Big-data Reliability in Informing the 15-Min City Modelling: A Comparison Between OpenStreetMap and Google Maps

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Abstract. The 15-minute city model relies on accurate spatial data to assess proximity between residents and essential urban services. A multiscale, transversal, and replicable decision-support model cannot depend on manual surveys alone and must necessarily rely on web-based geographic databases. This paper investigates the reliability of two widely used Open Data sources—OpenStreetMap (OSM) and Google Maps (GM)—in supporting such modelling efforts. Through a comparative analysis of four European urban contexts (Versilia, Nice, Wien, and Gothenburg), the study evaluates data consistency in terms of volume, spatial distribution, and classification structure, across both macro (urban) and micro (neighbourhood) scales. Findings reveal substantial differences between the two datasets, underscoring how the choice of dataset—and how it is used—can significantly affect 15-minute city modelling outcomes, potentially leading to misleading analyses or decisions. Specifically, OSM tends to return a larger volume of data, including private and non-accessible amenities, while GM provides fewer but more curated features, though constrained by download limits. Additionally, semantic inconsistencies in place categorisation, especially for multifunctional or culturally specific amenities, further restrict cross-platform interoperability or reliable comparison. The study concludes that a context-sensitive evaluation of datasets is essential. This should be supported by scale-aware analyses, empirical validation through ground-truthing, and the development of data cleansing protocols or adaptive frameworks to strengthen decision-support tools and ensure the reliability of data used in urban planning processes.

Keywords: Big data · Volunteered Geographic Information · 15-minutes city · Open Street Map · Google Maps · Data reliability

1 Introduction

The idea of the 15-minute city—where everyday necessities are accessible within a short walk or bike ride—has emerged as a compelling yet complex urban planning paradigm. While the concept evokes a sense of nostalgia for a human-scale, temporally balanced

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urban experience, it has gained newfound relevance in the aftermath of the COVID-19 pandemic. Carlos Moreno's foundational manifesto [1], along with the pandemic-induced reassessment of urban living, has led to a resurgence of interest in proximity-based urban models, especially within the European context. This renewed interest has brought back into the spotlight earlier urban theories such as Perry's "neighbourhood unit" [2], which were previously sidelined by the consumerist and mobility-driven logic of modern capitalist cities.

The policy shift – exemplified by Anne Hidalgo's Paris 15 minutes city project – demonstrates the increasing need to rigorously assess the feasibility, scalability, and sustainability of the 15-minute city model across different urban contexts [3, 4].

Central to this assessment is the role of spatial modelling and urban analytics, which can help determine whether and under what conditions it is beneficial—economically, socially, and environmentally—to implement proximity-based planning. These models can guide planners in identifying key characteristics of neighbourhoods aligned with the 15-minute city ethos, and evaluate whether investments in such transformations yield tangible returns in terms of public health, equity, environmental quality, and economic resilience.

In fact, the operationalization of the 15-minute city faces substantial methodological and empirical challenges. As highlighted by Pezzica et al. [5], the original framework by Moreno lacks a precise classification of urban functions, complicating efforts to translate it into actionable indicators. Further elaboration is needed on what activities qualify for each category of urban services [6], as well as on how existing datasets can effectively map these services in spatial terms. A key requirement in this context is the availability of accessible, harmonized, and reliable data sources that allow for fair and comprehensive evaluations across different geographical areas.

In this regard, Open Data platforms, such as OpenStreetMap (OSM) and Google Maps, offer promising tools for proximity-based urban modelling due to their wide coverage, openness, and frequent updates. Yet, the question remains: are these datasets simply abundant, or are they both abundant and reliable? This touches upon a broader epistemological debate regarding the "reliability" of big data in urban planning—echoing concerns over the so-called "5 Vs" of big data: volume, velocity, variety, veracity, and value [7].

But in the specific case of the 15-minute city, where proximity is a spatial condition defined by distance to essential services, the reliability and consistency of locational data become foundational. The identification of where services are located, what types they are, and how densely they are distributed is the first step toward evaluating walkability, service equity, and accessibility through isochrone-based analyses. As such, the trustworthiness and structure of the data underpinning these models play a decisive role in shaping urban policy recommendations.

In this vein, this paper explores the suitability of OSM and Google Maps for informing spatial models of the 15-minute city by providing a comparative analysis of their outputs in four diverse urban contexts: Nice (France), Versilia (Italy), Wien (Austria), and Gothenburg (Sweden). The study investigates how these datasets differ in terms of the quantity, categorization, and spatial distribution of urban services. In doing so, it aims to

highlight the implications of data source selection for the modelling and implementation of proximity-based urban policies.

The structure of the paper is as follows: Sect. 2 presents the datasets and outlines the key differences between OSM and Google Maps; Sect. 3 describes the methodological framework, including the activity classification and the case study approach; Sect. 4 reports and discusses the results, focusing on quantitative service coverage, classification robustness, and their potential implications for planning; Sect. 5 concludes with a reflection on the role of data reliability in supporting the 15-minute city model and offers directions for future research.

2 Datasets

The data sources analysed in this study are OpenStreetMap (OSM) and Google Maps, which are among the most extensively used Open Data platforms in contemporary urban studies. As highlighted in recent literature [8, 9], these platforms have become foundational tools for spatial analysis and urban modelling, particularly within the context of accessibility and service coverage. Their widespread adoption in planning-related research can be largely attributed to their global coverage, regular updates, and ease of access—either freely available, as in the case of OSM, or accessible through APIs at relatively low cost, as with Google Maps. The following sub-sections just briefly analyse the different type of data-sources used, to highlight the main characteristics and differences, then useful for the discussion.

2.1 OpenStreetMap

OpenStreetMap is the most well-known example of Volunteered Geographic Information (VGI), based on crowdsourcing. It is an open-source platform that allows users to freely interact by uploading and downloading data. This ensures continuously updated information; however, it is strongly user-based, leading to inconsistencies and a lack of uniformity in the system [10].

The database consists of elements (nodes, ways, and relations) characterized by specific properties (tags). Tags are composed of key-value combinations that describe the geographical attributes of each element at varying levels of detail. There is no official classification of tags, as they are freely created and updated by users. However, the most frequently used tags are listed and categorised in online services such as Taginfo and OSM Map Features [11].

Data can be downloaded from various sources: the official OpenStreetMap website, the PlanetOSM database, and the GeoFabrik.de and BBBike.org portals, which allow data retrieval by geographical area. Meanwhile, Overpass Turbo, via the Overpass API, and the QuickOSM plug-in integrated into QGIS enable customised extraction based on area and data type through queries. For this research, data were downloaded using the QuickOSM plug-in within the QGIS software.

2.2 Google Maps

Google Maps is the most popular geographic internet service [12]. It is not strictly a Volunteered Geographic Information (VGI), as it incorporates data sources beyond crowdsourcing and employs data control mechanisms that prevent it from being entirely open to modification. Nevertheless, user interaction with the platform – particularly by registered commercial activity owners – remains a fundamental aspect, as the visibility of places depends on it. The density of locations displayed on the map varies according to the zoom level, based on ranking criteria linked to user engagement and positioning factors relative to the requestor.

Google Maps data can be queried – with some limitations – via the official Application Programming Interface (API) in the Google Maps Platform suite. The download was performed in the form of a vector layer on QGIS using the program's Python Console. There are two main types of data requests: a TextSearch, which allow for searching activities using keywords, and a NearbySearch that operates from a point defined by coordinates and a radius, selecting places of interest. Among all the information available, only the PrimaryType field is considered. The platform provides a list of Place Types (listed in the Table A of the platform) to perform queries, which reflect the main types of activities on Google Maps; however, no official or complete list exists, as it is continuously evolving. For this research, to analyse a functional mix, a NearbySearch was employed, relying on the provided categorisation and eliminating the discretionary aspect of keyword searches.

3 Methods

3.1 Categorization Issue

Before conducting the analyses, it was necessary to assess the categorisation of the locations considered. In literature, no single, universally accepted classification of urban places exists, given the wide variability of the topic. Regarding the 15-minute city concept, Carlos Moreno introduced six essential functions of urban life: living, working, commerce, healthcare, education, and entertainment [1]. However, these remain rather generic and do not directly translate into distinct groups of real-world activities. This leads to interpretation issues concerning the 15-minute city concept, including the selection of urban amenities to be considered [6]. Papadopoulos et al. [6] provide a literature review that identifies macro-categories of urban places by grouping the terms commonly used in studies on the 15-minute city. For this study, the different categories from OSM and Google Maps need to be aligned into a unified classification to enable qualitative and quantitative comparisons. Therefore, the OSM tags and Google Maps place types are classified according to the macro-categories proposed by Papadopoulos et al. [6]. For this reason, the study focuses on some macrocategories which can be strictly associated both OSM 'values' and Google Maps 'place types' data. Specifically, the following macrocategories are considered: health services, entertainment facilities, retail services/trade, sports facilities, restaurants, economic facilities, and food/grocery stores.

3.2 Case Studies

This study focuses on four European urban contexts selected from the EMC2 project, conducted under the *Driving Urban Transitions (DUT)* partnership [13]: the Versilia conurbation (Italy), the city of Nice (France), the city of Wien (Austria), and the city of Gothenburg (Sweden). These areas serve as testbeds for evaluating whether the quality and operational consistency of spatial datasets—specifically OpenStreetMap and Google Maps—are uniform across diverse urban settings, or whether significant discrepancies emerge. In the latter case, understanding the root causes of such heterogeneity would require further investigation.

The **Versilia conurbation** represents a linear urban agglomeration comprising multiple municipalities along the northern Tuscan coast. Historically, these municipalities retained individual autonomy until their post-World War II urban growth led to the merging of their built environments into a continuous coastal urban fabric. Versilia displays pronounced morphological diversity, spanning transversally from the Tyrrhenian coastline to the inland Apuan Alps, and is longitudinally connected by a network of transportation infrastructures [14]. Excluding the compact historical centers, the area is characterized by medium-to-low residential density, averaging approximately 800 inhabitants per square kilometer [15].

Nice, the core of the Nice Côte d'Azur metropolitan area, is a Mediterranean urban hub that also evolved through the gradual merging of adjacent municipalities. Similar to Versilia, its urban morphology extends from the coastline to the foothills of the Maritime Alps. With a population density of approximately 4622.3 inhabitants per square kilometer [16], Nice ranks among the most densely populated cities in France. The city's development has been shaped by both natural topography and infrastructural integration within a larger metropolitan conurbation.

Wien, capital of Austria and one of its nine federal states, exemplifies a historically stratified urban form. Its urban growth followed a radial-concentric pattern, structured around successive historical boundaries—first the medieval walls, and later the 18th-century fortifications, now transformed into major ring roads that demarcate the city's inner zones [17]. Wien today is one of the most populous cities in Europe, with a residential density of approximately 4655.0 inhabitants per square kilometer [18].

Gothenburg, Sweden's second-largest city, developed along the Göta River with a radiocentric structure emerging from its medieval core. During the 18th century, the city expanded within crescent-shaped defensive walls, characterized by an orthogonal grid of streets and canals [19]. Like Versilia and Nice, Gothenburg is a coastal city and functions as Scandinavia's largest port. Over the 20th century, the city underwent progressive suburbanization, expanding toward surrounding hills and forming sprawling residential areas interspersed with substantial green cover [20]. Despite its size, the city maintains a medium-to-low population density, estimated at 1291.6 inhabitants per square kilometer.

3.3 Analyses Performed

A multi-scalar analytical framework was employed to assess and compare the two datasets—OpenStreetMap and Google Maps—with the aim of investigating data variability from both quantitative and qualitative perspectives. The analyses were conducted

at two spatial scales: the urban (macro) scale and the neighbourhood (micro) scale, with the type of extracted information varying depending on the analytical objective. This dual-level approach facilitates the comprehension on how data characteristics influence the modelling of service accessibility in the context of 15-minute city planning and how datasets specificities could impact on it. The analytical process was structured in two main phases:

First, all activities corresponding to the macro-categories defined in Sect. 3.1, for both datasets, within a spatial buffer that fully encompasses each case study area have been extracted. Specifically, an 8000-metre radius was used from the centroid of the historical cores of Wien and Gothenburg, while the entire municipal area of Nice and the Apuan municipalities of Carrara, Massa, and Montignoso (for the Versilia case) were considered in full. An initial comparison was then conducted by evaluating the total number of features retrieved and spatial discrepancies in the geolocation of points of interest across the two datasets. This allowed for the identification of potential differences in data density and coverage. Following this, a targeted assessment was conducted to detect systematic divergences in how data are retrieved or represented across the two sources and their impact on proximity assessments—central to the 15-minute city concept.

Second, to complement the macro-scale evaluation, specific categories of urban functions have been tested. As discussed in Sect. 2, OpenStreetMap and Google Maps follow different logic in the classification and representation of place markers, reflecting their divergent user bases and data structures. Rather than undertaking an exhaustive comparison of classification systems – beyond the scope of this paper – this study demonstrates the implications of categorical divergence for urban planning models. Three types of urban amenities were selected as test cases—cinemas, bookstores, and bars—based on their presence across both platforms and their relevance for urban life. The analysis compared how each dataset identifies, categorises, and spatially locates these amenities, shedding light on how differences in data semantics and categorisation schemes can influence downstream modelling outcomes and, as a consequence, impact decision-support systems in planning practice.

4 Results and Discussion

4.1 Quantitative and Position-Based Assessment

This section aims to explore the differences between the two datasets at both the urban scale and with a localised spatial focus, in line with the dual-scope analytical framework described in Sect. 3.3. The first step involves a quantitative evaluation of the total number of retrieved place markers and a qualitative assessment of their spatial distribution across the case study areas, while the second step briefly highlights how different datasets could impact also isochrone-based minute city score.

As previously explained in Sect. 3.1, the analysis was conducted by extracting all selected urban functions within an 8000-metre radius. The results reveal that, in all cases, OpenStreetMap (OSM) provides a higher total number of activities compared to Google Maps (GM). However, the extent of this difference varies significantly across the four urban contexts.

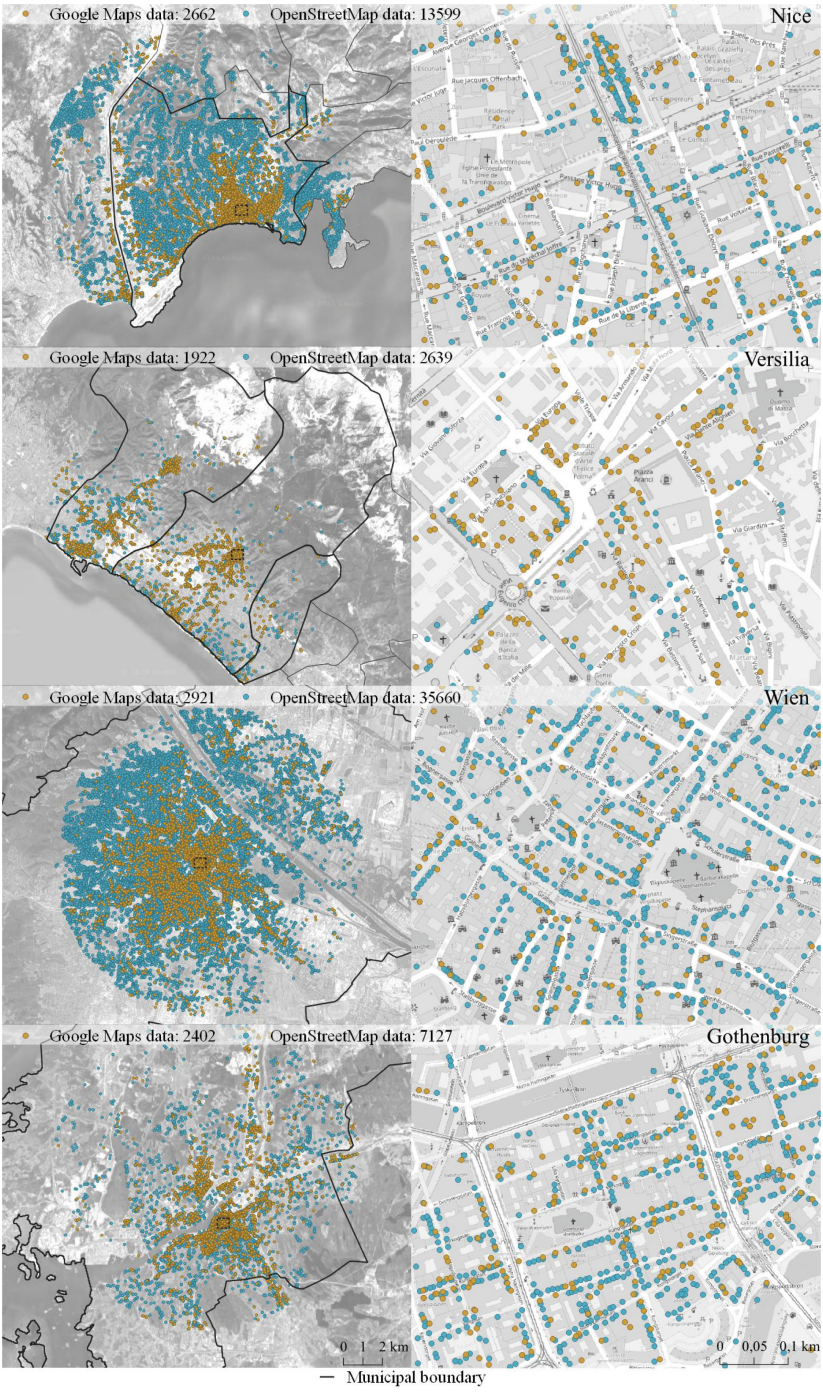

Fig. 1. Spatial comparison of the total retrieved places. On the right, detailed views highlight distribution differences.

In particular, Nice and Wien exhibit substantial quantitative discrepancies, with OSM yielding markedly more entries than Google Maps. A smaller, yet still evident, difference is observed in the case of Gothenburg, while the results for the Versilia conurbation are relatively comparable across the two datasets (Fig. 1).

Moreover, as illustrated on the right side of Fig. 1, even in areas where both datasets show high densities of place markers, the spatial distribution of the points often diverges. This spatial misalignment suggests differing data collection or classification protocols between the platforms and raises questions about spatial accuracy and completeness.

To quantify these discrepancies, a Relative Percentage Difference (RPD) metric was calculated for each city (1). The RPD expresses the deviation between the number of places extracted from OSM and GM in relation to their mean value. Low RPD values indicate a high degree of numerical similarity between the two datasets, whereas high RPD values reveal significant divergence in the amount of retrievable information. The detailed results of this comparison are presented in Table 1.

Table 1. Overview of the total activities downloaded across the urban scale.

Case studies	Google Maps	OpenStreetMap	RPD
Nice	2662	13,599	135%
Versilia	1922	2639	31%
Wien	2921	35,660	170%
Gothenburg	2402	7127	99%

$$RPD\ (\%) = \frac{|OSM\ \ value - GM\ \ value|}{(OSM\ \ value + GM\ \ value)/2} * 100 \tag{1}$$

In light of the characteristics of the four cities discussed in Sect. 3.2, one might hypothesize that the large number of place markers retrieved from OpenStreetMap (OSM)—a fully crowdsourced platform—for Nice and Wien could be linked to their status as two of the most populous cities in their respective countries, both exhibiting high residential densities. Another possible explanation could relate to their intense tourist activity, which might stimulate a higher volume of voluntary contributions or business-led inputs to the platform, particularly for promotional visibility.

However, a closer examination of the extracted data reveals critical insights that challenge this assumption. For instance, in the case of Nice, a disproportionately high number of entries are labelled as "swimming pools"—specifically, 7075 out of 13,599 total entries. A similar pattern is observed in Wien, where 4970 swimming pools were identified among 35,660 total entries. A qualitative verification indicates that these entries predominantly refer to private swimming pools, located within residential properties.

This phenomenon highlights a key distinction in the data collection logic between the two platforms. OSM tends to register all physically existing structures—both public and private—based on their spatial footprint, regardless of their accessibility or functional

relevance as public amenities. In contrast, Google Maps prioritizes commercial and publicly accessible points of interest (POIs), typically geared toward user interaction and visibility.

This discrepancy has important implications for urban modelling. Depending on the objective of the analysis, the inclusion of physically present but functionally irrelevant features—such as private amenities—can skew interpretations of service availability and proximity, particularly when relying on top-down, automated data extraction methods. It therefore becomes essential to critically assess the nature of each dataset before employing it in decision-support systems or urban policy evaluations related to the 15-minute city framework.

Shifting the focus to a local scale, this study explores how the choice of one database over another can influence urban analysis at the neighbourhood level. An isochrone analyses were implemented to measure accessibility within a 15-minute walking radius. The numerical discrepancy between the two datasets significantly affects the perceived vibrancy of an area, shaping interpretations of its urban activity and liveliness. For example, when examining a suburban area in the city of Gothenburg, both datasets reveal a concentration of activities in the eastern part of the neighbourhood, closer to the city centre. However, OpenStreetMap shows a wider spatial distribution of places across the entire area, and reports a higher number of entries compared to Google (Fig. 2).

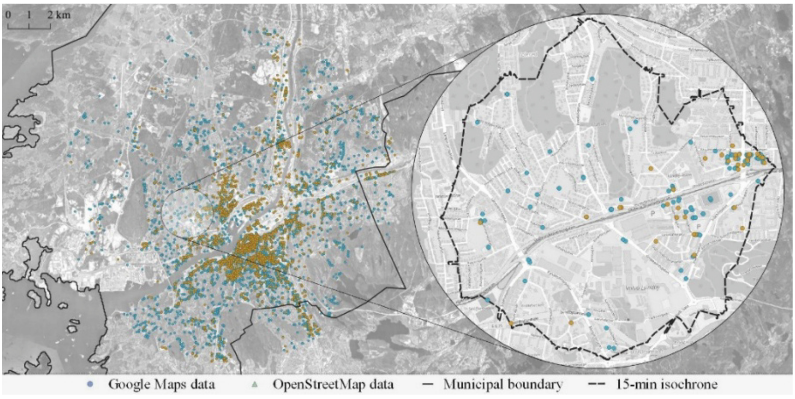

Fig. 2. 15-minute isochrone in a suburban area of Gothenburg. Comparison of place retrieval and representation across the two data sources.

Considering the activities identified within the 15-minute isochrone under study, and with reference to the categories proposed by Papadopoulos et al. (see Sect. 3.1), notable differences also emerge in the typological composition between the two datasets. These discrepancies directly affect the perceived functional character of the area. Specifically, Google Maps suggests a predominance of commercial activities, whereas OpenStreetMap, in addition to indicating a commercial profile, highlights a strong presence of restaurants and sports-related functions (Table 2). The choice of database, therefore, has a significant impact on the interpretative assumptions underlying urban studies conducted at the local scale.

Table 2. Categories from Papadopoulos et al. [6] identified within a 15-minute city isochrone in a suburban area of Gothenburg.

Place categories	Google Maps	OpenStreetMap
Total places	38	112
Economic facilities	2	4
Entertainment facilities	1	7
Food/grocery stores	3	12
Health services	5	7
Restaurants	2	18
Retail services/trade	24	30
Sports facilities	1	34

4.2 Categorization-Based Assessment

To further refine the comparative analysis, this section investigates how **categorisation differences** between OpenStreetMap (OSM) and Google Maps (GM) affect their respective datasets and, by extension, their suitability for urban studies. The focus is placed on a **marker-based comparison**, which evaluates individual place types to better understand how classification structures shape data availability and reliability. Three categories of **urban amenities** were selected as representative markers: cinemas (OSM value = "cinema" and GM place type = "movie_theatre"), bookstores (OSM value = "books" and GM place type = "book_store"), and bars (OSM value = "bar" and GM place type = "bar"). These categories were chosen due to their relevance in urban life, their presence across all case studies, and their apparent semantic alignment across the two platforms.

The first step consisted of computing the total number of features for each marker type within an 8000-metre radius from the city centre of each case study. The datasets were compared using a non-standard Relative Percentage Difference (RPD), calculated without applying the absolute value. This version of the metric allows for interpretation of directional discrepancies, indicating whether OSM under -or over-represents specific categories compared to Google Maps.

Contrary to the results observed in the broader multi-category extraction (see Sect. 4.1), this focused analysis reveals that OSM tends to underrepresent specific categories when compared to Google Maps. In most cases, the RPD values are negative, indicating that fewer features are identified by OSM (Table 3). The only notable exception is the category of bars, for which OSM consistently returns higher values than Google Maps across the case studies.

Table 3. Quantitative assessment of place markers at the urban scale (8000-metre radius).

Case studies	Cinema			Bookstore			Bar		
	GM	OSM	%	GM	OSM	%	GM	OSM	%
Nice	26	9	−97	60	24	−86	60	130	74
Versilia	6	4	−40	45	7	−146	60	130	74
Wien	60	34	−55	60	165	93	60	409	149
Gothenburg	11	7	−44	43	31	−32	60	46	−26

Furthermore, spatial comparison of the features reveals that the datasets are not nested or hierarchically inclusive; in many instances, the features retrieved from one platform are spatially distinct from those retrieved from the other. As shown in Fig. 3, this spatial divergence is particularly evident in the case of bars in Gothenburg, where a large proportion of data points from both datasets do not overlap geographically. This suggests that the classification logic and point-of-interest (POI) collection strategies differ significantly across platforms, likely reflecting their underlying data acquisition models and user contribution mechanisms.

These findings underscore the importance of understanding data semantics and classification granularity when selecting datasets for urban modelling purposes. Seemingly comparable categories may yield non-overlapping spatial realities, which could lead to misleading conclusions if not critically assessed in advance.

A closer examination of the retrieved values suggests that the consistent presence of exactly 60 bars in the Google Maps dataset across all four case studies at the urban scale may indicate a download limitation imposed by the API or platform. To test this hypothesis and further evaluate scale sensitivity, the spatial scope of the analysis was reduced from the urban scale to a local scale, focusing specifically on the historic cores of each city. The same three markers—cinemas, bookstores, and bars—were re-extracted within a 1200-metre radius from each historic centre.

When comparing the two data retrievals (urban vs. local), a clear distinction emerges: the OpenStreetMap (OSM) dataset shows no variation between the two spatial scales, indicating that data availability is not constrained by area extent;
the Google Maps dataset, by contrast, returns significantly more features at the local scale than at the urban scale for the same categories (Table 4). This confirms that the platform imposes retrieval limits which can be partially bypassed by reducing the area of extraction.

However, the refined analysis reveals an additional layer of complexity. Specifically, within the cinema category of the Google Maps dataset, the platform consistently returns exactly 60 features for each of the four case study areas, even when queried at a reduced local scale. Upon closer inspection, none of these returned features are classified as "movie_theatre," despite this being the explicitly specified query parameter.

A ground-truth validation indicates that, in reality, Gothenburg contains no cinemas within the examined areas, whereas the remaining three cities contain 7, 1, and 19 cinemas, respectively. This discrepancy raises significant concerns about the behavior

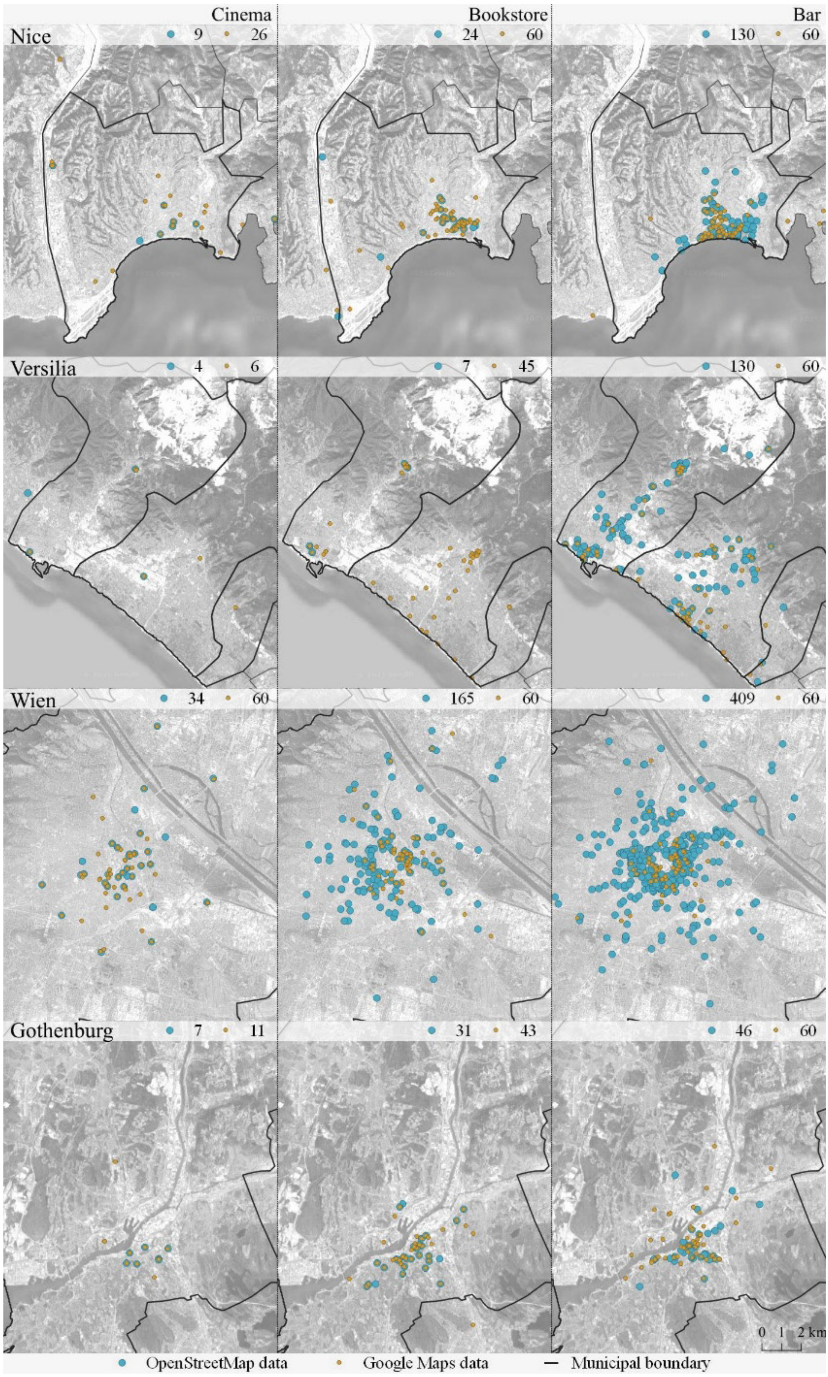

Fig. 3. Comparison of place marker representation at the city-wide scale (8000-metre radius) across the two data sources.

Table 4. Comparison of place marker extractions at the city-wide scale (8000-metre radius) and the local scale (1200-metre radius).

Radius	Markers	Nice		Versilia		Wien		Gothenburg	
		GM	OSM	GM	OSM	GM	OSM	GM	OSM
8000 m	Cinema	7	4	1	0	19	9	0	0
	Bookstore	36	14	14	0	23	31	2	2
	Bar	39	46	6	17	23	119	4	1
1200 m	Cinema	60	4	60	0	60	9	60	0
	Bookstore	38	14	13	0	57	31	2	2
	Bar	58	46	43	17	59	119	9	1

of Google Maps, which appears to return a fixed number of 60 entries regardless of the actual presence or absence of the targeted amenity. The features extracted from Google Maps encompass a wide array of unrelated categories, including "lodging," "bar," and "café," as well as generic labels such as "locality" and "point of interest." Although a detailed examination of these anomalies lies beyond the scope of the present study, these findings highlight the necessity of rigorous validation when using platform-generated geospatial data and caution against assuming the accuracy or relevance of such outputs without appropriate verification.

This finding highlights a semantic inconsistency between query input and database response, suggesting either a misclassification or a breakdown in the platform's internal categorisation logic. Unlike the previous situation—where some relevant features were omitted due to quantity limits but remained semantically aligned—this case reveals a more critical issue: Google Maps returns irrelevant or misclassified entries despite a correct query structure.

These limitations have important methodological implications. They underscore the non-transparent filtering mechanisms that may affect the integrity of data retrieved from commercial platforms, particularly when relying on automated or reproducible extraction procedures. For urban studies and planning applications, such inconsistencies pose risks to data reliability, validity, and reproducibility, reinforcing the need for careful dataset validation and cross-verification when using VGI sources in applied research.

Despite the apparent semantic clarity of the three selected markers—cinemas, bookstores, and bars—a more in-depth review of the platforms' categorisation systems (OSM Map Features and the Google Maps Platform) reveals that unambiguous one-to-one correspondence across databases is not always feasible. While the selected markers may seem clearly defined in theory, in practice, category definitions vary considerably between platforms, both in terms of taxonomy and data structure.

As highlighted by Biljecki et al. [21], local cultures, linguistic variations, and socio-spatial perceptions significantly influence how urban amenities are tagged and recorded on open data platforms. Consequently, a single place marker (e.g., "bar") may correspond to multiple entries across both datasets—entries which do not always align in meaning, visibility, or function. This introduces substantial divergence between datasets depending on which platform is queried.

In OpenStreetMap (OSM), a given feature is typically associated with one or two "values" within a tagging hierarchy. Conversely, Google Maps adopts a more layered approach: each feature is linked to a "Place Type", which may include multiple tags drawn from both primary and additional categories. This means that a single amenity may be classified under several overlapping labels, increasing its likelihood of being retrieved under different query parameters.

From a modelling perspective, this results in a double-edged dynamic. On one hand, the greater flexibility of Google Maps enhances its potential for capturing complex or multifunctional urban places, especially in diverse cultural settings. On the other hand, the lack of hierarchical structure and the multiplicity of associated tags can make it difficult to identify the main functional category of a place. This complicates efforts to map features into discrete, non-overlapping categories, especially when fine-grained functional differentiation is required.

This issue is particularly evident in the case of bars. As shown in Table 5, a wide range of entries in both databases may be culturally or functionally interpreted as belonging to this category. The use of broader or culturally contingent definitions significantly increases the number of retrieved entries, as illustrated by the results in Table 6. These findings underscore the importance of not only understanding platform-specific classification systems, but also accounting for semantic ambiguity when defining and interpreting functional urban categories in data-driven research (Fig. 4).

Table 5. Semantic ambiguity in the definition of the urban category "bar". List of considered tags.

Marker	Google Maps	OpenStreetMap
Bar	"bar"	"bar"
Bar^{+}	"bar", "cafe", "coffee_shop", "cafeteria", "cat_cafe", "dog_cafe", "tea_house", "internet_cafe", "bar_and_grill", "pub", "wine_bar"	"bar", "café", "internet_cafe", "biergarten", "pub"

Table 6. Semantic ambiguity in the definition of the urban category "bar". Quantitative assessment at the local scale (1200-metre radius).

Case studies	Bar			Bar+		
	OSM	GM	%	OSM	GM	%
Nice	46	58	−23	162	176	−8
Versilia	17	43	−87	32	120	−116
Wien	119	59	67	337	166	68
Gothenburg	1	9	−160	17	78	−128

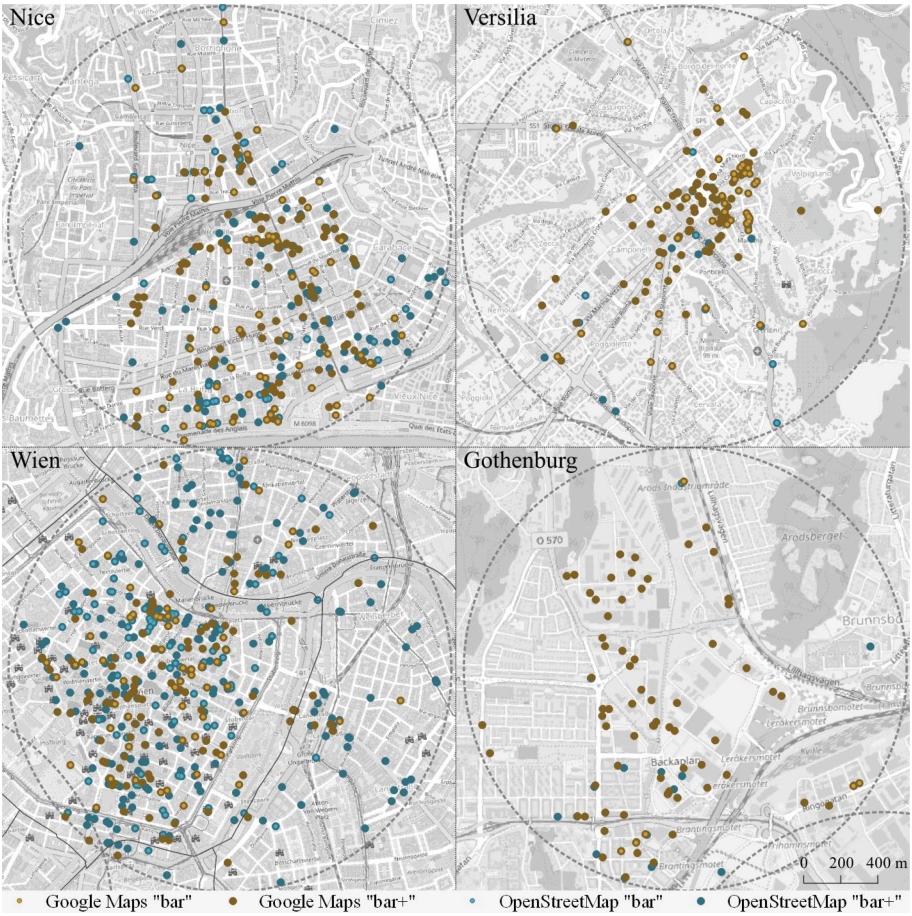

Fig. 4. Semantic ambiguity in the definition of the urban category "bar". Graphical representation in the historic centres of the case study areas.

5 Conclusion and Further Developments

This study has examined the reliability and internal consistency of OpenStreetMap (OSM) and Google Maps (GM) as spatial data sources for modelling the 15-minute city. Through a comparative analysis of four European urban contexts (Versilia, Nice, Wien, and Gothenburg) at both macro and micro scales, several critical discrepancies have been identified in terms of data volume, classification logic, and spatial distribution.

Results reveal that OSM often provides more features, partly due to its inclusion of private amenities, while Google Maps offers fewer but more curated entries, albeit subject to query and download limitations—especially at larger scales. However, neither platform demonstrates clear superiority in accuracy or completeness. Crucially, this study underscores that open datasets are not interchangeable and must be carefully validated prior to use.

While structural differences and retrieval anomalies were identified, the actual data quality remains undetermined. Ongoing field validation is necessary to assess their real-world correspondence, and to explore the impact of semantic mismatches across platforms. These inconsistencies pose major challenges for comparative and integrative modelling, calling for the development of a data cleansing protocol or adaptive framework tailored to specific planning needs and contexts.

Beyond academic implications, the findings also offer practical insights for data providers. Improving metadata standards, classification transparency, and query functionality could significantly enhance the reliability and usability of these platforms for spatial planning purposes.

Ultimately, this study raises a broader and more fundamental concern: the epistemological fragility of using open data as the sole basis for spatial planning. Without rigorous validation, there is a real risk that digital representations of proximity—and thus, of the 15-minute city—may diverge significantly from lived urban realities, potentially compromising planning outcomes. As such, open data must be treated not as a neutral reflection of the urban environment, but as a construct requiring critical scrutiny, contextual adaptation, and empirical support.

Future research should prioritize the development of a data cleansing protocol or an adaptive framework that can be calibrated based on the intended use, and optimized to maximize dataset reliability and usability. Such a framework should be supported by rigorous testing of dataset effectiveness in different urban settings.

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