Towards a fair and comprehensive evaluation of Walkable Accessibility and Attractivity in the 15-minutes city scenario based on demographic data

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Abstract. Accessibility is a critical dimension in agendas involving urban policies. Furthermore, the notion of accessibility has recently gained further popularity since the formulation of the '15-minutes-city' paradigm and the consequences of the COVID-19 pandemics in the life routines. However, when interested in accounting for accessibility from a formal perspective, researches and practitioners should fairly and comprehensively use pertinent indicators, in accordance with the density of potential destinations, such as those functions that are typically related to the everyday life of residents (e.g., schools, healthcare) and facilities used by most of the users' categories (e.g., restaurants, groceries, ATMs). Furthermore, both the evaluation of the accessibility of a city and whether it can be effectively ascribed among the '15-minutes' eligible cities should take into account the demographic profile of residents, as they may have different needs and mobility behaviours. This is particularly significant when the accessibility is intended as a measure of walkability of neighbourhoods. With this latter regard, the majority of the previous researches focused on indicators that don't explicitly consider the population characteristics, such as age. Additionally, most of the indicators focus on the number of facilities reachable within a given time cutoff, while the counterpart of the latter, i.e., as a measure of attractiveness, such as the number of users that can reach that given area, is not evaluated explicitly. In this paper, a comprehensive formulation able to capture both accessibility and the attractivity, as well as the different degree of 'walkable' accessibility according to the socio-demographic profiles of population, will be presented and tested across some Italian cities. This indicator is aimed to provide an operative tool for urban and transportation planners, as well as for private stakeholders, when they are in charge of evaluate the degree of 'walkable' accessibility. Furthermore, the use of open and standardized data is intended being a main strength of the proposed methodology, as it can be easily replicated in other contexts.

Keywords: Accessibility, Open Data, Smart city.

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1 Introduction

Accessibility is a key notion in several disciplines [1], [2], emerging in the last decades as a prominent topic of research. Different definitions have been formulated to capture some aspects of this comprehensive concept [3]. They range from the ability to reach a specific location [4], [5] to the focus on individuals and their freedom of satisfying the trip purposes towards the desired activities [6] and the related benefits, given the economic impacts related to the access to a specific destination [7], [8]. As pointed out by [9], several components are included and should be considered simultaneously when accounting for accessibility. Measures of accessibility typically combine the costs of transport, which can be expressed either as travel distance or monetary cost, or as the attractivity of the destination, related to the number of activities located at the desired destination [1], [10]. With regards to attractivity, the location and the density of activities at the potential destinations [11], as well as their variety and diversity in their typology [12], may influence citizens' predispositions and habits, and consequently may affect the accessibility of a place. Given their role in transportation and urban planning domains, accessibility and attractivity have been analyzed as major and critical components of the so-called '15-minutes-city' (15MC) paradigm. This concept has been defined by academia [13] and gained appeal from applications and strategies put in practice in different contexts [14]. Despite the use of several time thresholds [15], [16], [16], in the domain of accessibility the '15 minutes' is still the most popular and investigated time window. From a wider perspective related to urban planning, the 15MC paradigm is rooted in the idea that different aspects of everyday life should be located in the same area and integrated, e.g., at neighborhood level, thereby providing citizens and city users with a reasonable and adequate number of facilities related to the routinary needs of people [17]. A non-exhaustive list of facilities may include both public services, such as schools, healthcare structures or banks, and commercial activities, such as restaurants, groceries or shops. In concrete terms, this assumption advocates that facilities and services should be accessible and in proximity to places of residence [12], within a travel time not exceeding 15 minutes [18] covered by active mobility modes, such as walking [8] or cycling [19]. Consequently, the 15MC paradigm includes both physical and social factors. About the previous, built environment [20], [21] and land-use mix [22] provide the underlying conditions towards the full implementation of the paradigm. About the social factors, several authors [14], [19], [23], [24] refer to social inclusion and demographic profile of population as main aspects. This latter is of paramount importance, as different socio-demographic groups may have dissimilar needs and mobility habits and behaviors, especially when focusing on walking. However, although the theoretical framework of the 15MC paradigm may appear straightforwardly implementable and measurable in any circumstances, it has been pointed out that there is a need for contextual solutions and local reinterpretations [12], [15], [17]. In particular, since the distribution of facilities may denote the stratified socio-economic development of a neighborhood or a city, a fair and comprehensive measure of the actual 'walkability' of a site requires adequate instruments that effectively combine the abovementioned dimensions related to the 15MC paradigm.

Based on these premises, two comprehensive indicators able to capture the accessibility and the attractivity of an area will be presented and tested in three Italian cities, namely Brescia, Milano and Venezia. The choice of these cities is justified by their characteristics, either the size and the number of major functions that may attract several categories of users (Milano and, yet at lower grade, Brescia), or the characteristics of urban fabric that may affect the walkability (Venezia). The proposed measures include the sociodemographic profiles of the registered population, as well as some main facilities related to the typical everyday life of most users' categories. Therefore, the proposed approach is aimed at being an operative tool for urban and transportation planners, as well as for private stakeholders, when they are in charge of evaluating the degree of 'walkable' accessibility within the context of the 15MC. Results will be confronted with some measures, namely the Closeness Centrality [25] and the Anselin Local Moran's *I* [26], to test the ability of the metrics in unveiling the spatial patterns of accessibility and attractivity. Regarding the previous, it is proposed to consider the role of the road network in the computation of the metrics. About Anselin Local Moran's *I*, this index is intended as an appropriate tool in the detection of specific patterns and spatial relationships, as it identifies clusters of features with similar or dissimilar values.

2 Previous works

Several previous researches elaborated indexes and metrics to analyze the walkability of a place, and some of them are specifically devoted to analyses of 15MC. The most famous walking-related index is the WalkScore [27], which proposes a measure of proximity to facilities within a 0-100 scale. Today, it is a commercial-oriented platform, providing analyses related to the facilities reachable by walking, as well as information related to the real estate market. A main drawback is the limited performance in some countries, while it is fully implemented in the US, UK, Canada and Australia. A recent example aimed at providing a comprehensive analysis of 15MC is the 15min-City index proposed in [17], where scores related to walkability and cycling of several cities can be accessed by a web platform. The scores are centered on a regular grid made of a hexagonal tessellation, and they refer to the number of facilities and the related travel time. An analogous scoring procedure is the 15min City Score Toolkit elaborated by [28], which is based on the intersection between isochrones pivoted to the Uber H3 hexagonal tessellation and the facilities reachable within a 15-minutes walking trip. Tested only in Italy, at least to the best of authors' knowledge, the Next Proximity Index (NEXI) [29] provides a scalable index which considers also the potential discomfort of walking accessibility. Both the 15min-City index, the 15min City Score Toolkit and the NEXI extract the list and the location of facilities from OpenStreetMap (OSM) [30].

Based on this review, it is possible to identify some commonalities and differences between the methodology described in this paper and those implemented elsewhere. In particular, the proposed approach is aimed at an enhanced and easy scalability, replicability and interoperability in several contexts, based mostly on open data. Like some of the methods mentioned above, the Uber H3 hexagonal tessellation and OSM database have been used as spatial reference and main source, respectively. However, a dynamic integration of POIs on the network, the use of fine-grained information related to the registered population, as well as the computation of distances based on routing rather than the use of buffering measures such as the isochrones, are noteworthy novelties. Moreover, the proposed approach focuses on both direct and indirect measures, namely attractivity and accessibility, while most of the previous works focus on accessibility only.

3 Materials and Methods

In this section, we explore the dataset employed, the analytical procedures applied, and the metrics developed. The analysis was conducted using Python 3.12, leveraging several packages for data extraction [31], tessellation [32], geospatial data analysis [33], geometric object manipulation [34], and network analysis [35]. The street network and the facilities were extracted from OpenStreetMap (OSM) [30], the largest and most successful example of Volunteered Geographic Information (VGI) project. The density of facilities is plotted in Figure 1. Specifically, Protocol Buffer data for each city was downloaded from [36] and analyzed locally using the Pyrosm library. Using Pyrosm, we extracted the walkable street network and POIs across the following categories: restaurants, bars, schools, healthcare structures, grocery stores, parks, arts and cultural venues, and banks. For each city, administrative boundary polygons were sourced from ISTAT's "Confini Amministrativi" [37] dataset, while resident population data was taken from the Italian 2021 Census. Population groups were categorized by age to assign different walking speeds, as described in Table 1. The density of population is plotted in Figure 2. It is worth noting that a quartile scale has been used to allow an easier comparison between the cities analyzed. Additionally, the geometries of Census sections were retrieved from ISTAT's "Basi Territoriali" [37].

Figure 1 – Distribution of facilities.

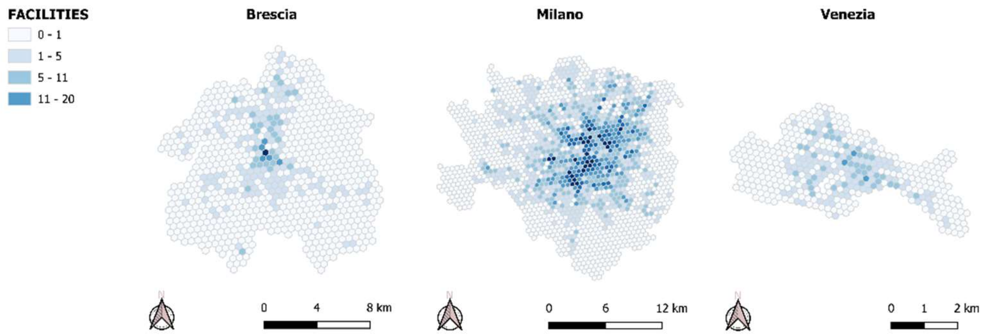

Figure 2 – Distribution of population.

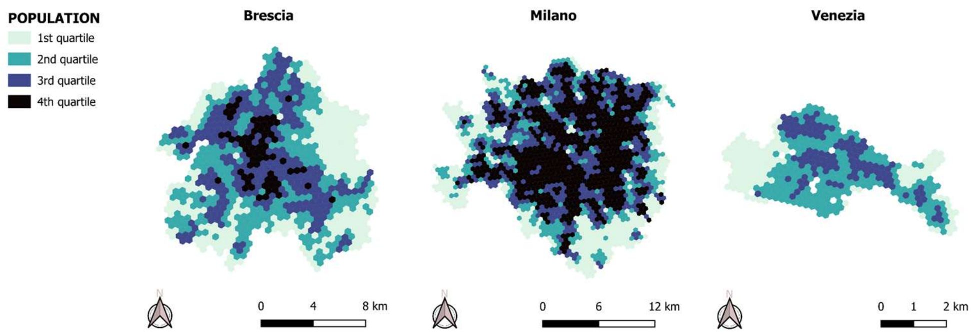

***Table 1 - Velocity for each population age category group, according to* [36]. *The ISTAT tags are the labels used by the Italian Census for these categories* [37].**

Age *a*	ISTAT tag	Velocity (m/s)
[10 - 29]	P-(16, 17, 18, 19)	1.34
[30 - 49]	P-(20, 21, 22, 23)	1.26
[50 - 59]	P-(24, 25)	1.23
≥ 60	P-(26, 27, 28, 29)	1.21

3.1 Data Preparation

Data preparation consists of three phases: tessellation (Section 3.1.1), i.e., representing the city on a regular grid; network preparation (Section 3.1.2), i.e., cleaning OSM road network data and geometries; network matching (Section 3.1.3), i.e., assigning each facility and tessellation's center to the closest edge of the road network.

3.1.1 Tessellation

Each of the analyzed cities was divided into a regular tessellation made up of hexagonal cells [38]. Next, the tessellations were enriched with residential population data from the Census sections. For each hexagon in the tessellation, we identified the Census sections intersecting it and updated the hexagon with population information weighted by the fraction of the intersection area. Specifically, let *S* be the set of Census sections and *p(s, a)* the resident population of age category *a* within section *s*. The resident population of age category *a* in tessellation *t*, denoted as *p(t, a)*, is computed as:

$$p(t,a) = \sum_{s \in S} \frac{\text{area}(s \cap t)}{\text{area(s)}} p(s,a)$$

3.1.2 Network preparation

Then, we extracted the walkable street network as a dataset comprising nodes and edges. From this dataset, we built a weighted graph, assigning edge weights based on street lengths in meters. The tested workflow, along with the choice of the libraries, allowed a significantly faster performance compared to other similar platforms [39] used elsewhere [28], particularly for shortest path computations. To enhance the reliability of our analysis, we focused on the largest connected component *G* of the graph and applied a sanitization process to handle closely clustered graph components. This method proved effective in addressing cases where OSM data contained missing edges or imprecise intersections, ensuring a more connected and accurate graph representation. Specifically, we iteratively incorporated sub-graphs with at least one node within a Euclidean distance of less than 10 meters from any node in the largest connected component, by creating an edge between the closest pair of nodes and assigning the Euclidean distance as the edge weight. This process continued until no remaining sub-graphs were close enough. This issue was relevant in Venezia, where OSM street network produced a disconnected component for Cannaregio.

3.1.3 Network Matching

After extracting the facilities from OSM using Pyrosm and creating the tessellation, the next step involved mapping them onto the network. Each facility is represented as a point, while each tessellation is represented by its centroid. Points were dynamically integrated into the network by identifying the closest edge in G for each point. Each point is projected onto the identified edge, added as a new node in G, and the edge is split to accommodate the newly added node. Finally, the distance matrix was computed. For each tessellation t and each facility i_c of category c, the distance in meter $d(t, i_c)$ is computed as the shortest path distance in G.

3.2 Metrics

We divide this section into *attractivity* and *accessibility* metrics. The former measures the ability of each facility to attract users, the latter measures the level of attractive facilities within 15-minutes walking distance of a given census area.

3.2.1 Attractivity Measures for POIs

We assigned each facility an attractivity index that measures its ability to attract residents who can reach it within a 15-minute walking distance. This index is a ranked statistic that compares the number of residents visiting the facility to those visiting other facilities of the same category. It was calculated separately for each population age. Let P_c be the set of facilities of category c. For any facility $i_c \in P_c$, let $T(i_c, a)$ denote the set of tessellation cells from which residents of age a can reach i_c within 15 minutes. Let $p(i_c, a) = \sum_{t \in T(i_c, a)} p(t, a)$ be the total number of residents of category a that can reach i_c within 15 minutes. We define the attractivity index of i_c for residents of age a as

$$\mathrm{Att}(i_c, a) = \frac{1}{|P_c|} \mathrm{rank}_{P_c}(p(i_c, a)),$$

where the rank is defined as $rank_X(y) = |\{x \in X : x \leq y\}|$. For convention, equal values are associated with their minimum rank. Finally, a unique attractivity index is computed by a weighted average over the population age classes where $w(a)$ is a positive weight associated with each population category. In our results we used uniform weights.

$$\mathrm{Att}(i_c) = \langle \mathrm{Att}(i_c, a) \rangle_{w(a)} := \frac{1}{\sum_a w(a)} \sum_a \mathrm{Att}(i_c, a) \cdot w(a),$$

3.2.2 Refinement Using Gravity Model

The total resident population of age a that can reach facility i_c within 15 minutes, represented as $p(i_c, a)$, is already a valuable indicator that approximates the workload of i_c. However, it lacks insights into resident movements. Without relying on sensitive data and using only open-source information, we introduce an attractivity indicator designed to capture resident mobility. In the absence of actual mobility data, we simulate movement patterns using the Gravity model [39]. This model estimates the probability of movement based on a gravity law, where the masses are the populations at the origin and destination, and the probability decreases with the square of the distance between them. Here, we use as population masses the total population in each tessellation cell $p(t) = \sum_a p(t, a)$ and the total population that can reach each facility within 15 minutes $p(i_c) = \sum_a p(i_c, a)$. Thus, the probability of a movement from a tessellation cell t to a facility i_c is

$$\Pr(t, i_c) = k\frac{p(t) \cdot p(i_c)}{d(t, i_c)^2},$$

for some normalization constant k. This constant can be computed by assuming that for each tessellation, for each category of facilities, and for each population age, the residents must visit at least one facility within a 15-minutes walk. In other words, we assume that the residents do not walk more than 15 minutes. Specifically, let $P_{t,c,a}$ be the set of facilities of category c that population of age a can reach from tessellation t within 15 minutes. Then, by our assumption we have

$$1 = \sum_{i_c \in P_{t,c,a}} p(t, i_c) \Rightarrow k_a = \left(\sum_{i_c \in P_{t,c,a}} \frac{p(t) \cdot p(i_c)}{d(t, i_c)^2} \right)^{-1},$$

meaning that a different normalization is needed for each population age a. Thus, we have that the probability of a movement of population of age a from a tessellation cell t to a facility i_c is

$$\Pr(t, i_c, a) = \left(\sum_{j_c \in P_{t,c,a}} \frac{p(j_c)}{d(t, j_c)^2} \right)^{-1} \frac{p(i_c)}{d(t, i_c)^2}.$$

With these probabilities, we can compute the population that goes to each facility according to the model, which we define as $p^g(i_c, a)$. This is computed as an expected value

$$p^g(i_c, a) = \sum_{t \in T(i_c, a)} p(t, a) \cdot \Pr(t, i_c, a),$$

which can substitute $p(i_c, a)$ to compute the attractivity index.

3.2.3 Accessibility Measures for Tessellation

Our attractiveness measure builds on the approach proposed in [40], where the authors computed a weighted rank statistic for the number of facilities reachable within 15 minutes from each tessellation cell. Here, we adapt this idea by integrating the attractivity index defined in the previous section. The key distinction is that we account for the varying importance of facilities, assigning greater weight to less attractive ones to better reflect their contribution to accessibility. The attractiveness index of a facility, which accounts for how many people can reach the facility, acts as a proxy for its workload. A lower workload is expected to correspond to better accessibility, as it is likely to translate to shorter waiting times and reduced crowding. Let T be the set of all tessellation cells, the accessibility index of a tessellation cell t for category of facilities c and for population age a is

$$\mathrm{Acc}(t, c, a) = \frac{1}{|T|}\mathrm{rank}_T\left(\sum_{i_c \in P_{t,c,a}} (1 - \mathrm{Att}(i_c))\right),$$

where the rank is calculated over the values of the summation argument for all tessellation cells, and $P_{t,c,a}$ is the set of facilities of category c that population of age a can reach from tessellation t within 15 minutes. The term 1-$Att(i_c)$ encapsulates our assumption that an increase in a facility's attractiveness corresponds to a decrease in its accessibility. This inverse relationship arises because higher attractiveness typically leads to greater demand, thereby increasing the facility's workload. As the workload intensifies, the facility becomes less accessible to additional users, reflecting a trade-off between desirability and availability. The key difference from [40] is that this approach ranks facilities by their inverse attractivity, whereas [40] counts the number of reachable facilities. As introduced in the previous section, an aggregated accessibility index can be computed as

$$\mathrm{Acc}(t) = \left\langle \langle \mathrm{Acc}(t, c, a)\rangle_{w(c)} \right\rangle_{w(a)},$$

where first a weighted aggregation is computed for the category of facilities and then is computed for population age. In our results we used uniform weights for both population age and category of facilities.

4 Results and Discussion

This Section will present and discuss results. Some notable relationships between the metrics and areas will be described and referenced in accordance with the typology of land use and the name of some neighborhoods (Figure 3). Through a correlation analysis (Pearson's ρ) [41] (Table 2, Table 3,
Table 4 and Table 5), results will be analyzed and confronted with the metrics introduced in Section 1, namely Closeness Centrality and Anselin Local Moran's I. As previously introduced, the aim of this analysis is to test the effectiveness of the metrics and to unveil relevant spatial patterns related to the accessibility and attractivity across the analyzed cities.

As a general remark, the distribution of accessibility and attractivity values is quite similar across the cities (see Figure 4 and Figure 5). Correlations in Table 2 and Table 3 suggest that there is a notable relation between the two metrics, albeit at different degrees (Milano ρ>0.8, Brescia and Venezia 0.6<ρ<0.7; all p-value <0.001). Moreover, an additional computation was undertaken to compare the overall consistency of the metrics based on the walking speed as described in Section 3 against a computation based on an equal speed for all the groups (1.24 m/s). The results (cosine similarity analysis; all the values >0.9 for both the cities and measures) suggest that, despite the use of different values to provide a more accurate model of human behaviors, speed should not be considered a factor in enhancing accessibility and attractivity.

In details, Brescia is more 'accessible' and 'attractive' along a 'L-shaped' corridor between the neighborhoods of Prealpino, Mompiano and Casazza, the historical city center, the train station and the business district of Brescia Due, while some other high values can be found at two major residential neighborhoods, such as San Polo and Buffalora. Notably, this corridor is overlaid by the subway line, the backbone of the local transit system, thus indicating that accessibility and attractivity in Brescia are influenced by both natural and anthropic factors. The natural factors comprise geographical features, such as the hills located in the eastern part of the city, while the anthropic factors are characterized by the presence of major facilities, such as the Hospital, the University campus or the business district at Brescia Due. While the former can be regarded as physical constraints that influenced the location of urban functions and facilities, the latter may have been a contributing factor in the locating activities. As for Milano, the plots report higher accessibility and attractivity within the historical city center (Brera, Duomo), as well as the increasing values in proximity to several strategic business districts and densely populated neighborhoods (Garibaldi, Isola, Stazione Centrale, Città Studi, Porta Romana, Tre Torri, Portello). The results of both metrics find correspondence with the spatial pattern that has historically characterized the urban development of Milano, namely several concentric 'cores' corresponding to the ancient city walls (recognizable by the red and pink background in Figure 3), with linear extensions corresponding to the main access roads. About Venezia, Figure 4 and Figure 5 suggest that the most 'accessible' and 'attractive' areas are located between San Marco and Castello, in a narrow area boarding the Canal Grande. It is worth noting that both measures overlay the most touristic areas, namely Rialto Bridge and San Marco Square, located in San Polo and San Marco. In both metrics, peripheral areas were found generally to be less 'attractive' and 'accessible' than the central areas, described in Figure 3 as the historical city centers. This finding supports the consolidated view of the city centers as the areas with notable presence of facilities and enhanced walking capability. Notably, results reported in Table 2 and Table 3 corroborate this insight even in Venezia, which is generally considered to be a fully pedestrian-friendly city, at least in terms of its infrastructure. Nevertheless, notable clusters of higher attractivity can be found in some peripheral and populated areas of Milano (e.g., San Siro, Affori, Baggio, Niguarda, Gallaratese; about distribution of population refer to Figure 2). This latter result is supported by values in Table 2 and Table 3, as the coefficients describe a moderate correlation between the metrics, the population and the density of facilities, with higher values for Milano.

In view of these trends, some consistent results can be discussed. First, findings suggest that facilities are not equally distributed across the cities, where some neighborhoods result in oversupplied, while others lack an adequate provision of services for everyday life. This is more evident in Venezia (ρ<0.65, p-value <0.001), where several populated areas are not supplied by the analyzed facilities. Consistent with the abovementioned findings, coefficients related to the population (0.45<ρ<0.72, p-value <0.001) suggest that a considerable portion of residents live in 'fully accessible' neighborhoods, while some of them currently need longer walks to get to the desired destinations. Consequently, results have implications for the degree to which cities conform to the 15MC paradigm, as the 15MC-based planning approach should aim to bring facilities to neighborhoods, thus promoting a more livable and functional city [15]. Furthermore, although the distribution of facilities is a determining factor in the computation of the metrics, the moderate correlation (0.50<ρ<0.64, p-value <0.001) suggests that a high concentration in some areas fosters the location of additional facilities nearby and, conversely, hinders new settlements in other areas. A similar factor was previously observed in relation to the location of economic activities and their distribution across cities [42]. This conclusion is of paramount importance when dealing with touristic destinations, as the number of facilities may be strongly skewed in favor of those related to non-residential users, while residents may suffer the lack of everyday-life facilities [43], [44].

From a wider perspective, results suggest that the analysis based on the distributions of residents and facilities is effective in addressing local socio-economic dynamics [45]. This latter conclusion is corroborated when confronted with consolidated touristic patterns, such as in Venezia, as tourists' needs may lead to inequalities and the replacement of the functions and accommodations traditionally devoted to residents [46], [47], [48]. Along with the previous analyses, a focus on Closeness Centrality and Anselin Moran's I is proposed to test the spatial distribution of metrics and the effects of contextual factors e.g., the shape of the urban fabric. About Anselin Local Moran's I, the cluster and outlier can be plotted in accordance with the surrounding elements of each feature (in the Figure 6 and Figure 7, COType). When I is statistically significant and positive, the features are part of a cluster, while when I is statistically significant and negative, the features are outliers. Conversely, when I is not statistically significant, the features are randomly distributed. The three cities report some clustering effect, albeit with different patterns, and wide areas without any significant result. However, the presence of 'hot spots' and 'cold spots' is only partially confirmed by the correlation analysis. While results related to Brescia are consistent, with a moderate correlation between I and the two metrics (ρ~0.6, p-value <0.001), Milano and Venezia report dissimilar values. Regarding the latter city, coefficients suggest that the more accessible a location, the lower its degree of clustering. About Closeness Centrality, low correlations (ρ<0.5, p-value <0.001) are found with the value of the metrics, and weak or absent in relation to I. These results suggest that the structure of the road network plays a prominent role in determining the access from and to a specific area, although there are marked differences among cities, while it has no substantial effect on the spatial patterns related either to accessibility or attractivity.

Figure 3 – Land use types and notable neighborhoods across the analyzed cities.

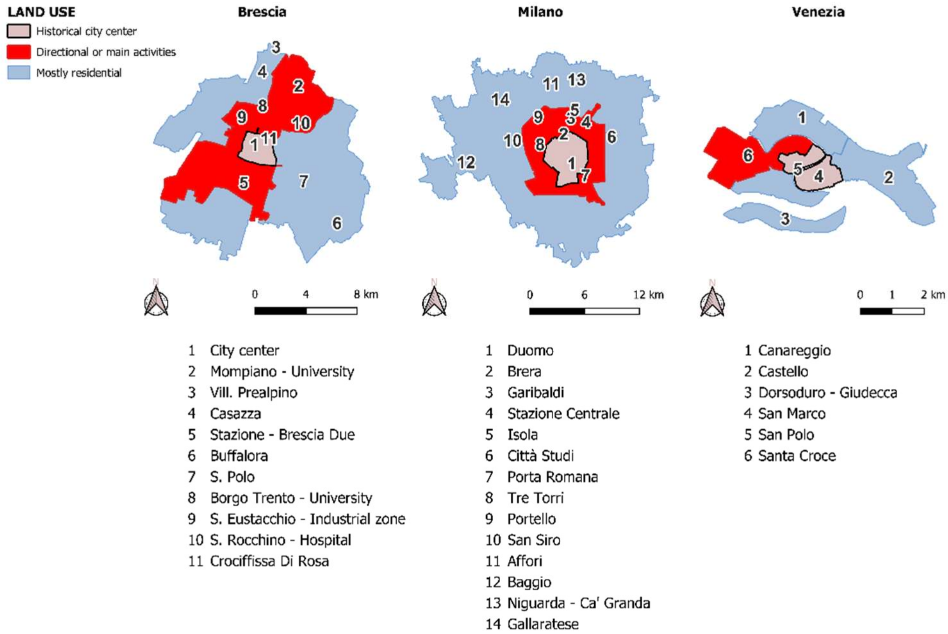

Figure 4 – Accessibility across the analyzed cities (numbers are referenced in Figure 3).

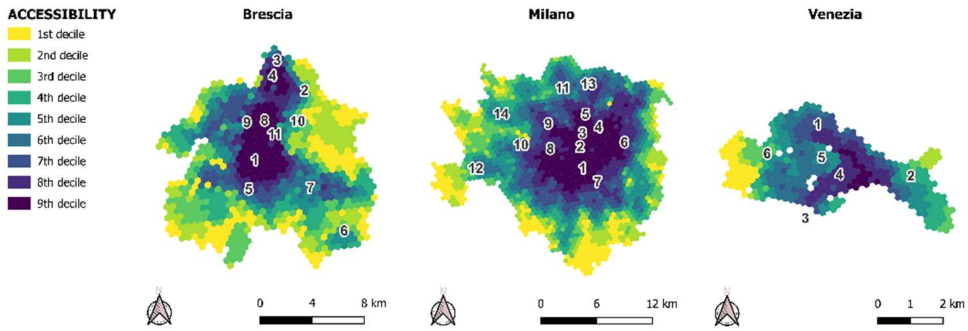

Figure 5 – Attractivity across the analyzed cities (numbers are referenced in Figure 3).

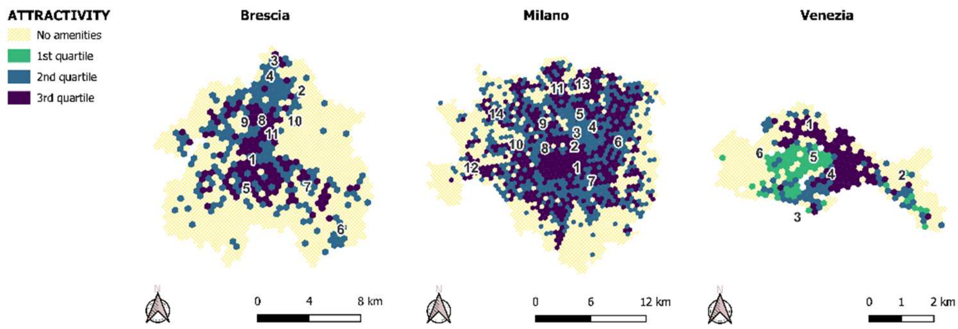

Figure 6 – Anselin Moran's I *– Accessibility (numbers are referenced in Figure 3).*

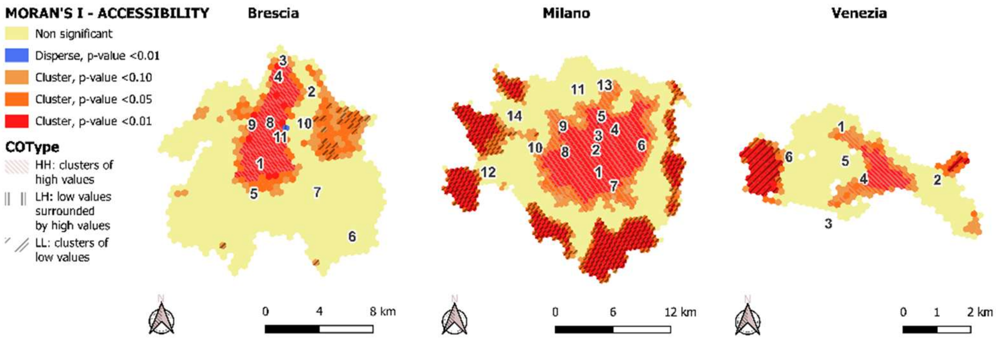

Figure 7 – Anselin Moran's I *– Attractivity (numbers are referenced in Figure 3).*

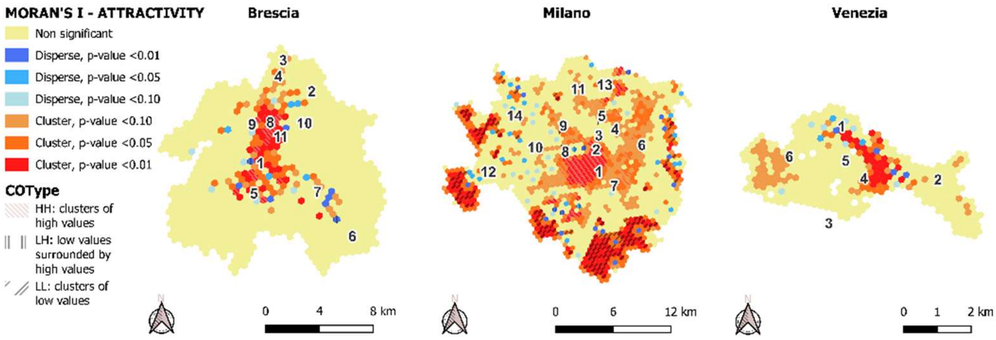

Table 2 - Correlation analysis – Accessibility.

	Attractivity	Population	Facilities	Centrality
Accessibility$_{Overall}$	0.660***	0.611***	0.572***	0.391***
Accessibility$_{Brescia}$	0.669***	0.690***	0.546***	0.495***
Accessibility$_{Milano}$	0.830***	0.711***	0.639***	0.617***
Accessibility$_{Venezia}$	0.626***	0.560***	0.505***	0.348***

Note: *** p-value < 0.001

Table 3 - Correlation analysis – Attractivity.

	Accessibility	**Population**	**Facilities**	**Centrality**
Attractivity $_{Overall}$	0.660***	0.451***	0.498***	0.169***
Attractivity $_{Brescia}$	0.669***	0.583***	0.540***	0.412***
Attractivity $_{Milano}$	0.830***	0.698***	0.534***	0.548***
Attractivity $_{Venezia}$	0.626***	0.486***	0.621***	0.258***

Note: *** p-value < 0.001

Table 4 - Correlation analysis – Anselin Moran's* I *for Accessibility.

	Accessibility	**Centrality**
I Accessibility $_{Overall}$	0.132***	-0.078***
I Accessibility $_{Brescia}$	0.600***	0.368***
I Accessibility $_{Milano}$	0.104***	-0.049*
I Accessibility $_{Venezia}$	-0.266***	-0.010

Note: * p-value < 0.05; *** p-value < 0.001

Table 5 - Correlation analysis – Anselin Moran's* I *for Attractivity.

	Attractivity	**Centrality**
I Attractivity $_{Overall}$	0.458***	-0.040
I Attractivity $_{Brescia}$	0.549***	0.267***
I Attractivity $_{Milano}$	-0.228	-0.359**
I Attractivity $_{Venezia}$	0.532***	0.099*

Note: * p-value < 0.05; ** p-value < 0.01; *** p-value < 0.001

5 Conclusions

In this paper, a comprehensive method to account accessibility and attractivity in urban areas is presented and tested in three Italian cities, namely Brescia, Milano and Venezia. The metrics are tested within the 15-minutes-city (15MC) paradigm. Coherently to the principles the 15MC is rooted in, the socio-demographic profile of population, the characteristics of the road network and the density of facilities for everyday life of users are considered. Subsequently, some well-known metrics, such as Closeness Centrality and Anselin Moran's I, were adopted to test the effectiveness of the results. Based on the outcomes, Authors posit that the method provides a scalable and intuitive tool for public and private stakeholders to enhance policies aligned with 15MC paradigm. Indeed, this paradigm aims to ensure that essential services are accessible within a short distance from residents' homes. The use of open and standardized data sources, such as official statistics, and information from the open databases, facilitates informed decision-making, promotes stakeholder engagement, and enhances transparency and accountability in the policymaking process. Moreover, the scalability and the adherence to diverse urban contexts of the proposed method enable the development of tailored strategies that address local needs while contributing to overarching sustainability objectives, including the enhancement of public health. Moreover, the adoption of standardized data facilitates continuous monitoring and evaluation of policy impacts, thereby instigating a continuous improvement cycle that, in turn, contributes to the creation of more resilient, equitable and habitable urban environments. Some further researches may be built upon these findings. Authors mention the shift from static, i.e., the registered population, to dynamic inputs, e.g., the number of presences inferred from big data sources. This is intended to enhance the findings and address a significant limitation affecting the use of registered population data, which may be outdated and non-representative of the actual population composition, which encompasses residents and some city user categories, e.g., tourists, workers, commuters. Additionally, an approach based on the 'real' users may capture the effective needs of population and the provision of adequate services. This latter has been already demonstrated effective for modelling dynamics in urban areas [49], [50], [51]. Furthermore, the 15-minutes time window may be considered a vague or restrictive threshold when confronted with the wide spectrum of modal alternatives, which can potentially result in the under- or over-representation of accessibility and attractiveness. To address these concerns, the incorporation of transit infrastructures in a more advanced simulation model is proposed for subsequent developments of the research.

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