Crowdsourced Data for Urban Planning: A Critical Evaluation of OpenStreetMap Accuracy and Completeness

Federica Deri(✉), Federico Mara, and Chiara Anselmi

Department of Energy, Systems, Territory and Construction Engineering, University of Pisa, Largo Lucio Lazzarino, 56122 Pisa, Italy
federica.deri@phd.unipi.it

Abstract. Urban planning relies on accurate and comprehensive spatial data to analyse existing urban configurations, design new development scenarios, and evaluate their feasibility. OpenStreetMap (OSM), the largest freely accessible and editable geographic database, is increasingly used to support such tasks. However, as a crowdsourced platform, OSM presents both strengths and vulnerabilities, particularly regarding the consistency and reliability of its data. This study assesses the accuracy of OSM data in the municipalities of Massa and Viareggio (Tuscany, Italy) – focusing in particular into commercial activities and amenities related to the 15-min city concept – with the objective of identifying and characterizing errors within the dataset. The analysis involved a comparative evaluation between point of interests (POIs) extracted from OSM and a ground-truth dataset obtained through extensive on-site surveys. Rule-based manual matching in a GIS environment was applied to align POIs entries across the two datasets and to quantify discrepancies. For each unmatched OSM entry, the type of error was classified, and results were further disaggregated by functional category. Findings reveal a general underrepresentation of POIs in the OSM dataset, along with frequent positional inaccuracies and outdated information. A limited number of redundant entries were also identified. These results underscore the inherent limitations of Volunteered Geographic Information (VGI), which can be affected by contributor discretion and uneven data coverage. Given that such data increasingly inform spatial analyses and planning decisions, their unreliability poses a critical risk to evidence-based urban design.

Keywords: Crowdsource · Open data · OpenStreetMap · Volunteered Geographic Information · Urban Planning · Evidence-based Urban Design

1 Introduction

Geospatial data are fundamental to urban planning. The greater the accuracy and completeness of available datasets, the more reliable the models become for simulating how urban systems and environments respond to specific planning decisions. Accurately interpreting the current configuration of urban areas provides the necessary foundation for designing new settlement scenarios and assessing their feasibility in terms of infrastructure, mobility, environmental impact, and sustainable development.

© The Author(s), under exclusive license to Springer Nature Switzerland AG 2026
O. Gervasi et al. (Eds.): ICCSA 2025 Workshops, LNCS 15897, pp. 403–420, 2026.
https://doi.org/10.1007/978-3-031-97660-5_27

Recent planning paradigms, such as the "15-min city" model, emphasize the development of pedestrian-oriented urban environments where multifunctional land use and sustainable mobility networks ensure residents have easy access to essential services and amenities. Implementing and testing such models requires up-to-date data on public services, transportation infrastructure, commercial activities, and mobility patterns.

The rise of big data has enabled access to vast and varied sources of spatial information, often more accessible than traditional authoritative datasets. Among these, crowdsourced data have become particularly relevant. Crowdsourcing refers to the practice of collecting information through voluntary user contributions, typically via digital platforms. In the field of geographic information, this practice is known as Volunteered Geographic Information (VGI).

Notable examples of VGI used in urban planning include OpenStreetMap (OSM), Wikimapia, Mapillary, and Geo-Wiki. OpenStreetMap, in particular, is an open-source, collaborative mapping project where anyone can contribute to building a freely available and editable global map. Due to its large volume of data, ease of access, and zero cost, OSM is widely used across a range of sectors, including academic research, environmental disaster response, game development, traffic simulation, navigation, and urban planning [1–4].

Within urban planning, OSM is frequently employed to obtain large volumes of geographic data [5–7]. Numerous studies have used the OSM database to investigate various topics such as urban morphology [6–9], urban amenities [10, 11], street network configurations [12, 13], and mobility and traffic management [14, 15]. Contributions by Hacar et al. [16] have also enriched the methodological tools available for evaluating spatial data in urban contexts.

However, the extensive and diverse use of open data also raises critical concerns about their reliability, which can significantly affect the outcomes of spatial analyses and policy decisions. Validating the accuracy of such data – or, once their limitations are understood, establishing protocols for their improved use – would strengthen the legitimacy of existing findings and encourage a more systematic adoption of these sources in applied research.

This issue has led to a growing body of literature focused on evaluating and improving data quality [17–19]. Researchers have developed metrics to assess dataset characteristics [20–23] as well as methods for data cleaning and enhancement. At the European level, the Open Data Maturity Report provides a benchmark for assessing the maturity of national open data portals, including aspects such as data quality, governance, impact, and technical features [24].

In the specific case of OpenStreetMap, a vast literature has explored data quality by comparing OSM datasets with institutional or commercial mapping sources [5, 25–30]. Key dimensions of evaluation include completeness, consistency, positional accuracy, temporal accuracy, and attribute accuracy, typically in reference to roads, points of interest (POIs), and buildings.

In this vein, the present paper investigates the reliability of OSM data on commercial activities in two Italian municipalities – Massa and Viareggio – by comparing OSM records with ground-truth data – hereafter referred to as 'real data' – obtained through on-field surveys. The paper is structured as follows: Sect. 2 introduces the structure

and characteristics of the datasets used; Sect. 3 outlines the methodology, including the selection of case studies and amenities selection (3.1) and the procedural steps for data processing and database construction (3.2); Sect. 4 discusses the results; Sect. 5 summarizes the key findings and suggests directions for future research.

2 Datasets

2.1 OpenStreetMap

OpenStreetMap (OSM) is one of the most significant crowdsourced projects for the collection and dissemination of geographic data, categorized under the broader concept of Volunteered Geographic Information (VGI). The project is based on the principle of creating a free, editable, and constantly updated global map, maintained through the voluntary contributions of users worldwide [2, 31]. As of December 2024, the platform had registered more than ten million users [32].

OSM maps are composed of three fundamental elements – nodes, ways, and relations – each described through user-defined tags, consisting of key–value pairs. Tag creation in OSM follows a folksonomy-based approach, allowing contributors considerable flexibility. Although this openness allows for extensive customization, tools such as Taginfo provide summaries of the most commonly used tags to guide user contributions [2, 33].

Due to this flexibility, each feature in OSM may potentially be described by an unlimited number of attributes. As a result, the OSM database lacks a unified or formally standardized classification. However, the OSM community has defined conventions for frequently used key–value combinations, grouping them into broad functional categories such as amenity, building, emergency, highway, and leisure, among others [34].

Data can be added or edited using a range of software tools. The iD editor, a browser-based application, is OSM's default editing interface and is designed for beginners [2]. In 2024, approximately 204,810 users – accounting for 78% of all mappers – used iD, contributing around 426 million edits (33.1% of total edits) [35]. The editor provides a guided interface for choosing existing tags or creating new ones, enabling contributors to describe geographic features in increasing detail.

Although the iD editor has the highest number of users, the desktop-based Java OpenStreetMap (JOSM) editor – more suitable for advanced users – accounts for the majority of edits, with 761 million edits in 2024 (59.1%) [35].

The open and flexible nature of OSM, which allows anyone to contribute without technical expertise, is both a strength and a limitation [2, 31]. On the one hand, it facilitates continual data updates; on the other, it introduces variability and subjectivity, which can compromise data reliability [27, 36, 37].

Once submitted, OSM data are immediately published in the database without undergoing any formal peer review. Data reliability is instead managed by the OSM community through quality assurance tools, which identify potential errors and inconsistencies that must then be validated and corrected by users [2].

As an open-source platform, OSM offers several methods for free data extraction. The official website allows for manual selection and download of specific areas. PlanetOSM

provides a large, continuously updated dump of the full database. Alternatively, services such as GeoFabrik.de and BBBike.org offer regional extracts – GeoFabrik by continent, country, and region; BBBike by custom-defined areas. For tailored data extractions based on specific tags or features, users can employ Overpass Turbo, which queries the OSM database through the Overpass API [2]. A convenient QGIS plugin, QuickOSM, integrates Overpass Turbo into the GIS environment, allowing for easy and customizable data downloads.

For this study, various extraction methods were compared to determine the most suitable for the project. Data downloaded directly from the OSM website, based on predefined geographic bounding boxes, proved to be partial and inconsistent. Although the datasets from GeoFabrik and BBBike were more compact and better organized, they lacked completeness when compared to those obtained through Overpass Turbo. For this reason, the final dataset was downloaded using the QuickOSM plugin in QGIS, with a Quick Query configured to extract nodes, ways, and relations represented as points and multipolygons.

2.2 Real Data

An ideal benchmark for evaluating OSM data reliability would be a national authoritative database. However, in Italy, due to privacy regulations, official datasets of commercial activities – which represents the main category tested in this contribution – are not publicly available in full. The *Camera di Commercio* (Chambers of Commerce) maintain the *Registro delle Imprese* (Business Register), which contains legal and fiscal data on all companies operating in the country. However, this information is accessible to the public only through limited, case-by-case queries or partial datasets made available on specific portals.

In the absence of comprehensive government data, a custom reference dataset was constructed through on-field surveys, designed to directly verify the presence and exact location of POIs in the study areas. This method ensured an accurate and up-to-date snapshot of the local business landscape at the time of the research.

The surveys were conducted during the first two weeks of February 2025, on weekdays and during standard business hours (approximately 9:00–12:00 and 16:00–19:00). The data collection was independently carried out by the three authors on separate dates to reduce errors due to business temporary closures or observer oversight. Each observation recorded the address, business name, and type of POIs based on its category.

After cross-verifying the observations, the three individual datasets were merged to create a definitive, validated ground-truth database. Each activity was then manually geocoded in QGIS, using the recorded address information (street name, number, and any secondary street identifiers). The spatialization was manually performed using the Ortophoto from Geoscopio [38] as a cartographic base for manual geolocation, which was applied consistently throughout the process.

3 Methods

3.1 Case Studies and Amenities Selection

This study focuses on two municipalities in Tuscany, Italy: Massa and Viareggio. Both are located along the coastal strip of the Versilia area, with Massa situated in the northern sector and Viareggio in the southern sector.

The municipality of Massa covers an area of 93.58 km^2 [39] and features a longitudinal spatial development extending from the coast to the mountains. The coastal zone includes the district of Marina di Massa, while the compact historical centre of Massa lies in the foothills. The eastern portion of the municipality includes part of the Apuan Alps mountain range. The suburban agricultural plains are mainly characterized by urban sprawl, whereas the area north of the *Frigido* River has both industrial functions – linked to marble processing – and tourism, with numerous campsites along the coast.

The municipality of Viareggio covers an area of 32.48 km^2 [39] and, in contrast to Massa, follows a coastal-parallel development restricted to the flat alluvial plain. The *Burlamacca* Canal divides the municipal territory in two: the majority of the city lies to the north, where the railway separates the compact historical centre from the suburban zones, which are marked by dispersed settlements and agricultural lands. The southern part of the municipality includes both the port area and the *Migliarino-San Rossore-Massaciuccoli* Natural Park, which borders the coastal area. The surrounding agricultural-productive plain is fragmented by suburban neighbourhoods such as *Versilia*, *Ex Campo d'Aviazione*, and the village of Torre del Lago Puccini.

Both municipalities are integrated within a continuous infrastructural network that connects them to the broader Versilia area and neighbouring provinces. Key infrastructures include the A12 motorway, which links Genoa (Liguria) to Cecina (Tuscany, province of Livorno); the Strada Statale 1 – Via Aurelia, which follows the route of the ancient Roman consular road and connects Rome with France through the entire Tuscan coastline; and the coastal road, which connects the seaside towns of the Versilia conurbation, from Viareggio to Marina di Massa. Additionally, the area is crossed by the Genoa–Pisa railway line and the Lucca–Viareggio line, as Fig. 1 shows [40].

As explained in Sect. 2.2, the present research required the construction of a custom reference dataset that faithfully represented the real-world situation. Due to the complexity and workload involved, the study was limited to the urban centers of Massa and Viareggio, represented in Fig. 2.

The investigation focused on proximity-based services and facilities considered essential for the implementation of the 15-min city model, particularly referring to the 'Commerce' and 'Entertainment' categories defined by Moreno et al. [41]. Given the lack of a unified and widely accepted classification of such functions in the literature – and considering the topic remains actively debated [42] – this study adopted the macro-categories proposed by Papadopoulos et al. [42] as a basis for grouping OpenStreetMap elements by tag values (see Table 1). In both the OSM and real datasets, vacant lots were also mapped and included in the analysis.

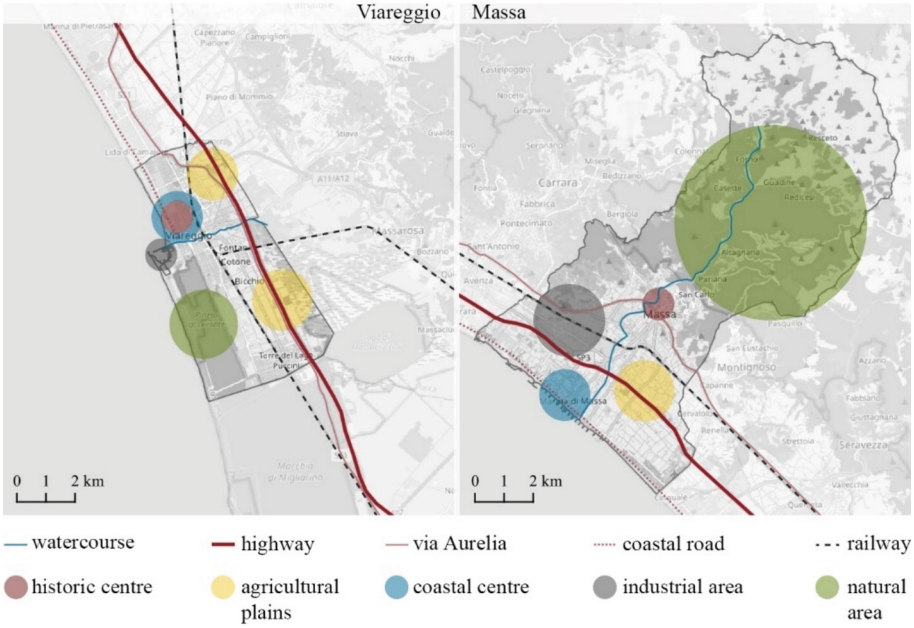


Fig. 1. Territorial framework of Viareggio and Massa municipalities.

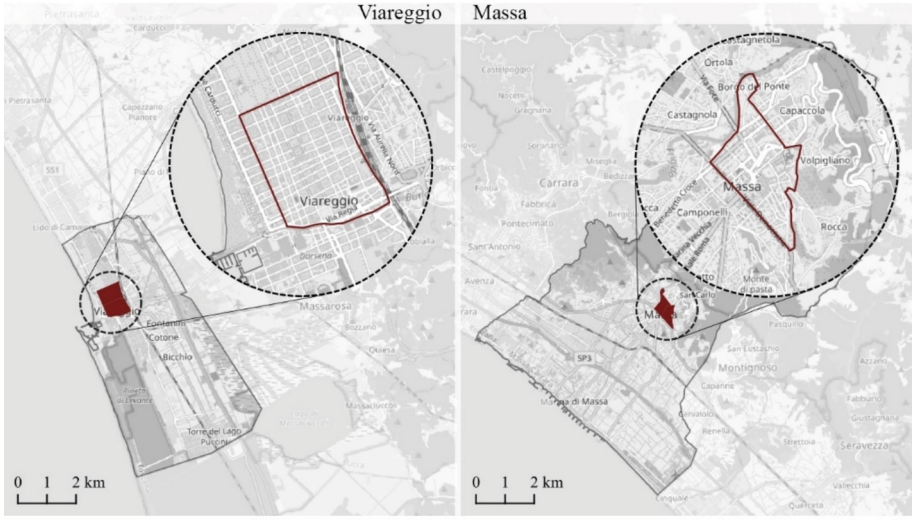


Fig. 2. Study areas within Viareggio and Massa municipalities.

Table 1. Urban amenities examined.

Moreno et al. (2021)	Papadopoulos et al. (2023)
Commerce	food/grocery stores
	retail services/trade
Entertainment	recreational areas
	green spaces
	parks
	sports facilities
	restaurants
	cultural facilities
	entertainment facilities

3.2 Database Processing

As mentioned in Sect. 2.1, the OSM data were extracted using the QuickOSM plugin in QGIS, based on specific values of the keys amenity, craft, leisure, shop, sport, and tourism, which were then assigned to the macro-categories outlined by Papadopoulos et al. [42], as presented in Table 1.

To enable comparison with the real-world data, each surveyed activity was assigned a unique identifier (ID) composed of the municipality acronym (VI for Viareggio, MS for Massa), followed by the letter R (for real data) and a progressive number in the format xxx. Based on spatial proximity and name correspondence between the two datasets, the same ID was manually assigned to matching entries in the OSM dataset. It was not possible to rely on address information for the matching procedure, as OSM entries often lacked address data or included incomplete or incorrect information.

An ID was also assigned to OSM elements that could not be matched with any surveyed activity. In these cases, the ID was composed of the municipality acronym and the prefix UR_ (for "unmatched OSM record"), followed by a progressive number (xxx).

This unique ID system made it possible to identify errors in both datasets related to the presence/absence of individual features and to their incorrect positioning on the map. To further qualify the nature of each discrepancy, an additional field named mismatch was added to the attribute table of the OSM layer.

The following error types were identified:

- "excess": when an OSM feature had no corresponding real-world activity in the vicinity;
- "ceased": when the mapped feature corresponded to a location currently vacant.
- "replaced/inconsistent": when an OSM feature corresponded to a business at the same location but with a different name. This category includes both businesses that have changed over time and those whose name differs from what is recorded on the shop sign.
- "redundant": when two or more OSM entries referred to the same real-world activity;

- "relocated/moved": when an activity's name was found in both datasets but associated with non-adjacent locations, suggesting either a move or an incorrect geolocation;

with the terms "vicinity" or "adjacent" referring to features located on the same side of the street and within a radius of 5 m from the actual activity.

By performing a join operation between the OSM and real-world vector layers using the unique ID as the linking field, a unified table was generated. This table includes all real activities (some of which match with OSM features, while others not), plus all unmatched OSM elements. The analysis results presented in the following section are based on this final integrated dataset.

4 Results and Discussion

The mapping of the real-world dataset yielded 651 entries for Viareggio and 333 for Massa. In Viareggio, these are evenly distributed across the entire study area, with notable concentrations around *Piazza Cavour*, *Corso Giuseppe Garibaldi*, *Via Cesare Battisti*, and *Via Giuseppe Mazzini*. In Massa, four main clusters were identified: *Galleria Leonardo da Vinci*, *Via Dante Alighieri*, *Via Agostino Ghirlanda*, and the intersection of *Viale Europa* and *Largo Giacomo Matteotti* – as depicted in Fig. 3 –, while Table 2 provides the number of mapped entries by functional category.

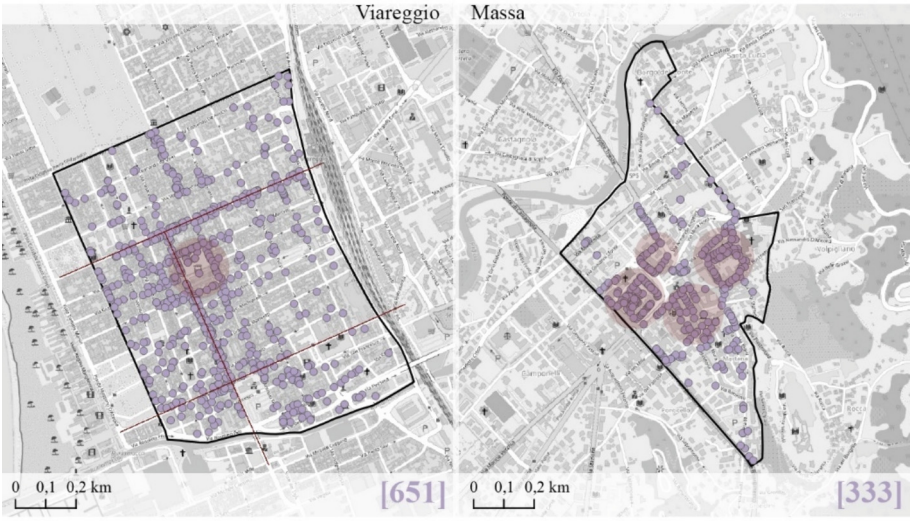


Fig. 3. Real data with an indication of highest density areas.

Table 2. Number of items of the real database based on functional categories.

Papadopoulos et al. (2023)	Number of items	
	Viareggio	Massa
food/grocery stores	50	26
retail services/trade	348	204
recreational areas	1	1
green spaces	0	0
parks	9	0
sports facilities	4	3
restaurants	54	27
cultural facilities	8	12
entertainment facilities	50	49
vacant	129	14

The OSM dataset extraction returned 93 entries for Viareggio and 117 for Massa, as illustrated in Fig. 4. Table 3 shows the number of OSM features per functional category.

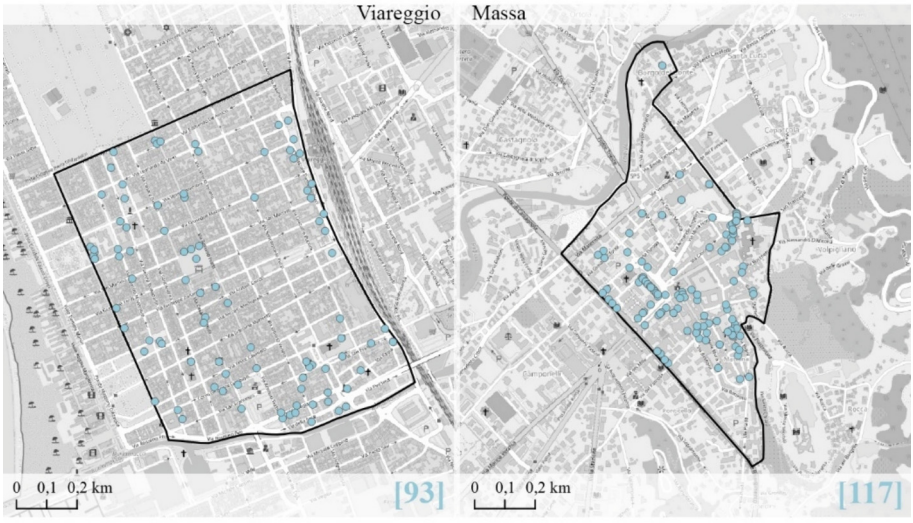


Fig. 4. OpenStreetMap (OSM) data.

While the amount ratio (i.e., the number of extracted OSM entries divided by the number of real entries) was higher in Massa than in Viareggio, the percentages remain quite low: 14.3% for Viareggio and 35.1% for Massa. The figures decrease further when considering the accuracy ratio (i.e., the number of correctly matched OSM features to real-world entries): 9.1% for Viareggio and 17.1% for Massa, as synthetized in the diagrams in Fig. 5.

Table 3. Number of items of the OSM database based on functional categories.

Papadopoulos et al. (2023)	Number of items	
	Viareggio	Massa
food/grocery stores	6	10
retail services/trade	16	46
recreational areas	1	1
green spaces	0	0
parks	14	2
sports facilities	0	1
restaurants	17	29
cultural facilities	14	11
entertainment facilities	20	17
vacant	3	0

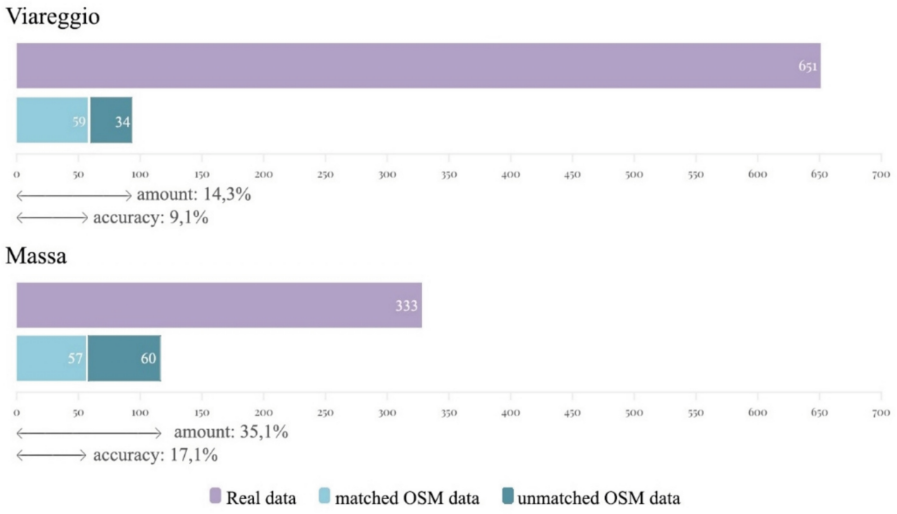


Fig. 5. Real data and OSM data. 'Amount': ratio between total extracted activities and real activities, expressed as a percentage; 'accuracy': ratio between matched extracted activities and real activities, expressed as a percentage.

Following the matching process between the two datasets, which distinguished matched and unmatched OSM entries through the assignment of unique IDs, a more detailed analysis was conducted on the unmatched entries to classify the types of errors present in the crowdsourced dataset.

As shown in Table 4, in both case studies the majority of unmatched OSM features were classified as "excess", meaning they could not be associated with any real-world

activity. Compared to Viareggio, Massa showed a higher number of entries classified as "replaced/inconsistent", referring to activities that had either changed over time or were recorded in OSM with a name different from the one observed on the actual shop sign. No "relocated/moved" features were identified in either of the two study areas, i.e., no entries in OSM were found at a significantly different location from their real-world counterparts.

Table 4. Mismatch categories for Viareggio and Massa case studies.

mismatch	Viareggio	Massa
excess	20	39
ceased	8	7
replaced/inconsistent	2	10
redundant real (R)	2	3
redundant unmatched (UR)	0	1
relocated/moved	0	0

These evaluations were extended to the functional categories (see Table 1) in order to identify potential trends. Table 5 reports the values for amount and accuracy—as defined above—for each functional category. While the overall scarcity of OSM data was already observed in the general case study metrics, the category-level analysis reveals interesting patterns.

In Viareggio, for example, the "retail services/trade" category yielded very few results in OSM, with an amount of only 4.6%. The accuracy was even lower, at 2.3%, as not all extracted OSM entries were successfully matched to real-world businesses. However, all matched entries in this category were functionally correct (AC_C = 100.0%).

In contrast, in Massa, the "restaurants" category showed a higher number of OSM entries than those recorded in the field (107.4%), yet only 44.4% of these corresponded to actual existing establishments, and among these, 75.0% were correctly classified in terms of function.

Figure 6 shows the correspondence between real and OSM entries based on functional category, as indicated by the trend of the AC_C parameter defined in Table 5. The image highlights discrepancies in the categorization of urban amenities; in the case of Viareggio, for instance, only 17 out of 20 entertainment facilities listed in the OSM database correspond to those identified through on-site survey. However, not all of these are correctly categorized, as some are actually food/grocery stores and others fall under retail services/trade.

These findings suggest that the incompleteness and inaccuracy of OSM data are not evenly distributed across functional categories, varying significantly in terms of both amount and accuracy.

Table 5. Evaluation of 'amount' (A), 'accuracy' (AC) and the accuracy of the categorization (AC_C) between real and OSM data in relation to functional categories. AC_C: ratio between extracted activities with correct categorisation and matched activities, expressed as a percentage.

	Viareggio			Massa		
	A [%]	AC [%]	AC_C [%]	A [%]	AC [%]	AC_C [%]
food/grocery stores	12,0	12,0	83,3	38,5	19,2	100,0
retail services/trade	4,6	2,3	100,0	22,5	13,2	96,3
recreational areas	100,0	100,0	100,0	100,0	100,0	100,0
green spaces	–	–	–	–	–	–
parks	155,6	88,9	100,0	*	*	*
sports facilities	0,0	0,0	-	33,3	0,0	-
restaurants	31,5	24,1	100,0	107,4	44,4	75,0
cultural facilities	175,0	75,0	83,3	91,7	58,3	71,4
entertainment facilities	40,0	34,0	70,6	34,7	16,3	100,0

* the on-field survey recorded 0 parks, while OSM returned 2 entries; therefore, the percentage cannot be calculated.

Figure 7 illustrates the distribution of mismatch types across functional categories. In Viareggio, different cases must be considered when mismatch values are zero for a specific category. For example:

- in "food/grocery stores" and "recreational areas", all extracted OSM entries were matched with real-world data, resulting in no recorded mismatches;
- for "sports facilities", the mismatch count was zero because OSM did not return any entries for this category;
- in the case of "green spaces", neither the field survey nor the OSM extraction yielded any data.

Similar observations apply to the case of Massa.

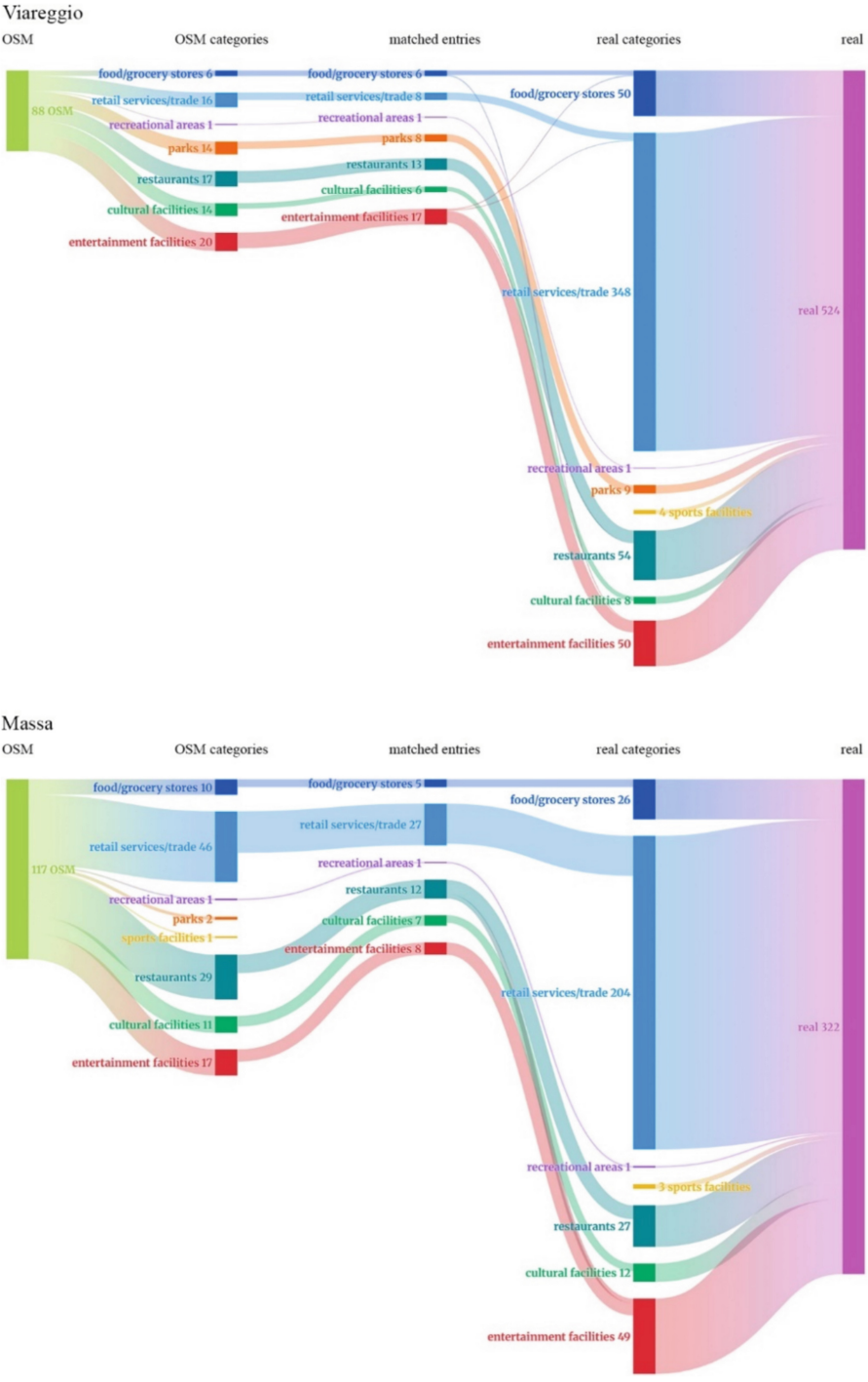
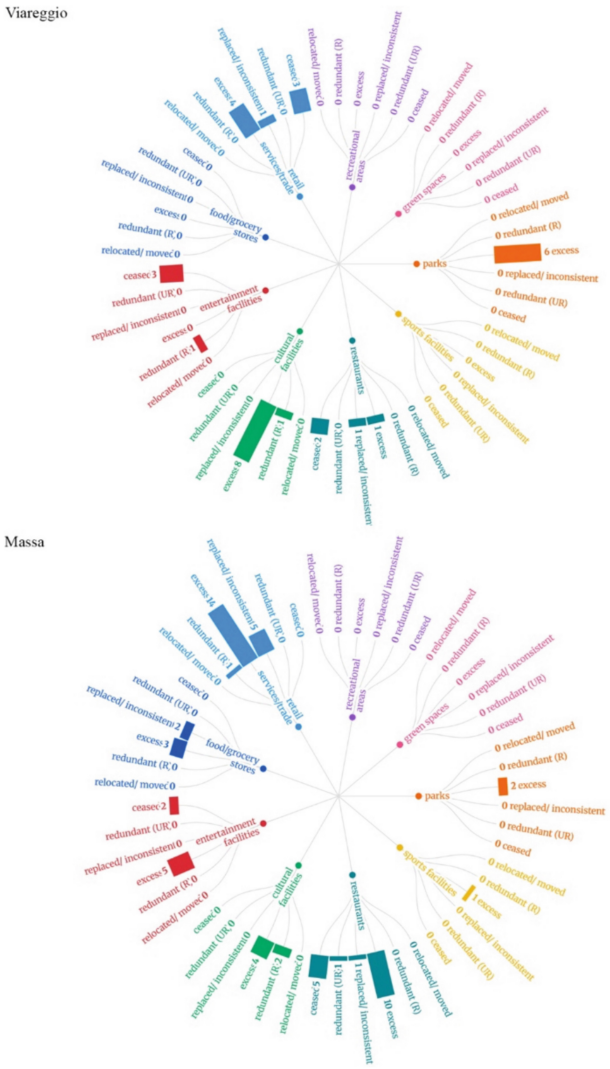


Fig. 6. Correspondence between real and OSM entries based on functional category.


Viareggio
Massa
parks
green spaces
sports facilities
recreational areas
restaurants
cultural facilities
entertainment facilities
food/grocery stores
retail
servicestrade
0 excess
0 replaced/ inconsistent
0 redundant (UR)
0 ceased
0 relocated/ moved
0 redundant (R)
6 excess
2 excess
1 excess
10 excess
0 replaced/ inconsistent
0 redundant (UR)
0 ceased
0 relocated/ moved
0 redundant (R)
0 redundant (UR)
0 redundant (R)
0 relocated/ moved
0 ceased
0 redundant (R)
0 excess
0 replaced/ inconsistent
0 redundant (UR)
0 redundant (UR)
0 replaced/ inconsistent
1 replaced/ inconsistent
0 redundant (R)
0 relocated/ moved
0 ceased
0 redundant (UR)
0 excess
0 replaced/ inconsistent
0 redundant (R)
0 relocated/ moved
0 ceased
0 redundant (UR)

urban or micro-urban scale – such as when analysing the proximity of essential services or planning for proximity-based models like the 15-min city – data quality plays a crucial role. The implementation of pedestrian-oriented settlement strategies requires urban planners and decision-makers to rely on accurate, up-to-date representations of distributions and functions of urban amenities. This is essential for identifying which services may be lacking, for assessing neighbourhood suitability, and for comparing the functional structure and organization of different urban areas, needed for promoting evidence-based planning processes.

Focusing on the Italian municipalities of Massa and Viareggio, the study assessed the accuracy and completeness of one of the most widely used open-access databases in spatial analysis: OpenStreetMap (OSM). The evaluation was based on a field-validated comparison between OSM entries and a custom-built reference dataset of real-world urban amenities.

The results clearly indicate that the vast availability of data does not necessarily translate into data quality. Although OSM offers a vast and continuously growing amount of spatial information – exceeding 9.7 billion nodes as of February 2025 [32] – the findings show a general shortage of data and multiple inaccuracies, particularly regarding feature positioning, updates, and redundancy.

The goal of this research was not to identify the underlying causes of these inaccuracies but rather to document the data quality issues within two specific urban contexts, with a close comparison with the real situation. These results are not intended to be generalized, as they respond to a focused research question and reflect localized conditions. In this sense, the adequacy of OSM should be assessed based on the specific analytical or planning objectives, as data reliability can vary significantly depending on the case study context or the types of amenities considered – just to name a few of the parameters that may affect the overall quality of the OSM dataset.

Considering this, future research directions could include the expansion of the amenity types analysed, as well as the application of the same validation procedure to a wider range of case studies – both in terms of geography and urban morphology – to more comprehensively assess the extent and causes of OSM data deficits. Additionally, OSM data comparison with other data sources – including institutional datasets or commercial mapping services – could prove valuable in evaluating whether some sources are systematically more accurate or complete than others. Such comparisons would help assess the context-specific effectiveness of different data types and, ultimately, enhance the reliability of data-driven decision support tools in urban and regional planning.

Although the findings of this study are robust, they should not be generalized, as the present case studies may not fully represent other urban contexts. In different cities or regions, the availability and accuracy of OpenStreetMap (OSM) data may vary significantly depending on factors such as the level of community participation, local territorial characteristics, or socioeconomic conditions. Future research should investigate how these variables affect data completeness and reliability through a broader and more systematic analytical framework. Such work would contribute to a deeper understanding of the strengths and limitations of Volunteered Geographic Information (VGI), helping

to define the conditions under which it can be considered usable and trustworthy – depending on the context, the mode of use, and the specific goals for which the data are employed.

Acknowledgments. This work was part of the EMC2 project, funded by ANR (France), FFG (Austria), MUT (Italy), and Vinnova (Sweden) under the Driving Urban Transition Partnership, which has been funded by the European Commission.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

References

1. Niu, H., Silva, E.A.: Crowdsourced data mining for urban activity: review of data sources, applications, and methods. J. Urban Plan. Dev. **146**(2), 04020007 (2020)
2. Mooney, P., Minghini, M.: A review of OpenStreetMap data. In: Foody, G., See, L., Fritz, S., Mooney, P., Olteanu-Raimond, A.-M., Fonte, C.C., Antoniou, V. (eds.) Mapping and the Citizen Sensor, pp. 37–59. Ubiquity Press, London (2017)
3. Sehra, S.S., Singh, J., Rai, H.S.: Using latent semantic analysis to identify research trends in OpenStreetMap. ISPRS Int. J. Geo-Inform. **6**(7), 195 (2017)
4. Biljecki, F., Chow, S.Y., Lee, K.: Quality of crowdsourced geospatial building information: a global assessment of OpenStreetMap attributes. Build. Environ. **237**, 110295 (2023)
5. Ciepłuch, B., Jacob, R., Mooney, P., Winstanley, A.C.: Comparison of the accuracy of OpenStreetMap for Ireland with Google Maps and Bing Maps. In: 9th International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Sciences, p. 337 (2010)
6. Boeing, G.: Spatial information and the legibility of urban form: big data in urban morphology. Int. J. Inform. Manag. **56**, 102013 (2021)
7. Biljecki, F., Chow, Y.S.: Global building morphology indicators. Comput. Environ. Urban Syst. **95**, 101809 (2022)
8. Crooks, A., et al.: Crowdsourcing urban form and function. Int. J. Geograph. Inform. Sci. **29**, 720–741 (2015)
9. Over, M., Schilling, A., Neubauer, S., Zipf, A.: Generating web-based 3D city models from OpenStreetMap: the current situation in Germany. Comput. Environ. Urban Syst. **34**(6), 496–507 (2010)
10. Burke, J., Alomà, R.G., Yu, F., Kruguer, J.: Geospatial analysis framework for evaluating urban design typologies in relation with the 15-minute city standards. J. Busi. Res. **151**, 651–667 (2022)
11. Pezzica, C., Altafini, D., Mara, F., Chioni, C.: Travel-time in a grid: modelling movement dynamics in the "minute city". In: International Conference on Innovation in Urban and Regional Planning, pp. 657–668. Springer Nature Switzerland, Cham (2023)
12. Boeing, G.: A multi-scale analysis of 27,000 urban street networks: Every US city, town, urbanized area, and Zillow neighborhood. Environ. Plan. B Urban Anal. City Sci. **47**(4), 590–608 (2020)
13. Mara, F., Anselmi, C., Deri, F., Cutini, V.: The spatial roots of urban growth: modelling urban dynamics with space syntax. In: International Conference on Computational Science and Its Applications, pp. 61–76. Springer Nature Switzerland, Cham (2024)

14. Carlino, D., Depinet, M., Khandelwal, P., Stone, P.: Approximately orchestrated routing and transportation analyzer: large-scale traffic simulation for autonomous vehicles. In: 15th International IEEE Conference on Intelligent Transportation Systems, pp. 334–339. IEEE (2012)
15. Ferster, C., Fischer, J., Manaugh, K., Nelson, T., Winters, M.: Using OpenStreetMap to inventory bicycle infrastructure: a comparison with open data from cities. Int. J Sustain. Transp. **14**(1), 64–73 (2020)
16. Hacar, M., Mara, F., Altafini, D., Cutini, V.: Preprocessing open data for optimizing estimation times in urban network analysis: Extracting, filtering, geoprocessing, and simplifying the road-center lines. In: International Conference on Innovation in Urban and Regional Planning, pp. 551–562. Springer Nature Switzerland, Cham (2023)
17. Cai, L., Zhu, Y.: The challenges of data quality and data quality assessment in the big data era. Data Sci. J. **14**, 2 (2015)
18. Sadiq, S., Indulska, M.: Open data: quality over quantity. Int. J. Inform. Manag. **37**(3), 150–154 (2017)
19. Quarati, A., De Martino, M., Rosim, S.: Geospatial open data usage and metadata quality. ISPRS Int. J. Geo-Inform. **10**(1), 30 (2021)
20. Senaratne, H., Mobasheri, A., Ali, A.L., Capineri, C., Haklay, M.: A review of volunteered geographic information quality assessment methods. Int. J. Geograph. Inform. Sci. **31**(1), 139–167 (2017)
21. Antoniou, V., Skopeliti, A.: Measures and indicators of VGI quality: an overview. In: ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. 2, pp. 345–351 (2015)
22. Ostermann, F.O., Granell, C.: Advancing science with VGI: reproducibility and replicability of recent studies using VGI. Trans. GIS. **21**(2), 224–237 (2017)
23. Fonte, C.C., et al.: Assessing VGI data quality. In: Foody, G., et al. (eds.) Mapping and the Citizen Sensor, pp. 137–163. Ubiquity Press, London (2017)
24. European Commission: Open Data Maturity Report 2024. Publications Office of the European Union (2024). https://data.europa.eu/en/publications/open-data-maturity/2024
25. Sehra, S.S., Singh, J., Rai, H.S.: Assessment of OpenStreetMap data-a review. Int. J. Comput. Appl. **76**(16) (2013)
26. Kaur, J., Singh, J., Sehra, S.S., Rai, H.S.: Systematic literature review of data quality within OpenStreetMap. In: International Conference on Next Generation Computing and Information Systems (ICNGCIS), pp. 177–182. IEEE (2017)
27. Haklay, M.: How good is volunteered geographical information? A comparative study of OpenStreetMap and Ordnance Survey datasets. Environ. Plan. B Plan. Design. **37**(4), 682–703 (2010)
28. Brovelli, M.A., Minghini, M., Molinari, M., Mooney, P.: Towards an automated comparison of OpenStreetMap with authoritative road datasets. Trans. GIS. **21**(2), 191–206 (2017)
29. Girres, J.F., Touya, G.: Quality assessment of the French OpenStreetMap dataset. Trans. GIS. **14**(4), 435–459 (2010)
30. Fan, H., Zipf, A., Fu, Q., Neis, P.: Quality assessment for building footprints data on OpenStreetMap. Int. J. Geograph. Inform. Sci. **28**(4), 700–719 (2014)
31. Haklay, M., Weber, P.: Openstreetmap: user-generated street maps. IEEE Pervas. Comput. **7**(4), 12–18 (2008)
32. OpenStreetMap – Stats. https://wiki.openstreetmap.org/wiki/Stats. Accessed March 2025
33. Ballatore, A., Mooney, P.: Conceptualising the geographic world: the dimensions of negotiation in crowdsourced cartography. Int. J. Geograph. Inform. Sci. **29**(12), 2310–2327 (2015)
34. OpenStreetMap - Map features. https://wiki.openstreetmap.org/wiki/Map_features. Accessed March 2025

35. OpenStreetMap - Editor usage stats. https://wiki.openstreetmap.org/wiki/Editor_usage_stats. Accessed March 2025
36. Jacobs, K.T., Mitchell, S.W.: OpenStreetMap quality assessment using unsupervised machine learning methods. Trans. GIS. **24**(5), 1280–1298 (2020)
37. Ballatore, A., Zipf, A.: A conceptual quality framework for volunteered geographic information. In: 12th International Conference, COSIT, pp. 89–107. Springer (2015)
38. Regione Toscana. Direzione Urbanistica e Politiche Abitative - Sistema Informativo Territoriale e Ambientale – SITA.: Ortofoto. https://www502.regione.toscana.it/geoscopio/ortofoto.html. Accessed March 2025
39. Istat, https://www.istat.it/classificazione/principali-statistiche-geografiche-sui-comuni/. Accessed March 2025
40. Regione Toscana: Piano di Indirizzo Territoriale. Deliberazione Consiglio regionale 27 marzo 2015, no. 37 (2015), https://www.regione.toscana.it/-/piano-di-indirizzo-territoriale-con-valenza-di-piano-paesaggistico. Accessed March 2025
41. Moreno, C., Allam, Z., Chabaud, D., Gall, C., Pratlong, F.: Introducing the "15-Minute City": sustainability, resilience and place identity in future post-pandemic cities. Smart Cities. **4**(1), 93–111 (2021)
42. Papadopoulos, E., Sdoukopoulos, A., Politis, I.: Measuring compliance with the 15-minute city concept: state-of-the-art, major components and further requirements. Sustain. Cities Soc. 104875 (2023)