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A Data-Driven Approach to Analyze Mobility Patterns and the Built Environment: Evidence from Brescia, Catania, and Salerno (Italy)

Rosita De Vincentis [1], Federico Karagulian [2], Carlo Liberto [2,*], Marialisa Nigro [1], Vincenza Rosati [1] and Gaetano Valenti [2]

[1] Department of Engineering, Roma Tre University, Via Vito Volterra 62, 00146 Rome, Italy
[2] ENEA Research Center Casaccia, Via Anguillarese 301, 00123 Rome, Italy
* Correspondence: carlo.liberto@enea.it

Abstract: Investigating the correlation between urban mobility patterns and the built environment is crucial to support an integrated approach to transportation and land-use planning in modern cities. In this study, we aim to conduct a data-driven analysis of these two interrelated parts of the urban environment through the estimation of a set of metrics to assist city planners in making well-informed strategic decisions. Metrics are computed by aggregating and correlating different types of data sources. Floating Car Data (FCD) are used to compute metrics on mobility demand and traffic patterns. The built environment metrics are mainly derived from population and housing census data, as well as by investigating the topology and the functional classification adopted in the OpenStreetMap Repository to describe the importance and the role of each street in the overall network. Thanks to this set of metrics, accessibility indexes are then estimated to capture and explain the interaction between traffic patterns and the built environment in three Italian cities: Brescia, Catania, and Salerno. The results confirm that the proposed data-driven approach can extract valuable information to support decisions leading to more sustainable urban mobility volumes and patterns. More specifically, the application results show how the physical shape of each city and the related street network characteristics affect the accessibility profiles of different city zones and, consequently, the associated traffic patterns and travel delays. In particular, the combined analysis of city layouts, street network distributions, and floating car profiles suggests that cities such as Brescia, which is characterized by a homogeneously distributed radial street system, exhibit a more balanced spread of activities and efficient mobility behaviors.

Keywords: mobility patterns; built environment; Floating Car Data; OpenStreetMap repository; road network; accessibility

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1. Introduction

The relationship between land use and mobility patterns has been a research topic for years, due to its importance in traffic management and urban planning [1]. Indeed, the knowledge of this relationship supports the adoption of policies regarding sustainable planning for the increase in the efficiency of transportation systems [2], for supporting the street network design [3], and for the improvement of social equity and inclusion in terms of access to services and activities [4,5].

The several studies on the topic can be differentiated in terms of investigated mobility options, data adopted, and related metrics computed.

For example, there are studies concentrating on walking mode, as in the case of the "15 min city" [6], where the positive effect of mixed-land-use policy to walking accessibility has been investigated in the city of Milan.

Other studies have focused on car travel mode: in [7], the impact of the built environment and activities on private mobility has been analyzed by taking into consideration the "3 Ds" (Density of population and workers; Diversity of types of activities and land-use; Design for transportation supply). Others have concentrated on the case of public transportation: [8], for example, used both land-use variables (population density, service facility density, etc.) and transport variables (bus stops, road density, etc.) to evaluate the public transport ridership in each traffic zone. Finally, studies exist considering together cars, walking, and public transportation, such as [9], which underlined that population and workers density allow the decrease in travel times and car use for the benefit of public transport, or [10], where the distance to transit and destination accessibility have been added to the "3 Ds" analyzed in [7].

About data, in [11], open data such as Points Of Interest (POIs) and the road network from Open Street Map have been used as independent variables for a model for the fruition of car-hailing, also demonstrating the changes in the impact of land-use on mobility patterns during the day. Indeed, infrastructural indicators, such as the length of the different road types in each zone, their density and distribution, as well as the capacity and the performances of the transportation supply, could give information about accessibility [12,13] or about the classification of the land-use (i.e., residential areas are characterized by local streets with low capacity and low speeds; instead, industrial hubs are often served by road with high capacity).

Floating Car Data (FCD) are adopted even more for exploiting human mobility behaviors and to derive useful insights into urban and transportation planning. For example, Ref. [14] captured the spatiotemporal evolution of urban hot zones from people's arrive-stay-leave (ASL) behavior, which is fundamental where changes or improvements in urban networks must be planned. Moreover, it is underlined how much the stay time by FCD and its correlation with additional sources of data such as Points Of Interest (POIs) could stimulate the research on transport and urban planning. Ref. [15] explored the relationship between urban mobility by FCD and specific built environment factors (e.g., average house price, scenic spots, or shopping areas) in Shanghai through an ordinal logistic regression (OLR) analysis to help better understand their relationship. Ref. [16] built a mobility-related typology of territorial zones by investigating vehicle movements by FCD in the Great Paris region; they found that the derived mobility types of zones have a correspondence with the common recognition of their social functions. In addition, in [17], significant places have been localized in the Metropolitan Region of Paris by mining trajectories and activity durations from FCD.

Our work is a first step to computing data-driven metrics for the investigation of the mutual interaction between the transportation system and the land use, with a specific focus on private transport. However, despite the analyses matching big data from traffic with the built environment usually focusing on large urban networks, we decided to focus on three medium-size cities. Taking inspiration from previous studies in the literature, metrics are computed by adopting different layers of data (Floating Car Data, Census data, and Open Street Map data); FCD allow one to derive traffic performances as seen in [18] and to use these performances for the computation of the zone's accessibility (similarly to the case in [19]); the built environment derives from population and employees data, together with the physical structure of the road network [20]. The 3 medium-size cities are Brescia, Catania, and Salerno, located in Italy and characterized by different urban forms (in terms of road network structure) and land-use activities.

The proposed data-driven metrics as well as their relationship could be the base for the development of a Decision Support System module supporting planners and engineers to localize the critical elements (e.g., zones) and to investigate the impact of planning policies.

The paper is structured as follows: the method of analysis is described in the following section, and then the results of the metrics computation for the three medium-size Italian cities are presented and discussed. Finally, the conclusion and the future research ideas are given.

2. Methods

The analysis framework is applied with the same criteria to three medium-sized cities (Brescia, Catania, and Salerno), allowing for a direct comparison based on the proposed zonal metrics and accessibility scores.

The three cities are selected for their differences in terms of shape, extension, and density. Catania and Salerno are in the south of Italy, respectively, in Sicily and Campania regions. Salerno is a city economically based on the commercial and tertiary sectors, with a port in the north of the city, which is hub of several commercial and touristic flows (due to the proximity with the Amalfi coast). Catania is a medium-sized city and the core city of a metropolitan region. Catania has a strong agricultural sector, an important commercial and touristic port (both commercial and for ferries), and a large industrial district (Etna Valley). The street networks of Catania and Salerno, in fact, extend along the coastline. Brescia, located in the north of Italy, is an important industrial and commercial city. Brescia has a more regular morphology characterized by a street network having both a grid and a radial structure.

Catania has an extension of 183 km^2, about 296,000 inhabitants, and 130,000 employees. Salerno is the smallest one, covering 59 km^2, with about 132,000 inhabitants and 25,000 employees; finally, Brescia extends over 90 km^2 with 196,000 inhabitants and 63,000 employees.

According to Figure 1, each city is divided with a regular hexagonal grid (side of length 500 m) in order to obtain normalized maps without irregular shapes and to perform standardized comparisons between different urban contexts. Thanks to its flexibility and generalization feature, this approximation has been used in several research contexts, such as the spatial accessibility analysis [21–23], where the availability of transport data collections is still growing [15,24]. Despite its higher computational complexity, hexagonal cell tessellation is able to cover an entire geographical region without any gaps and overlapping, ensuring a greater mapping accuracy with respect to other methods (e.g., circular or square shapes). Moreover, the method allows a better distribution of centroids, an optimal management of nearest neighborhoods, an easy matching of curve patterns, and irregular territorial boundaries.

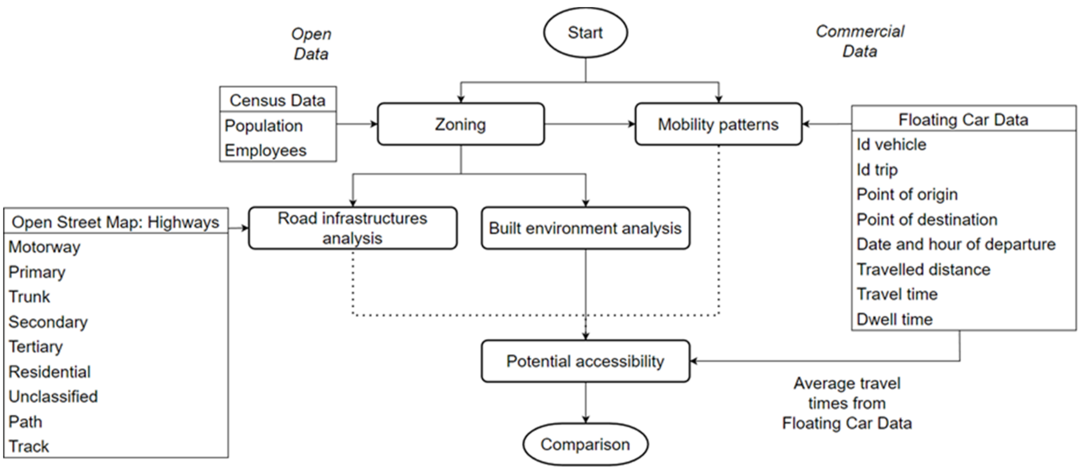

Figure 1. Workflow of the analysis framework.

The study adopts different sources and types of data for the analysis: open data (census data; Open Street Map database—OSM) and GPS traces data from a fleet of privately owned probe vehicles traveling across the three cities (Floating Car Data—FCD) (Figure 1).

Census data rely on the ISTAT database that provides information about inhabitants and employees in each city census zone [25]. The assignment of census data to the hexagonal grid is applied through a procedure. It is based on the hypothesis that inhabitants and employees are homogeneously distributed within the census zone; thus, the percentage of overlapping of each census zone and each hexagon is computed; the shares of population and employees are proportionally assigned to the hexagon through these percentages.

OSM data rely on the road network in terms of road link classification (Figure 1) and the related extension. Only infrastructures where cars are allowed to travel are selected. Particularly, the selected street types have different capacity and speed limits, starting from motorways to residential streets.

Census data and OSM allow us to compute metrics to fully characterize the built environment.

FCD, as a sample representing the whole mobility in the city, are used to deduce mobility and traffic patterns. FCD derive from probe vehicles, in particular, private cars, tracked by an On-Board Unit every 30–60 s. FCD are filtered to remove measurement errors and then aggregated by trip chains. Information extracted from the trip datasets includes the id of the vehicle, the starting GPS coordinates, the departure time, the destination GPS coordinates, the traveled distance, the travel time, and the dwell time. The resulting datasets are:

1. Brescia: 65,720 trips of 3445 vehicles tracked during November 2019;
2. Catania: 182,701 trips of 7393 vehicles tracked during November 2019;
3. Salerno: 178,545 trips of 7479 vehicles tracked during October 2019.

The whole set of metrics computed through the data previously reported are shown in Table 1.

Table 1. Mobility patterns and built environment metrics.

Mobility Patterns		
Metrics	**Unit**	**Note**
Origin-Destination matrices	(passenger car equivalent/time period)	FCD Demand Matrices for different time periods (whole month of data; average of weekdays; average of weekend days).
Generated trips	(passenger car equivalent/time period)	Average number of vehicles generated by each zone for different time periods (average of the whole period; average of weekdays during 7:00 a.m.–2:00 p.m.).
Attracted trips	(passenger car equivalent/time period)	Average number of vehicles attracted by each zone for different time periods (average of the whole period; average of weekdays during 7:00 a.m.–2:00 p.m.).
Time matrices	(Minutes)	Average travel times between origin and destination, during the whole period, during weekdays and during weekend days.
Travelled distance matrices	(km)	Average distances between origin and destination zone, for different time periods (during the whole period, during weekdays and during weekend days).
Distributions of trips during the day	(Vehicles/h)	Number of vehicles departing in the hour (average of weekdays; average of weekend days).
Travel times	(Minutes)	Average value, median value, and standard deviation for different time periods (the whole period; weekdays and weekend days).

Table 1. *Cont.*

Mobility Patterns		
Metrics	**Unit**	**Note**
Distribution of travel times	(%)	Statistical distribution of travel times during the whole period.
Distribution of average travel times during the day	(Minutes)	Average travel times of vehicles departing in each hour of the day (weekdays and weekend days).
Traveled distances	(km)	Average value, median value, and standard deviation for different time periods (the whole period; weekdays and weekend days).
Distribution of traveled distances	(%)	Statistical distribution of distances traveled during the whole period.
Distribution of average distances traveled during the day	(km)	The average traveled distances in each hour during weekdays and during weekend days.
Distributions of classes of dwell times	(%)	Statistical distributions of dwell times (short dwell times and long dwell times) during the whole month.
Mean speeds	(km/h)	Average value, median value, and standard deviation for different time periods (the whole period; weekdays and weekend days).
Distribution of mean speeds	(%)	Statistical distribution of mean speeds during the whole period.
Distribution of average mean speeds during the day	(km/h)	Average mean speeds in each hour during weekdays and during weekend days.
Built Environment		
Metrics	**Unit**	**Note**
Zone Population	(Number)	Number of inhabitants living in zone z.
Zone Employees	(Number)	Number of employees working in zone z.
Population distribution	-	Computed adopting the Gini index reported in (1) to Zone Population.
Employees distribution	-	Computed adopting the Gini index reported in (1) to Zone Employees.
Total road network of type i	(km)	Total length of road type i in the city.
Total road network extension	(km)	Total length of all the roads in the city.
Total road network of type i in zone z	(km)	Total length of road type i in zone z.
Total road network in zone z	(km)	Total length of all the roads in zone z.
Percentage of road type i	(%)	The percentage of length of road type i in the city.
Percentage of road type i in zone z	(%)	The percentage of length of road type i in the zone z.
Road network distribution of type i	-	Computed adopting the Gini index reported in (1) to Total length of road type i in zone z.
Road network distribution	-	Computed adopting the Gini index reported in (1) to Total length of all the roads in zone z.

Table 1. *Cont.*

Interaction between Mobility Patterns and the Built Environment		
Metrics	**Unit**	**Note**
Active potential accessibility of zone z	(Employees/second)	Computed according to (2).
Passive potential accessibility of zone z	(Inhabitants/second)	Computed according to (3).

The spatial distribution of data is computed adopting the Gini index [26]. It is usually adopted to quantify the concentration of an economic variable and it assumes a value between 0 (homogeneous distribution of the variable) and 1 (high concentration of the variable), according to:

$$G = \frac{N-1}{N} * \frac{\sum_{i=1}^{N-1} (P_i - L_i)}{\sum_{i=1}^{N-1} P_i} \tag{1}$$

where:

1. N is the total number of the elements of the sample (i.e., zones of the cities);
2. $P_i = i/N$ is the rank of the i-th element;
3. $L_i = \frac{\sum_{k=1}^{i} x_k}{\sum_{k=1}^{N} x_k}$ is the concentration ratio to the i-th element of the variable x_k (e.g., in the case of computation of the Gini index for the distribution of population, x_k is the population assigned to the zone k).

As reported in Table 1, accessibility measures are also computed as a metric of the interaction between the mobility patterns and the built environment.

The concept of accessibility is well-known [27]. Accessibility can be defined as the easiness to reach activities from a starting zone or to be reached from several zones through transportation infrastructures and services. Several formulations have been defined for accessibility as a function of the selected variables [28,29], for example, based exclusively on the performance of the transportation supply or based on the spatial distribution of activities and on the cost to reach them. The proposed formulation for accessibility is inspired by the gravitational law [30], considering socioeconomic characteristics such as the attractive mass and the travel time between zones [31]. Particularly, two potential accessibility metrics are computed: (i) the active one (Figure 2a) that measures the possibility to reach several destinations and using their activities for a given zone; (ii) the passive one (Figure 2b) that measures the possibility for a given zone to be easily reached from the inhabitants of several origins.

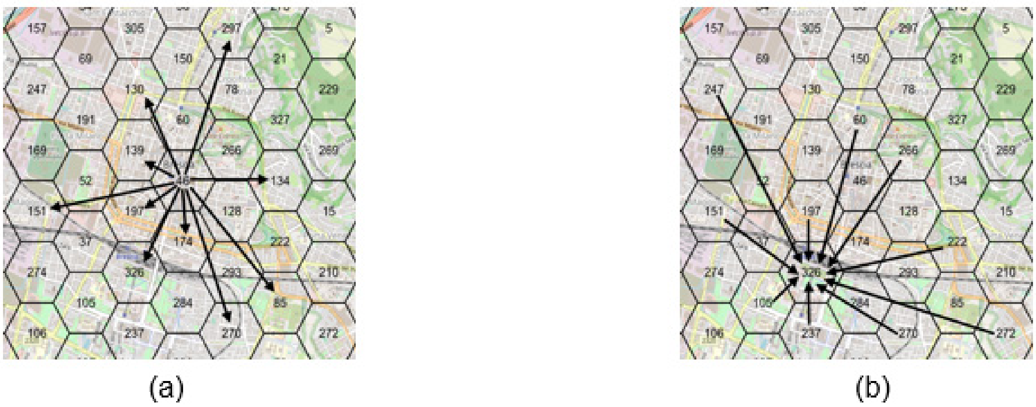

Figure 2. Example of potential accessibility: (**a**) active; (**b**) passive.

The proposed formulation for the computation of active potential accessibility is:

$$AA_i = \sum_{j=1} \frac{empl_j}{t_{ij}^{FCD}} \tag{2}$$

where:

1. i is the origin zone;
2. j is the destination zone;
3. $empl_j$ is the number of employees in zone j;
4. $\bar{t}_{ij}^{FCD}$ is the average travel time between zones i and j as derived by FCD.

In a comparable way, the passive potential accessibility assumes the following formulation:

$$PA_j = \sum_{i=1} \frac{inhab_i}{\bar{t}_{ij}^{FCD}} \quad (3)$$

where $inhab_i$ is the number of inhabitants of zone i.

3. Results

3.1. Mobility Patterns

Considering the 338 zones of Brescia, 522 of Catania, and 209 of Salerno, the trips, as derived by FCD datasets, cover, respectively, 12%, 6%, and 20% of the O-D pairs, thus obtaining very sparse demand matrices. However, the zones covered by at least one generated trip are 77%, 59%, and 78%, respectively, for the three cities; similar coverage has been obtained in terms of attracted trips. Comparing attracted trips and generated trips with the respective employees and inhabitants, a high correlation index is obtained (Pearson coefficient between 0.777 for Brescia and 0.908 for Salerno), demonstrating an adequate representativeness of FCD with respect to the built environment despite the low coverage in terms of O-D trips.

In terms of trip distribution during the daytime, Catania and Salerno show similar trends in both the weekends and the weekdays; Brescia shows an evening peak just one hour earlier with respect to Catania and Salerno during weekdays (two hours earlier on weekend), thus reporting some differences in terms of mobility behaviors (activity duration and/or departure time intervals).

Moving to traveled distances and travel times, the average of traveled distances per trip in the whole month (thus, despite the time interval and the specific day, if weekday or weekend) is equal to 4.64 km for Brescia (median 3.7 km, standard deviation 3.53 km), 5.17 km for Catania (median 3.9 km, standard deviation 4.27 km), and 5.05 km for Salerno (median 3.8 km, standard deviation 4.11 km). According to these metrics and as shown in Figure 3a, Brescia has 34% of trips with a traveled distance between 2 and 4 km, while datasets of Catania and Salerno have, respectively, 31% and 30% of trips belonging to this class, showing a stronger trend of Brescia for low distances than in the other two cities. This confirms a more compact city structure for Brescia or at least a more mixed one.

The average travel times in the whole period (thus, despite the time interval and the specific day, if weekday or weekend) are 14 min for Brescia (median 12 min, standard deviation 8 min), 18 min for Catania (median 15 min, standard deviation 10 min), and 16 min for Salerno (median 13 min, standard deviation 10 min). In the dataset of Brescia, the classes between 5 and 15 min represent 68% of the total trips, those in the dataset related to Salerno represent 60%, and those for Catania represent half of the total trips sample (Figure 3b). For travel time values over 15 min, the percentage of trips for the database of Brescia considerably drops, while the percentages in the datasets of Catania and Salerno decrease slowly. Again, as underlined in terms of distances traveled, it seems that Catania and Salerno have a sprawled structure with respect to Brescia.

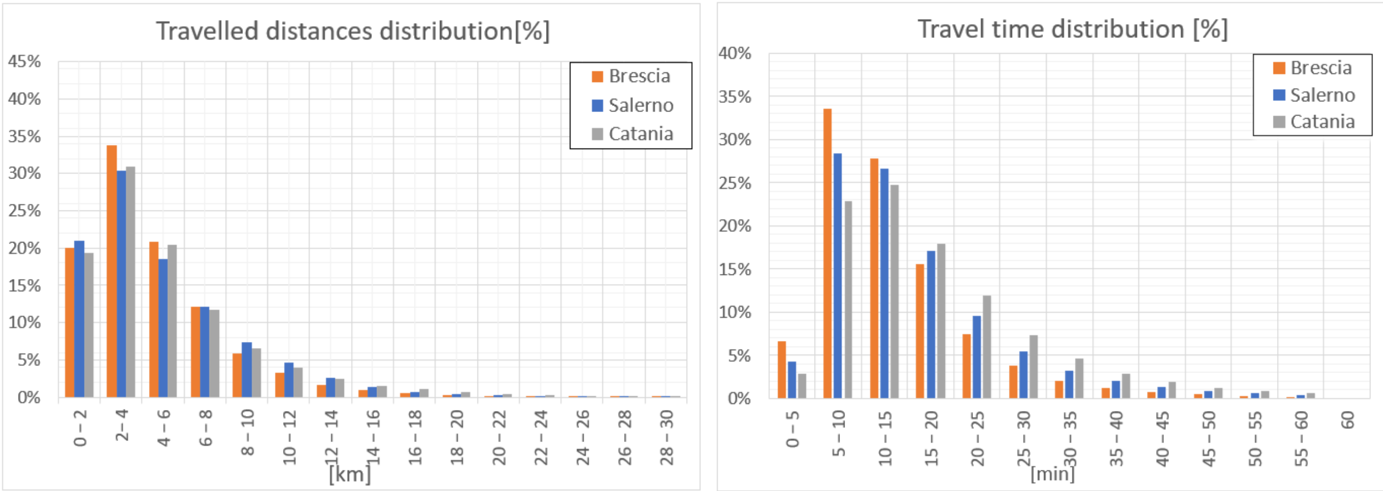

Figure 3. Distribution of traveled distances (**a**) and distribution of travel times (**b**).

The average mean speed is 20 km/h for the database of Brescia (median 19 km/h, standard deviation 8 km/h), 18 km/h for the database of Catania (median 16 km/h, standard deviation 9 km/h), and 20 km/h for the database of Salerno (median 18 km/h, standard deviation 9 km/h).

According to the distribution of Figure 4, mean speeds in the database of Brescia are concentrated in a medium speed range, 30% of trips experience an average speed between 15 and 20 km/h, while trips in the database of Catania are concentrated in lower-speed classes (between 10 and 15 km/h). If the observed speeds are analyzed according to the peak hour in the morning, previous values are amplified as they reach 16 km/h for Catania, while higher ones (about 19 km/h) are reached for both Brescia and Salerno.

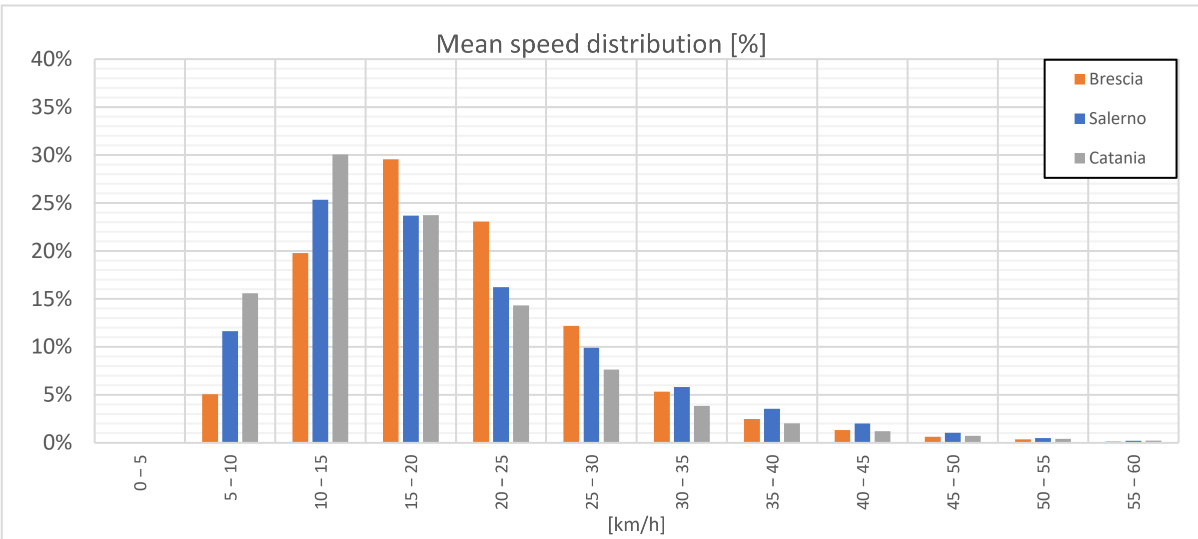

Figure 4. Mean speed distribution.

3.2. Built Environment Analysis

The analysis of the built environment is conducted through the computation of density of inhabitants (Figure 5) and employees in each hexagonal zone and of the Gini index for quantifying the spatial distribution.

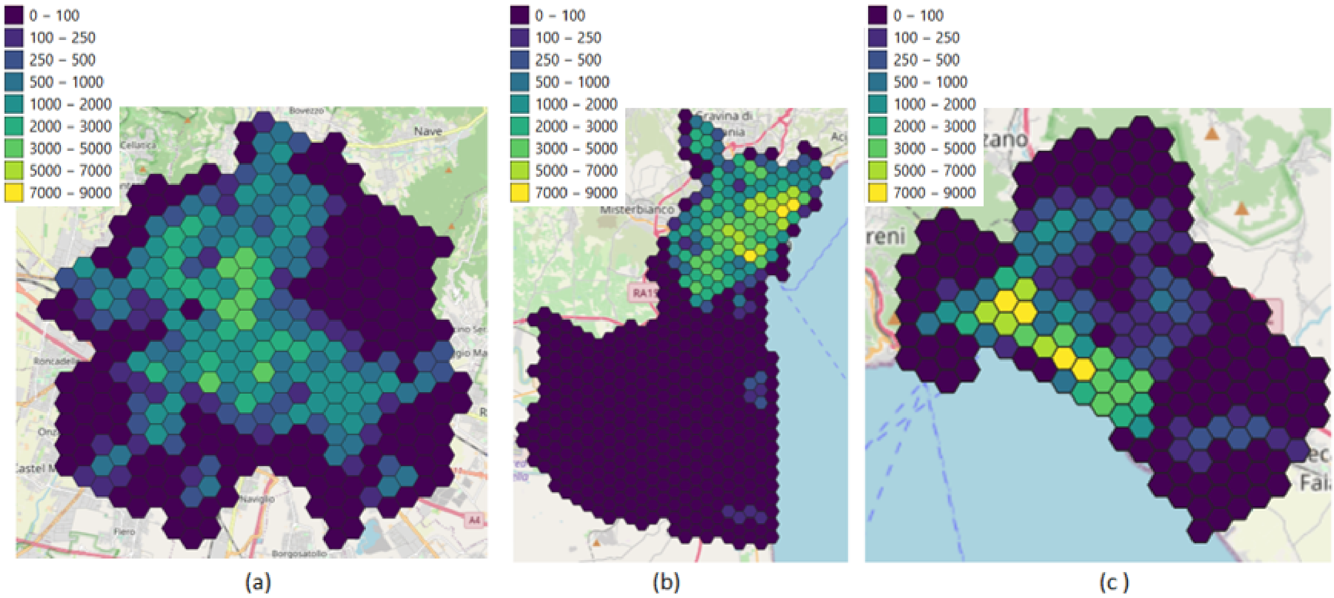

Figure 5. Distribution of inhabitants in each zone: Brescia (**a**), Catania (**b**), and Salerno (**c**).

The city of Brescia has a density of 2094 inhabitants/km^2 and 700 employees/km^2. The city shows a Gini index equal to 0.68 and 0.69 for the population distribution and for the employees, respectively.

The city of Catania is the largest one, with a density of 1602 inhabitants/km^2 (lower than Brescia). The Gini index for population is 0.86, with the concentration in few zones (in this case, in the northern part of the city, where its "core" center is located). Despite the density of activities being similar to Brescia (711 employees/km^2), it is also concentrated in the "core" center, with a Gini index of 0.88.

The city of Salerno is the smallest one, with a density of 2251 inhabitants/km^2 and a Gini index for population of 0.83, with a high concentration along the coast and very low values in the hinterland. Employees density is 423 employees/km^2 (lower than Brescia and Catania) with a Gini index of 0.87, showing a higher concentration near the harbor.

It must be underlined that, while both Catania and Salerno are city ports, the port of Salerno is more remotely located with respect to the downtown than Catania. The location of the port of Catania near the center of the city involves a higher concentration of employees, whereas the position of the port of Salerno allows a slight minor concentration of employees (in fact, the Gini Index is slightly lower than the one of Catania).

It should also be noticed that in Brescia, there are no zones with the highest-class value of inhabitants (i.e., no yellow zones are reported in Figure 5).

Moving to the road network structure (Figure 6), in the three cities, the main road type is the residential street covering more than 35% of the total network kilometers. Catania and Salerno have higher percentages of high-speed roads (motorway and primary) than Brescia. The Gini index of the road network is 0.26 for Brescia, demonstrating a more uniform distribution of the street network, while the Gini indexes for Catania and Salerno are, respectively, 0.57 and 0.44. Brescia has, in general, more roads for penetration in the city center than the other two cities. Salerno has in its municipality an important motorway—the A2 Salerno-Reggio Calabria.

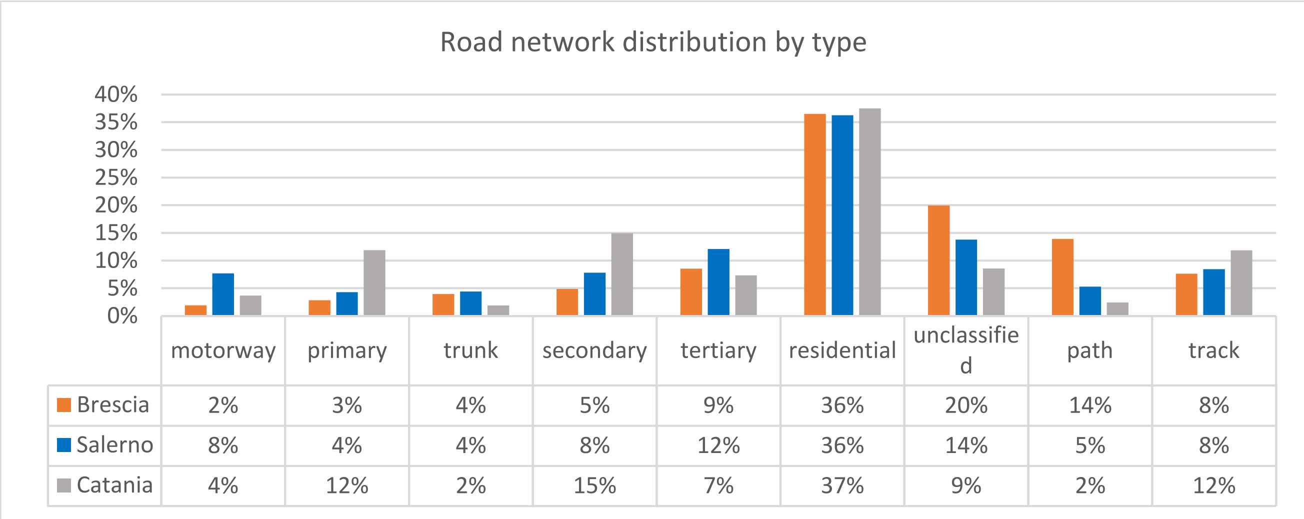

Figure 6. Distribution of road network by type.

3.3. Integrating Mobility Patterns and the Built Environment: The Potential Accessibility

The active potential accessibility, computed as reported in (2), is 22 employees/s for Brescia (standard deviation 46 employees/s) with a Gini index of 0.79, 26 employees/s for Catania (standard deviation 91 employees/s) with a Gini index of 0.91, and 13 employees/s for Salerno (standard deviation 41 employees/s) with a Gini index of 0.90. Gini indexes for active potential accessibility are slightly higher than the Gini indexes of employees.

Instead, for the passive potential accessibility (Figure 7), computed as reported in (3), the average value is 68 inhabitants/s for Brescia (standard deviation 121 inhabitants/s) with a Gini index of 0.77, 62 inhabitants/s for Catania (standard deviation 160 inhabitants/s) with a Gini index of 0.88, and 69 inhabitants/s for Salerno (standard deviation 186 inhabitants/s) with a Gini index of 0.87.

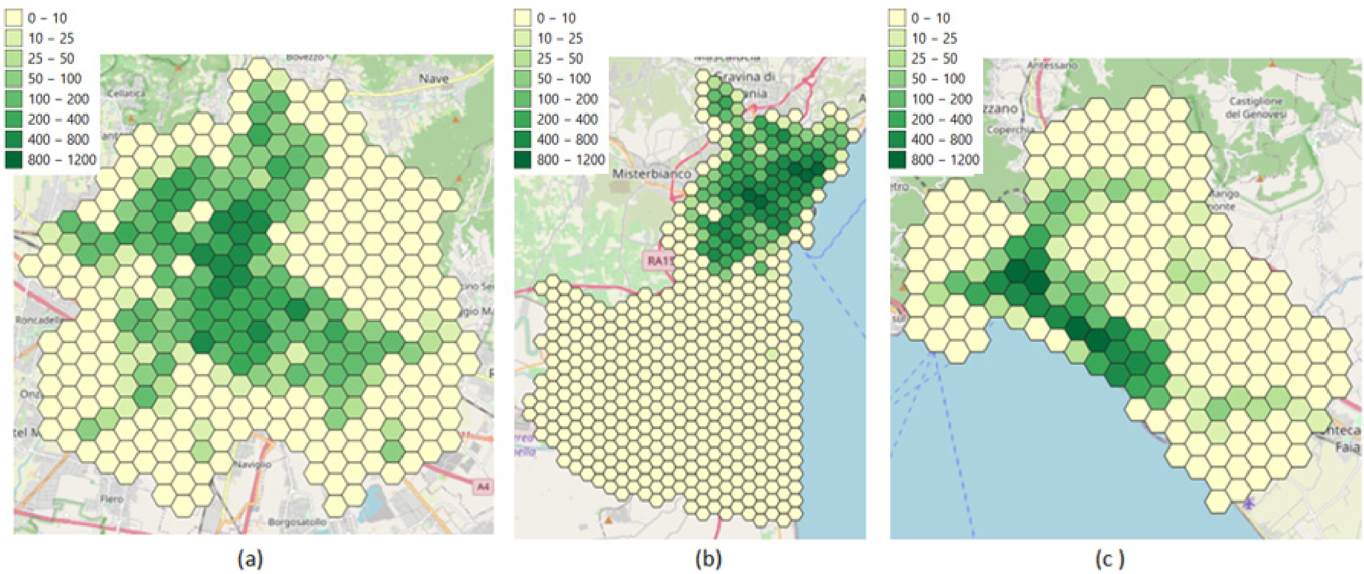

Figure 7. Distribution of passive potential accessibility: Brescia (**a**), Catania (**b**), and Salerno (**c**).

4. Discussion

In this work, we promoted a data-driven framework regarding the interrelation between mobility patterns, the built environment, and related accessibility in order to analyze the correlation between the private transportation system and the land-use in three cities.

As seen in the results section and summarized in Figure 8, potential accessibility indicators have slightly higher values of Gini indexes with respect to those of their respective variable (e.g., passive accessibility with population and active accessibility with employees). If the potential accessibility is higher than 0.8 (see Catania and Salerno, Figure 8), approximately the same values are obtained for population and employees' distribution. Brescia shows a reduction of approximately 0.1 between the Gini index of the potential accessibility and the related socioeconomic factor. This result can be summarized, postulating that more homogeneous conditions in terms of population and employees imply a higher possibility to reach a high level of accessibility on the whole city.

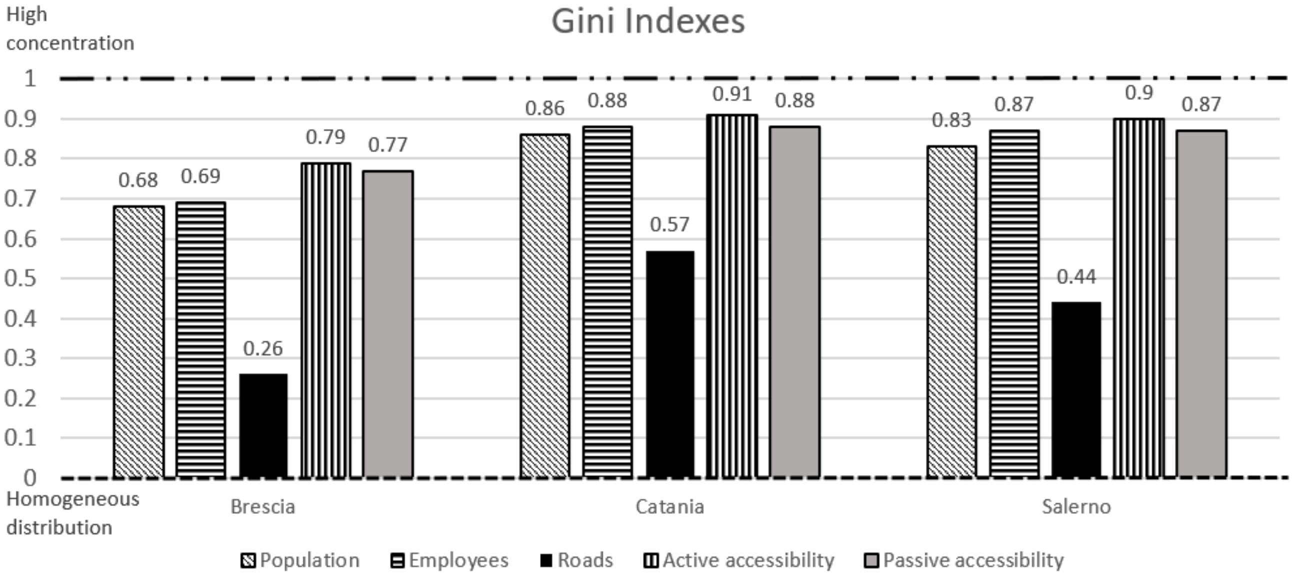

Figure 8. Summary of Gini Indexes for each city.

Instead, observing the differences between the Gini index for the potential accessibility and for the road network, the differences are higher where homogenous road structure conditions can be assured. Thus, a very uniform and distributed road network, as in the case of Brescia, can help in improving accessibility values, but it seems to be not sufficient alone.

The spatial distribution computed through the Gini index is demonstrated to be essential for this type of analysis: Salerno, in fact, shows the same passive potential accessibility of Brescia on average, but in Salerno, the higher values of accessibility (and population) are concentrated in few zones, while Brescia shows lower accessibility values (and population values) at the zone level but is more evenly distributed.

The layout of the city (compact for Brescia, sprawled for the other two cases) impacts the road infrastructures: Brescia has a radial structure that allows for the diffusion of the built environment (Figure 5a) and the transportation supply in all the directions; in fact, this city has the lowest Gini indexes for the distribution of population and employees and for the distribution of the road network. Instead, Catania and Salerno have been developed along the coast concentrating the built environment (Figure 5b,c) and the local road network in their "cores". The concentration of roads and activities impacts on the revealed mobility patterns: the database of Catania has lowest average mean speeds and highest trip times (Figures 3b and 4), while the database of Brescia reports the lowest average travel time and highest average mean speed. These findings could involve the hypothesis that Catania results as more congested than Brescia due to the concentration of traffic flows to specific destinations and on few corridors. Thus, the layout of the city, also dependent on its geographical location (in the hinterland for Brescia and along the coastline for Salerno and Catania), must be considered in the integrated planning of transportation systems and land-use. The structure of the city indeed allows the localization of potential areas to maximize the benefits of sustainable policies related to the growth of the city itself, along with the identification of the critical elements that must be solved. Moreover, the knowledge of the layout of the city and the metrics described above support the several best practices usually applied in urban planning (e.g., a deep analysis of the road infrastructures could avoid the construction of new buildings, directing the efforts toward sustainable management policies of the existing transportation supply).

5. Conclusions

The present work is focused on the evaluation of the mutual impact between the transportation systems and the land-use based on several metrics estimated from different data sources and applied to three Italian medium-size cities: Brescia, Catania, and Salerno.

The results highlight this well-known interrelation showing how the layout of the city and the geographical constraints impact the road infrastructures. In Brescia, the diffusion of the built environment and the transportation supply follow a radial structure, due to the lack of natural constraints in its potential territorial development, as confirmed by the low Gini indexes for the distribution of population and employees and for the distribution of the road network. Instead, Catania and Salerno have been developed along the coast and, thus, present a concentrated built environment and road network. In addition, the low mean speed and high travel times estimated for the municipality of Catania suggest that this city is more congested than Brescia due to the concentration of traffic flows to specific destinations and on few corridors. Catania also shows a high average value for potential active accessibility with respect to the other cities, with a maximum concentration along the coast, while Brescia has a lower value that is more distributed within the municipality, demonstrating an extended use of its whole territory.

This work represents a first step toward the development of an extended analytical framework aimed at investigating the complex relationship between private transportation and the built environment.

In this context, future research will focus mainly on two topics.

First, the framework could be improved by estimating mean travel speeds and delays in each city zone to obtain the spatial distribution of congestion [32,33]. Spatial distribution and duration of the dwell-time could also be exploited by FCD to classify the land-use of each zone (e.g., residential and commercial areas, industrial districts, and playgrounds) or to evaluate the effects of parking policies and traffic restrictions.

Moreover, the framework can be extended to include other modes of transport, such as public transport, in order to further capture the interaction between mobility and land-use [34,35].

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