how machines learn and improve through experience without being explicitly programmed. It has become central to many AI tasks, but it is only one of several technologies that are often presented in a nested hierarchy (Fig. 1) [36].

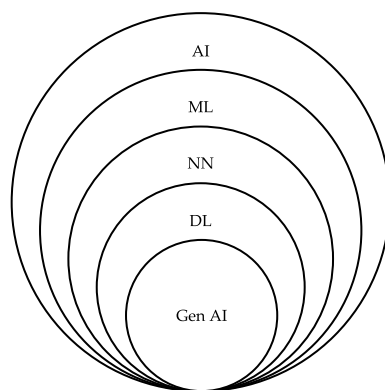
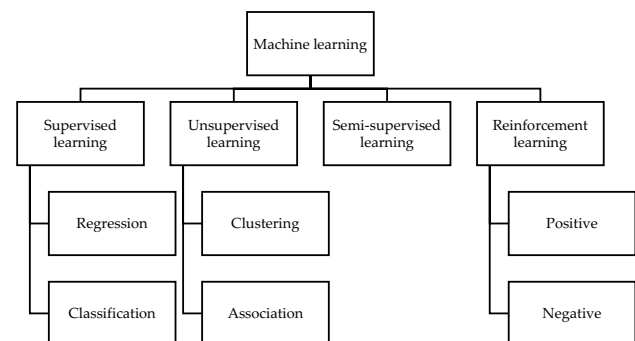
ML is the ability of a computer to improve its performance based on its previous performance [37]. ML has four general categories, each defined by the type of data used and the manner in which the model learns from experience (Fig. 2).

Supervised learning (SL) is ML approach in which an algorithm is trained using labeled data, where each input (feature set) is paired with a known output, allowing the model to learn the relationship between them and make predictions on new data [39]. Two common tasks in SL are regression, which predicts a continuous numeric value (e.g., price or temperature), and classification, which assigns data to a category (e.g., whether an email is spam).

Unsupervised learning (UL) is a type of AI that searches for previously unknown patterns in an information set without prior labeling and with minimal human intervention

Table 1 PPGIS platforms

Name	Participation mode	Performance	Cost
Mapbox	Web-based interactive participation via custom-built applications and APIs	Advanced map visualization, interactive dashboards, large dataset display, and customized stakeholder engagement interfaces	Commercial (subscription-based service)
Mapeo	Offline-first, community-based participatory mapping via mobile and desktop applications	Field data collection (GPS points, photos, observations), community-led environmental and human rights documentation, secure and privacy-focused mapping, and low-tech and multilingual contexts	Free and open-source
Maptionnaire	Online map-based surveys and a structured community engagement platform	Participatory planning, large-scale public surveys, spatial data collection and analysis, planning evaluation, and decision-making support	Commercial (subscription-based service)
Seasketch	Web-based participatory mapping and geodesign platform for collaborative planning	Marine and general spatial planning, geospatial data visualization, crowd-sourced spatial input, sketching and evaluating spatial plans, and interactive public engagement	Free and open-source
Sketch map tool	Participatory sketch mapping combining paper-based inputs with digital georeferencing	Capturing local knowledge of disasters, flood risk mapping, creating risk perception maps, and integrating with GIS and questionnaires for disaster risk reduction	Free and open-source
Survey123	Web-based map-enabled innovative forms for participatory data collection	Creating structured surveys with map-based questions, multimedia inputs, calculations, and offline/online data collection; integration with the ArcGIS Online ecosystem for visualization, analysis, and dashboards	Commercial (requires Esri licensing; pricing depends on subscription level)
Terrastories	Community-led participatory mapping with digital story databases	Mapping culturally relevant knowledge, multimedia-based community storytelling, low-tech participatory research, and Indigenous-led data projects	Free and open-source
Ushahidi	Crowd-sourced reporting via web and SMS for participatory mapping	Collecting, managing, and visualizing citizen-generated data in crises, disasters, human rights, governance, and community resilience efforts	Commercial (subscription-based service)
Map-Me	Web-based PPGIS survey with “spraycan” interface for vague spatial data	Capturing fuzzy and subjective spatial perceptions (e.g., where people think or feel something about a place), flexible community surveys with imprecise boundaries, and richer PPGIS datasets	Free and open-source

**Fig. 1** The nested hierarchy of AI, ML, neural networks (NN), deep learning (DL), and Generative AI (GenAI)**Fig. 2** Types of ML and their main categories based on [38]

[40]. Clustering is a key UL technique that groups similar data points, for example, segmenting users or areas with similar characteristics. Another important task is association, which identifies relationships between variables, for

example, by determining which products are often bought together.

Semi-supervised learning (SSL) is a practical approach that combines SL and UL learning paradigms to improve model performance. It addresses the challenge of limited labeled data by utilizing large amounts of unlabeled data to improve learning accuracy [41].

Reinforcement learning (RL) is a learning method in which an AI agent interacts with its environment through trial and error, learning an optimal behavioral strategy based on rewards received from previous interactions [42]. In this approach, an agent performs actions and receives feedback in the form of positive rewards or negative penalties. Over time, the agent learns to choose actions that maximize the overall reward.

In recent years, the use of ML in urban and geographical studies has grown rapidly, as illustrated by the increasing number of systematic reviews and empirical studies on the challenges of urban sustainability and planning. Shaamala et al. [43] studied a systematic review of ML applications in geospatial analysis, categorizing techniques, domains, and data types. El Baida et al. [44] conducted a systematic literature review of ML classification models applied to urban flood hazard mapping. Milojevic-Dupont and Creutzig [45] conducted a systematic review of ML applications related to climate change mitigation in remote sensing, urban transportation, and buildings, and proposed a meta-algorithmic framework for optimizing urban planning and infrastructure provision. Grekousis [46] conducted a meta-analysis and proposed reporting guidelines to improve the coherence and dissemination of artificial neural network (ANN) research in urban studies.

Yao et al. [47] aimed to develop a comprehensive model for evaluating the spatial quality of underground pedestrian

streets from a pedestrian perspective by using spatial syntax, multi-dimensional perception data, and ML algorithms (Random Forest (RF) and XGBoost). Aryal et al. [48] aimed to automate land use and land cover (LULC) performance modeling for city planning using ML algorithms by testing six ML models on Sentinel-2A imagery for Melbourne, demonstrating that RF achieves the highest classification accuracy and robustness across all evaluation measures. Tsagkis et al. [49] applied ML approach, using ANN, to model urban growth in five major Greek cities. Huang et al. [50] aimed to analyze the nonlinear relationship between air pollution and urban morphological factors using mobile monitoring data and ML.

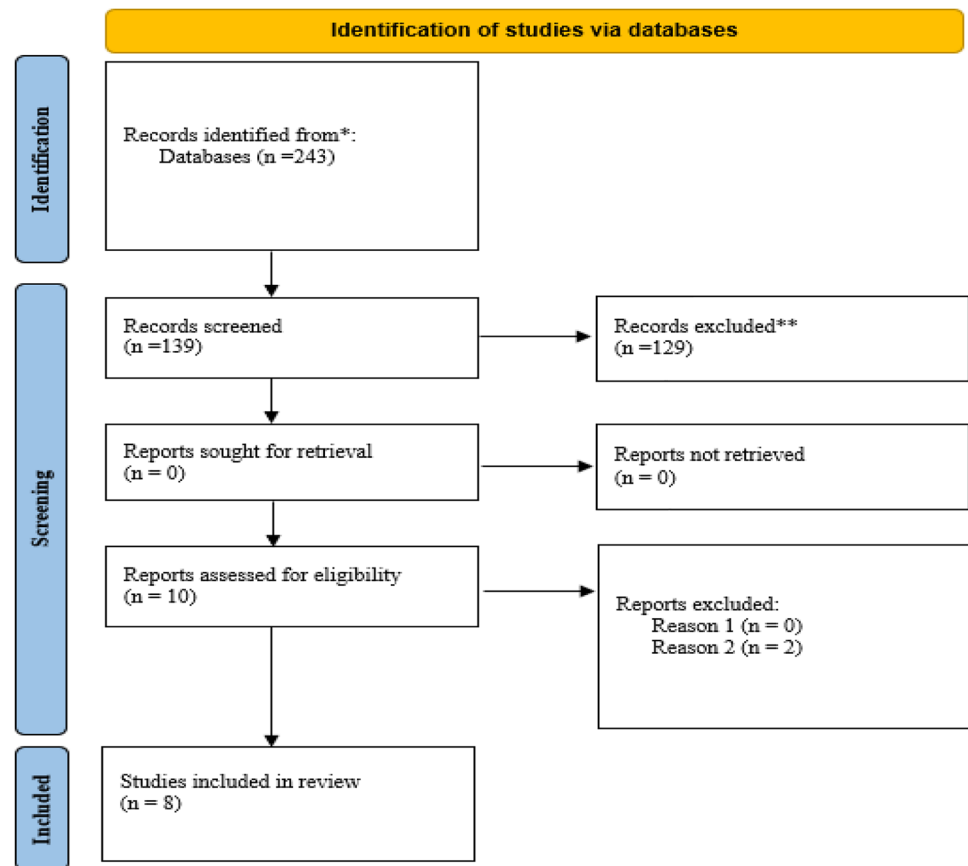
Ramirez et al. [51] developed a scalable methodology that combines surveys, discrete choice modeling, and image parametrization (including semantic segmentation and object detection) to measure heterogeneous perceptions of public spaces. Biljecki and Ito [52] presented street view images for urban analysis and GIS science, which are widely used in various fields, including vegetation, transportation, health, and socio-economic studies. Table 2 presents a structured overview of the main ML tasks used in urban and geographical studies, highlighting the types of learning, objectives, common algorithms, and their example applications.

2.2 Literature search and analysis

This study adopts an exploratory narrative review supported by a structured literature search and screening protocol. The aim was not to conduct a comprehensive systematic review of all ML applications in spatial information science, but to identify and analyze emerging patterns in the integration of ML and PPGIS. This approach is appropriate for a research

Table 2 Overview of major ML tasks in urban studies and geography

ML task	Type of ML	Purpose	Common models/algorithms	Applications in urban Studies & geography
Classification	SL	Categorize data based on predefined characteristics	RF, Support Vector Machine (SVM), ANN, XGBoost, k-nearest neighbors (kNN) [53–55]	LULC classification—Environmental risk mapping—Urban growth patterns—Air pollution exposure—Urban heat islands—Travel behavior modeling—Traffic congestion prediction—Urban flood vulnerability—Socio-demographic/accessibility neighborhood classification
Clustering	UL	Group data points based on similarities without predefined labels	K-means, Gaussian Mixture Model (GMM) [56, 57]	Understanding land-use patterns—Socio-economic assessments—Neighborhood grouping by population density or dominant land use—Identifying mixed-use or transitional urban areas
Regression	SL	Forecast continuous outcomes using predictor variables	RF, ANN, XGBoost, SVM, Gradient-Boosted Decision Trees (GBDT) [58, 59]	Urban growth prediction—Real-time traffic forecasting—Traffic accident prediction—Population density estimation—Modeling complex urban phenomena with nonlinear relationships
Optimization	Optimization-based ML	Find the most effective/efficient solutions under constraints	Non-dominated Sorting Genetic Algorithm (IINSGA-II), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) [43]	Spatial design & urban layouts—Site selection—Water management—Air quality improvement—Urban heat island mitigation—Transportation system optimization—Carbon emissions in urban waste management—Multi-objective planning tasks (e.g., land-use planning, environmental monitoring)

Fig. 3 Flow diagram of the literature search process**Table 3** Search strings used for literature search

Search String Type	Sentences
TITLE-ABS-KEY	("machine learning" OR "ML" OR "artificial intelligence" OR "AI" OR "deep learning" OR "neural network*" OR "supervised learning" OR "unsupervised learning" OR "predictive model*")
TITLE-ABS-KEY	("public participation GIS" OR "PPGIS" OR "SIGPP" OR "public participation geographic information system*" OR "PGIS" OR "participatory GIS" OR "participatory mapping" OR "community mapping" OR "participatory planning" OR "collaborative mapping" OR "citizen mapping")
Combined search	TITLE-ABS-KEY (("machine learning" OR "ML" OR "artificial intelligence" OR "AI" OR "deep learning" OR "neural network*" OR "supervised learning" OR "unsupervised learning" OR "predictive model*") AND ("public participation GIS" OR "PPGIS" OR "SIGPP" OR "public participation geographic information system*" OR "PGIS" OR "participatory GIS" OR "participatory mapping" OR "community mapping" OR "participatory planning" OR "collaborative mapping" OR "citizen mapping"))

area that remains fragmented and relatively underdeveloped, where the objective is to synthesize current knowledge, clarify conceptual relationships, and identify methodological and operational directions for future research [60].

The literature search was conducted using the Scopus database, selected for its broad coverage of peer-reviewed research in spatial information science, geography, urban studies, computer science, planning, and environmental research. The search focused on English-language journal articles published up to 2026. The final search was conducted in April 2026. No additional databases, study registries, or grey literature sources were included. While this limits the comprehensiveness of the review, it provides a transparent and replicable basis for identifying peer-reviewed studies at the intersection of ML and PPGIS (Fig. 3).

The search strategy combined terms related to ML and AI with terms related to PPGIS, participatory GIS, participatory mapping, and citizen-generated spatial data (Table 3). The search strings were applied to titles, abstracts, and keywords. The first group of terms included "machine learning," "ML," "artificial intelligence," "AI," "deep learning," "neural network," "supervised learning," "unsupervised learning," and "predictive model." The second group included "public participation GIS," "PPGIS," "public participation geographic information systems," "PGIS,"

“participatory GIS,” “participatory mapping,” “community mapping,” “participatory planning,” “collaborative mapping,” and “citizen mapping.” The combined search string used the Boolean operator AND to identify studies that connected these two areas.

A total of 243 records were initially identified. After restricting the results to English-language journal articles, 139 records remained for abstract screening. Studies were included if they met three criteria: first, they addressed ML, AI, or computational modeling techniques relevant to spatial data analysis; second, they included PPGIS, participatory mapping, or citizen-generated geospatial data; and third, they provided empirical findings, methodological insights, or conceptual contributions relevant to the integration of ML and participatory spatial information. Studies were excluded if they focused only on general geospatial ML without a participatory component, discussed public participation without computational or ML-based analysis, or lacked sufficient methodological detail.

During abstract screening, 129 records were excluded because they were not directly relevant to the research focus or did not provide sufficient information on the integration of ML and PPGIS. This resulted in 10 articles being selected for full-text review. After full-text assessment, 2 further studies were excluded because they focused on unrelated technical ML applications or lacked sufficient methodological detail. The final review, therefore, included 8 studies.

The selected studies were analyzed qualitatively to identify how ML techniques are currently applied in PPGIS-related research. The analysis focused on four aspects: the type of participatory spatial data used, the ML methods applied, the analytical purpose of the ML techniques, and the challenges or limitations identified regarding data quality, representativeness, interpretability, and operational use. ML methods were grouped into supervised learning, unsupervised learning, deep learning, and other statistical or computational techniques. The review also considered whether ML was used primarily as a post-hoc analytical

tool or as part of a wider participatory spatial information workflow.

Because the final corpus was small, the findings should be interpreted as evidence of emerging trends rather than as a comprehensive representation of the entire field. Nevertheless, the structured search and screening process provides a transparent basis for identifying current applications, methodological gaps, and future research directions for ML-enabled PPGIS within spatial information science.

3 Results

3.1 Review findings

ML has significant potential to improve PPGIS for the public by enhancing data analysis, pattern recognition, and bias correction. PPGIS often produces large volumes of spatial and survey data that can be difficult to process manually; ML algorithms, such as clustering and classification models, can effectively analyze this data and identify underlying trends and relationships [16]. In recent years, several studies have explored the integration of PPGIS and ML. These studies have been analyzed with the methodology presented in Section 2 to explore the use of ML techniques within the PPGIS context. A summary of the ML methods used in each study is provided in Table 4 and Figure 4, illustrating how ML can be used to analyze large spatial and survey datasets, identify patterns, and facilitate evidence-based decision-making.

Among the reviewed studies on PPGIS and ML, SL is the most frequently used approach. In studies employing SL, techniques such as BRT, DL methods, RF, and ANN were commonly used. Among these, BRT and DL techniques appear to be the most widely applied. In addition to SL, several studies used UL methods. Within the UL category, the most frequently used techniques were SOM and k-means clustering.

Table 4 Methods in the reviewed studies

Author	Year	Methods									
		Data collection	Data analysis							Others (statistical, etc.)	
			PPGIS	SL					UL		
				BRT	RF	ANN	DL	Others	K-means		SOM
Stefan et al. [61]	2025	⊗			⊗					⊗	⊗
Lehto et al. [62]	2024	⊗	⊗								⊗
Li et al. [63]	2024	⊗				⊗					
Stoltz et al. [64]	2024	⊗						⊗			
Li et al. [65]	2023	⊗				⊗					
Lehto et al. [66]	2023	⊗	⊗								
Schrammeijer et al. [67]	2022	⊗					⊗				
Huang et al. [68]	2022	⊗				⊗					⊗

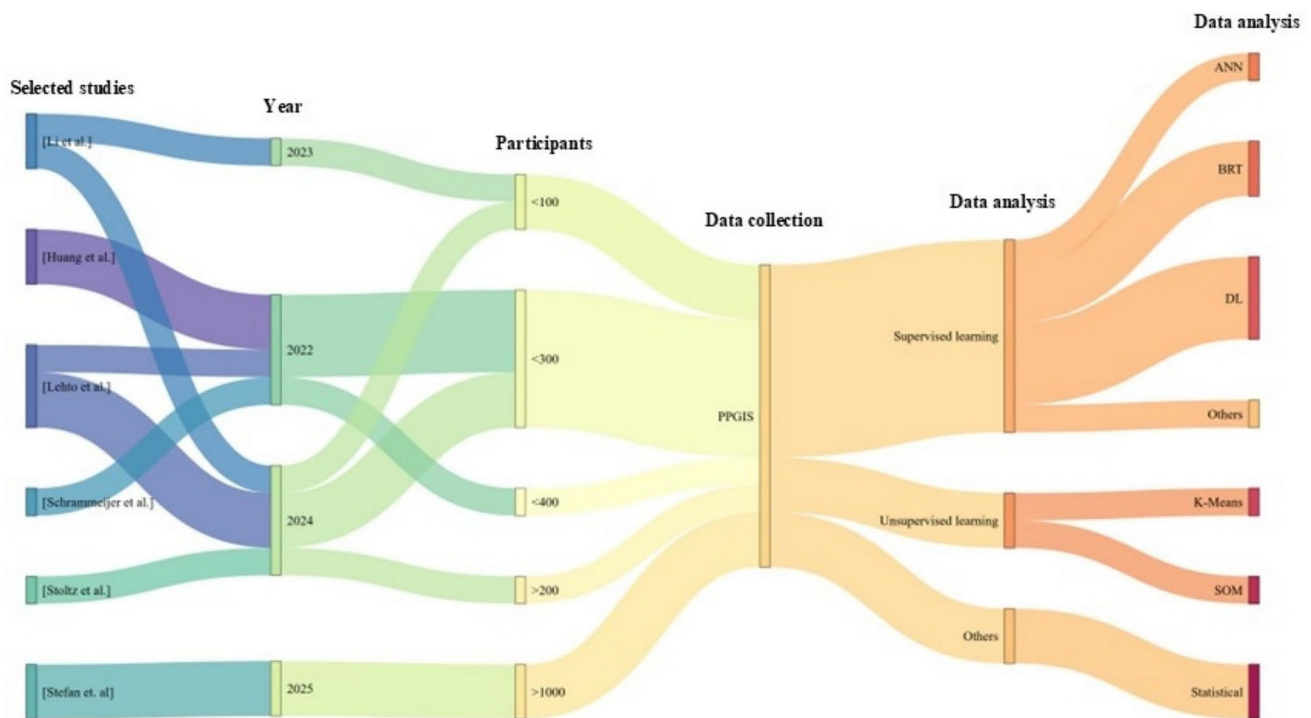


Fig. 4 Sankey-based overview of PPGIS studies

3.2 Analytical role of ML in PPGIS workflows

Figure 5 illustrates the study's framework for integrating PPGIS data and ML techniques to inform planning decisions. The framework begins with community input collected through PPGIS, including (1) spatial data such as mapped perceptions of landscape values, environmental conditions, or areas of concern; (2) structured survey responses (e.g., Likert-scale measures of perception, well-being, and environmental attitudes); (3) socio-demographic attributes; and (4) visual data derived from participant-submitted photographs.

The second phase involves data analysis through three complementary approaches: (1) descriptive and visual analysis to summarize and communicate key patterns, (2) spatial analysis to identify geographic distributions and clustering of variables, and (3) predictive modeling to explore relationships and potential future scenarios. Next, the processing phase applies ML techniques to extract deeper insights from the data. UL methods (e.g., clustering algorithms like K-means or SOM) uncover hidden patterns, while SL techniques (e.g., RF, BRT, or DL models) predict outcomes based on labeled data.

Also, according to some studies [90, 91] excluded from the selection due to criteria, XAI techniques are selectively applied in cases where nonlinear or ensemble models (e.g., RF, BRT) are used and where interpretability is necessary for planning and policy contexts. Tools such as Shapley

Additive Explanations (SHAP) and Partial Dependence Plots (PDPs) are used to assess variable importance, explore nonlinear relationships, and understand the direction and magnitude of model effects. The application of XAI is less common for simpler, inherently interpretable models.

Finally, the insights derived from these analyses are translated into planning decisions and policy recommendations, such as guiding spatial planning strategies, supporting environmental management and infrastructure upgrades, facilitating targeted social and public health interventions, identifying vulnerable or underserved populations, and promoting more effective community engagement. This comprehensive framework guarantees that planning processes are grounded in evidence, participative, and attentive to both spatial patterns and human perceptions.

4 Discussion

4.1 From descriptive mapping to ML-enabled spatial decision support

The results show that ML is being used to move PPGIS beyond its traditional role as a descriptive mapping tool and towards a more structured analytical element in spatial decision-making systems. While conventional PPGIS analysis typically focuses on visualizing the spatial distribution of citizen input (e.g., mapped values, perceptions, or

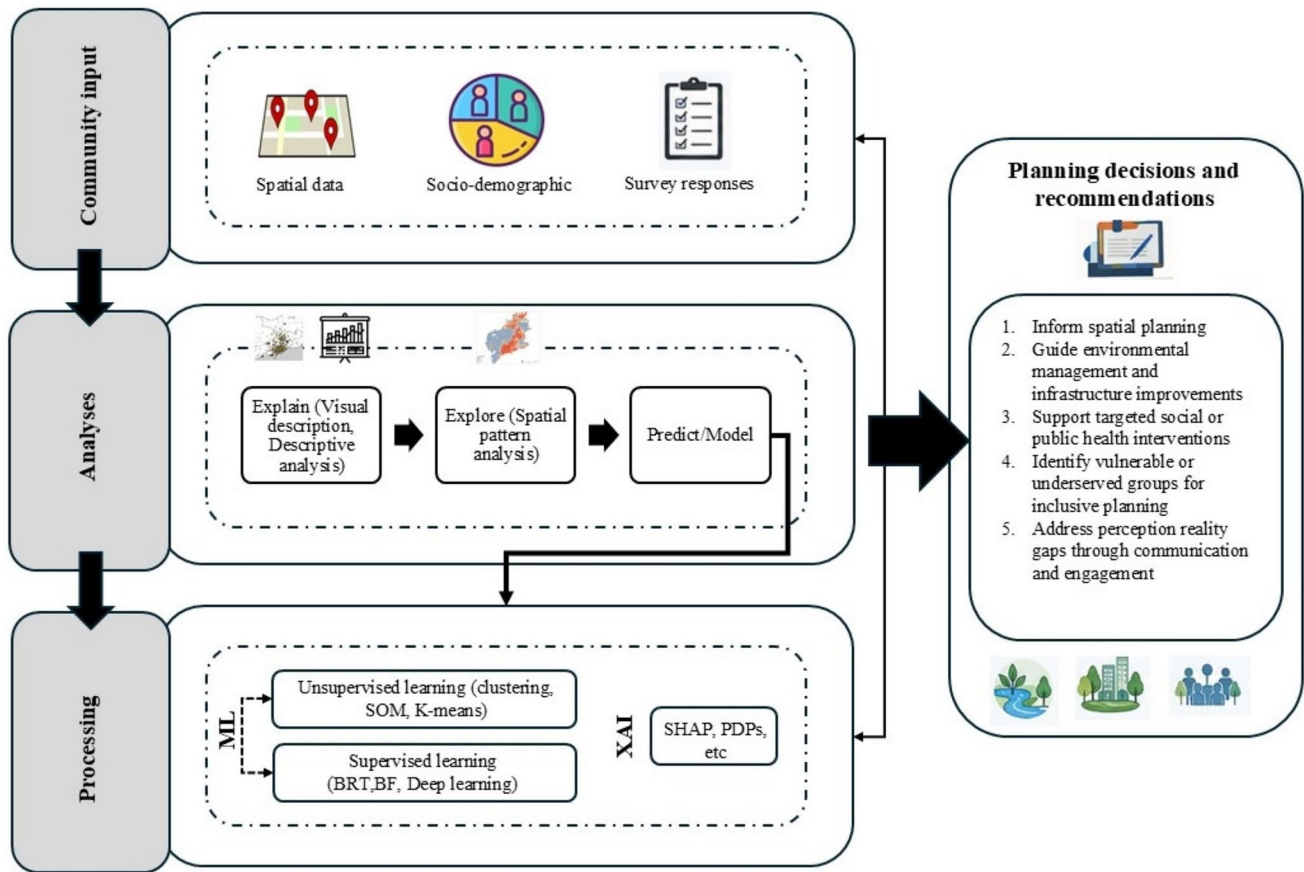


Fig. 5 Conceptual framework for integrating PPGIS and ML

concerns), ML enables deeper patterns to emerge by linking participatory data to environmental, socio-demographic, and spatial explanatory variables.

In the reviewed studies, SL methods (RF, BRT, ANN) are primarily used to model and predict the relationship between participatory responses and external spatial datasets, allowing researchers to identify factors associated with perceived landscape quality, recreational preferences, and environmental risks. At the same time, UL methods such as k-means clustering and SOM are used to group similar responses, reveal hidden perceptual differences, and identify spatially coherent clusters that are not easily detectable by a conventional GIS.

This analytical shift enables PPGIS outputs to be used more directly in spatial decision-support contexts. Instead of only describing where certain perceptions occur, ML-based approaches can help identify which environmental or spatial conditions are associated with these perceptions and how they vary across space. This supports a more structured interpretation of data generated by citizens in planning applications such as greening management, risk assessment, and urban environment assessment.

The findings also show that the effectiveness of this transformation depends on the quality and structure of the data collected by the citizens. Because PPGIS datasets are often unevenly distributed and context-dependent, ML outputs can reflect participant patterns as well as underlying spatial realities. Interpretation and validation are therefore crucial when ML is used in participatory spatial analysis.

4.2 Challenges and limitations

The use of ML in PPGIS poses several methodological and ethical problems. The main issue is representativeness, because ML models depend strongly on the quantity and quality of participatory data. In PPGIS, participation is voluntary and not equally distributed. Some regions or social groups may have less digital access or a lower willingness to participate and therefore be underrepresented in the dataset. This leads to spatial and social biases, and the model may learn participation patterns rather than real-world conditions.

For example, if people in a low-income or marginalized region do not participate in an online PPGIS survey about environmental risk, the dataset will have little or no data

from that region. When machine learning is used, the model may classify this region as having low risk perception.

Another challenge is transforming qualitative and experiential knowledge into a format that ML can use. PPGIS collects rich data, including perceptions, feelings, and personal experiences [69]. However, most ML methods require structured and numerical data. This means that qualitative inputs need to be simplified or coded into categories. During this process, important details and context can be lost. In addition, PPGIS data already has limitations, such as spatial inaccuracies, incomplete responses, and varying data quality. These issues make it more difficult to produce reliable ML results.

Another limitation is that PPGIS data is often based on point locations with limited attribute information. In many cases, participants mark only a location on the map without providing detailed explanations or narratives. When this type of data is analyzed using ML, the model primarily focuses on spatial patterns, such as clusters or densities. However, it cannot fully capture the reasons behind the points. For instance, two locations may both be marked as “negative,” but one may relate to air pollution and the other to noise or safety concerns. Without detailed attributes, the ML output may treat them as the same, and the main meaning of participation is partially lost.

4.3 Future perspectives

The integration of ML with PPGIS is likely to develop beyond post-hoc data analysis toward more interactive, transparent, and participatory forms of spatial decision support. Current applications show that ML is mainly used after PPGIS data have been collected, particularly for classification, clustering, prediction, and pattern recognition. Future research should therefore explore how ML can become more closely embedded in participatory processes themselves, rather than remaining at a separate analytical stage.

A key direction is the use of XAI to improve the transparency and interpretability of ML-enabled PPGIS. Many ML models, especially ensemble and DL approaches, can identify complex spatial and perceptual relationships but are difficult for planners, stakeholders, and community participants to interpret. XAI methods, such as SHAP and PDPs, can help clarify which spatial, environmental, social, or perceptual variables influence model outputs. In PPGIS contexts, such techniques may support more transparent planning discussions by showing why certain areas are classified as vulnerable, attractive, risky, restorative, or underserved. However, explanation techniques should not be treated as purely technical outputs. Their usefulness needs to be tested with end users through participatory validation, workshops, or co-design sessions to ensure that

explanations are meaningful, accessible, and actionable for different stakeholder groups. It should also be noted that, in theory, a more complex XAI system could provide more detailed results [70]. However, for the end user in particular, greater detail can make interpretation more difficult, potentially leading to cognitive overload [70].

A second priority is the development of bias-aware and equity-sensitive modeling approaches. PPGIS data are often shaped by uneven participation, digital access, spatial familiarity, socio-demographic differences, and varying levels of trust in planning institutions. If these biases are not recognized, ML models may reproduce or amplify existing inequalities by treating uneven participation as objective spatial evidence. Future studies should therefore examine how sampling strategies, weighting procedures, uncertainty measures, and model evaluation criteria can be adapted to participatory spatial data. This includes testing whether ML outputs reflect actual spatial conditions or merely the geography of participation. Greater attention is also needed to underrepresented groups, missing data, and areas where low response rates may conceal rather than indicate low public concern.

A third future direction concerns real-time and adaptive PPGIS systems. Instead of using ML only after data collection, future platforms could provide immediate feedback to participants and planners throughout the engagement process. For example, ML could help identify emerging spatial clusters, highlight under-represented areas, propose follow-up questions, or support simulation-based scenarios. Adaptive survey design could also make PPGIS more responsive by adjusting prompts based on respondents' input, spatial coverage, and data gaps. Such systems may improve the richness and balance of participatory datasets, but they also require careful design to avoid steering participants too strongly or narrowing the range of responses.

Finally, future ML-enabled PPGIS research needs stronger governance frameworks. The use of citizen-generated spatial data raises important questions about privacy, consent, data ownership, algorithmic accountability, and the institutional use of model outputs. These issues become more significant when ML is used to inform planning decisions, resource allocation, environmental management, or public health interventions. Future work should therefore develop clear protocols for ethical data use, communication of uncertainty, stakeholder review, and accountability in decision-making. ML should support, not replace, deliberation and situated judgment in participatory planning.

Overall, future research should move ML-enabled PPGIS from technical optimization toward participatory intelligence. Its value will depend not only on predictive accuracy but also on transparency, inclusiveness, usability, contextual sensitivity, and public trust. This requires methodological

advances in ML, as well as stronger collaboration among Geoscience, planning, urban studies, data ethics, and participatory design.

5 Conclusion

This study examined how ML techniques are used in PPGIS and what this combination means for analyzing citizen-generated spatial data in planning and spatial exploration. It reviewed existing studies to understand the types of data involved, the methods used, and the main impacts of combining participatory mapping with computational modeling.

The results show that ML is mainly used to process and analyze complex participatory datasets and to identify relationships that are difficult to capture with traditional GIS methods. SL approaches are most often used, particularly ensemble and neural network models, to relate participatory inputs to environmental and socio-spatial factors for explanation and prediction. UL methods are applied less frequently and are primarily used to group similar responses and to reveal patterns in perceptual data. In most cases, ML is applied after data collection, rather than being integrated into the participatory process itself.

These applications offer clear analytical benefits, particularly in handling large and diverse data sets and linking public input with spatial and environmental information. The results also depend heavily on how participation is distributed across the different social groups. Unequal participation may shape the model's output, leading to results that reflect response patterns rather than actual spatial conditions. The translation of qualitative and practice-based input into structured formats may also reduce the depth of the meaning conveyed by the original data.

Overall, the study shows that ML is expanding the analytical use of PPGIS, but has not altered its core participatory nature. Further development is needed to ensure that these methods better reflect the participatory bias, preserve the importance of citizen input, and promote a more transparent use of results in planning and decision-making.

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Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

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