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SMART MOBILITY IN MILAN, ITALY: A DISTRICT-LEVEL SPATIAL AND CLUSTER ANALYSIS

Nicola Cornali
Independent Researcher, Milano, Italy

Matteo Seminati
Societe Generale - Securities Services, Milano, Italy

Paolo Maranzano [1]
Department of Economics, Management and Statistics (DEMS), University of Milano-Bicocca, Milano, Italy & Fondazione Eni Enrico Mattei (FEEM), Milano, Italy

Paola Maddalena Chiodini
Department of Statistics and Quantitative Methods (DISMEQ), University of Milano-Bicocca, Milano, Italy.

Abstract We evaluate the level of mobility services and infrastructures in Milan to identify which areas are best equipped to serve citizens. We explore the overall degree of smart mobility by ranking the 88 administrative districts according to their transportation services. A statistical analysis both quantifies and groups the neighborhoods by their degree of mobility. We first built a set of composite indicators, including the AMPI and the Static Jevons Index. The robustness of the index is validated through a sensitivity analysis of behavior when varying the underlying indicators. A spatial cross-correlation analysis is conducted to contextualize the degree of mobility estimated in the neighborhoods with respect to some infrastructural variables. Second, the composite indices are used to cluster the districts into homogeneous groups with similar mobility levels. The results show that, whether using the indices individually or in combination, the cluster analyses successfully distinguish key areas of the city, such as the interchange hubs, university zones, city center, workplaces, and suburbs. We identify four classes of districts characterized by increasing levels of smart mobility, and highlight critical differences between the city center and the peripheral areas of Milan.

Keywords: *Cluster analysis; Spatial cross-correlation; Aggregative indices; AMPI index; Milan NILs; Smart mobility;*

1. Introduction

Some research has tried to provide answers and propose solutions to improve different aspects of mobility management in large urban centers. In this context, Businge et al. (2019) analyzed Milan's metropolitan area to compare models of public transportation and to evaluate their impacts and benefits. The authors indicate that policies establishing disincentives for the use of cars, accompanied by a substantial investment in technological development aimed at the greater diffusion of electric cars, were successful. Another approach is depicted in Battarra et al. (2018), who examined 11 large urban centers of Italy, some of which represent the peculiar urban environments that characterize the country. The study compared both the urban development structures and the

[1] Corresponding author: paolo.maranzano@unimib.it

presence of information and communication technologies (ICTs) and infrastructure. The results show that cities that invested large amounts of resources in developing ICT infrastructures and smart urban transport systems met the high standards for smart cities that have already been achieved by many European cities.

In this paper, we measure the overall degree of smart mobility in the city of Milan and identify the essential characteristics within the municipal territory. We also assess the levels of mobility services in Milan's 88 administrative districts, or *Nuclei di Identità Locale* (NIL), to determine which areas are best equipped with respect to citizens' needs. We propose a data-driven statistical modeling approach to estimate the degree of smart mobility in the NILs. The estimation algorithm is based on the construction of composite indicators that summarize the level of mobility starting from a set of elementary variables. We implement four composite indicators to quantify the mobility level, weighted by the population of each neighborhood of the city based on a set of mobility variables. Furthermore, estimates of the mobility degrees are accompanied by a sensitivity analysis (i.e., a robustness check of the empirical estimates). The estimated smart mobility values are then analyzed to answer two research questions.

The first question concerns the study of the factors that fostered the mobility levels measured in the analyzed NILs. The second research question is related to the identification of homogeneous groups of neighborhoods with similar mobility levels. In answering both questions, we aim to understand whether the estimated differences in smart mobility levels among Milan's neighborhoods are due to some social and economic phenomena (e.g., growing tourism in the city, or the presence of commuters from surrounding provinces), or whether they are the result of an exogenous pattern of urban development. To answer these questions, we use two analytical tools. First, the spatial cross-correlation between indicators and a set of infrastructure variables (school, health, tourism, and size) are analyzed. The results allow us to further explore the spatial association between mobility and the presence of essential services (infrastructure) for the population. Second, we use a K-means clustering algorithm to cluster the NILs into homogeneous groups with similar smart mobility levels. The combination of the two approaches allows us to characterize the levels of smart mobility across Milan in relation to the neighborhoods' (infra)structural characteristics, and to assess whether mobility can be associated with key aspects of citizens' lives.

The remainder of the paper is structured as follows. In Section 2, we present the case of Milan as an example of a smart city in the Italian context, highlighting its strengths and weaknesses as discussed in the literature and comparing it to other European cities. In Section 3, we present the concept of smart mobility in detail, giving a definition of this development paradigm in light of the current economic and urban development literature. In Section 4 we present the neighborhood-level mobility data provided by the municipality of Milan. The information is updated to 2018 and covers various spheres of mobility: public transportation, bicycles, and ride-sharing. The data are used in the subsequent sections for the empirical analyses. In Section 5, we explain: (1) the statistical approach used to estimate neighborhood smart mobility levels using the composite indicators (Section 5.1), (2) the sensitivity analysis for the robustness of the estimates (Section 5.2), (3) the spatial cross-correlation methodology and data on the infrastructures considered (Section 5.3), and (4) the clustering analysis algorithm used to identify the homogeneous groups of neighborhoods (Section 5.4). In Section 6 we report the empirical results for Milan's NILs obtained through the procedure described above. Finally, Section 7 summarizes the main findings and concludes the paper.

2. Milan: the Italian Smart city

The paper focuses on the study of mobility in the city of Milan. This focus is motivated by several considerations. In particular, in 2014, the municipal administration in Milan approved a document that defines the guidelines for making Milan a smart city (Comune di Milano, 2022). The objectives to be achieved are clear and well defined: there must be technological growth accompanied by economic development, social inclusion, innovation, training, research, and participation. The document states that the city must be:

- a global city, national and European laboratory;
- a laboratory of sustainable urban mobility;
- a laboratory of environmental and energy policies;
- a laboratory of social inclusion and diversity;
- a laboratory of well-being;
- a simplification workshop for public administration; and
- a business-generation workshop.

Milan 2030 (Comune di Milano, 2019b) is the articulated project that the municipal administration is implementing for massive urban redevelopment that will lead to the expansion of green areas, the deindustrialization of the city's territory with the related recovery of buildings, accessible urban development, and the reorganization of public and private transport (Comune di Milano, 2019a). Over the years, the city has been suffocated by private traffic, as reported in the Milan Sustainable Urban Mobility Plan (PUMS). In fact, it was only in 2013 that an initial inversion between public (48%) and private (43%) traffic loads could be observed, even though, of the 5.3 million daily trips, 2.3 million are inbound. This has led the administration to start thinking about radical solutions for the management and reorganization of transportation in the city. New highway routes have been built to the north and east of the city, rail services have been strengthened to facilitate access to the northwestern sectors, limited traffic zones have been established (Areas C and B), pedestrian and bicycle lanes have been extended, bike- and car-sharing services have been introduced, and metro lines have been expanded, to name just the most important changes. Over the years, these interventions have produced considerable improvements in city traffic and the quality of air and life in Milan. Other interventions are on the agenda, including the reorganization of bus lines, the extension of metro lines beyond city boundaries, and the construction of new highway and railway connections that link the city more efficiently to the rest of the Lombardy territory.

Another interesting aspect of Milan is the administrative structure of the city and its subdivisions. As well-described by Bernini et al. (2019), the municipality is divided into nine boroughs, the so-called *municipi*, each with its own council and president . The nine borough councils are coordinated at the city level by the city council, which decides the general rules for the use of goods and services. On the other hand, borough councils have independent administrative power and responsibility on some local but important matters, such as schools, social services, waste collection, roads, parks, libraries, and local commerce. Indeed, each borough includes districts with different social and cultural aspects. Accounting for these characteristics, the city was further subdivided into 88 districts with unique social and cultural identities called Local Identity Neighborhoods (NILs).

Milan emerges as an important city in different studies. According to ICity Rank, the annual report that photographs the most technologically advanced and sustainable Italian cities, Milan has been ranked as the smartest city in Italy for several years, followed by Florence and Bologna. Only in the last two years, 2020 and 2021 (ICity Rank, 2021),has Milan dropped from the number-one spot but remained near the top of the list of the smartest cities. Furthermore, Milan leads the mobility ranking, thanks to its vast public transportation network and the spread of innovative carpooling services (with 24.3 cars per 10,000 inhabitants). Its weakness is the modest extent of pedestrian areas, which is limited to 46.3 square meters per 100 inhabitants.

Looking outside Italy, Milan is comparable to the very best performing European cities (Negri et al., 2020), for example, regarding forms of alternative mobility, especially ride-sharing (with 2,224 cars per 1 million inhabitants). Milan is also heavily investing in sensors and in the enhancement of data collected through, for example, the publication of open data (723 datasets in November 2019 vs. 292 and 250, respectively, in 2018 and 2017). In terms of the use and evaluation of services by residents, Milan is well positioned and is most similar to Barcelona (particularly in terms of the city app and online payment services). Compared with Europe, however, the smart environment remains weak based on access to green areas and air quality. Also, Battarra et al. (2018) argue that cities in northern Italy have managed to achieve more efficient public transportation and better sustainability over time, also thanks to their considerable use of ICT systems. However, in spite of these large investments, the results achieved are not yet comparable with those of other large European cities (e.g., Amsterdam). The aim of the institution of Area C, being a congestion charge, was to reduce traffic within the historical city center, namely the Cerchia dei Bastioni, thanks to telematic control of the gates, and to make local public transportation

(LPT) faster, improving air quality. In support of LPT, the "traffic light preference" that uses AVM technology and Wi-Fi reduces waiting times at traffic lights. While they are stopped, users can find out the waiting times of vehicles through the variable message Infopaline or by connecting to the Infomobility portal to receive interactive and real-time information on disruptions, schedules, or critical issues. The service uses a multimodal route planner software program, a platform for data acquisition and management through on-board systems.

The mobile ticketing system that uses near field communication (NFC) technology allows users to purchase and validate tickets directly with a cell phone. Mobile Pass is based on NFC short-range technology that interacts with the electronic ticketing system of the transport company (ATM). The Infoalert service reduces road congestion with information shared in real time and by sending alerts through social networks or SMS for special situations (e.g., accidents, construction sites, manhole flooding, political, and social events). The bike-sharing service BikeMi (Maranzano et al., 2021) aims to increase cycling and facilitate intermodality with LPT as well as GuidaMi, a car-sharing system that adheres to the national circuit IO Guido.

Taking a different approach, the Digital Islands program increases sustainable mobility with the creation of computerized areas for supplying and recharging electric vehicles and providing services. They encourage the use of non-polluting electric vehicles and provide services with multimedia touchscreens, such as institutional information, SOS Point, cabs, infoviability, Wi-Fi, and NFC payments. The Converse project experiments with new ways of implementing low emission zones in urban areas by tracking the routes of heavy construction vehicles.

Transportation represents an essential service in daily life Mariotti et al. (2018). On one hand, people travel to reach offices and schools, for tourism, and to visit family and friends; on the other hand, mobility is essential in modern logistics and economic systems. According to the European Commission (European Commission, 2021), the transport sector contributes 5% to European GDP and directly employs around 10 million workers. According to the annual report from the European Environmental Agency (European Environmental Agency , EEA), transportation is one of the main sectors responsible for total emissions. However, on a positive note, the extent of pollutants has declined over the years despite the growth of mobility.

Even though the European transportation sector has achieved significant reductions in the emissions of certain major air pollutants, more work is needed to continue to reduce pollution levels and to achieve the "zero pollution" ambition set by the European Green Deal, which has targeted a 90% reduction in transportation emissions by 2050. As a result, there is growing political, media, and public interest in air quality issues and increased public support for action. Moreover, the spread of COVID-19 has posed serious challenges for the global community: as observed during the lockdowns, a substantial reduction in mobility might have important, yet unknown, implications for air quality. For example, Ciarelli et al. (2021) found that lockdown measures reduced nitrogen dioxide (NO_2) air concentrations by up to 46% and 25% in the Po Valley and Swiss Plateau regions, respectively, whereas fine particulate matter ($PM_{2.5}$) air concentrations were reduced only by up to 10% and 6% in each location.

3. Smart Mobility in a Smart City: a new paradigm

In recent years, the idea of the smart city has attracted growing interest, as most of the global population lives in urban contexts and new emerging problems are affecting urban ways of life. With the expansion of cities and increasing technological developments, new needs are being defined that necessitate the search for innovative and strategic solutions, such as co-working Mariotti et al. (2017). At the same time, great migratory movements and globalization contributes to profound changes in the social fabric as well as in language, which absorbs and assimilates new vocabulary, becoming varied with new idioms Arnaboldi et al. (2017). Specifically, the concept of the smart city has been recently introduced as a strategic means to establish a common framework on the growing importance of ICT, social, and environmental capital in profiling cities' competitiveness and sustainability Caragliu et al. (2011). In Balducci and Ferrara (2018), the authors identified the key components that synthesize the complexity of smart policy at urban level and defined several smartness domains (e.g., diffusion of IT, green energy, smart mobility, etc.) for the cities. The smartness domains were then used to investigate the spatial interactions among nearby cities and to evaluate the impact on territorial and socio-demographic aspects of the innovations introduced by municipal policies to transform urban centers into smart cities.

Whereas there is no univocal definition of a smart city in the literature, as it is a multidimensional and fuzzy phenomenon, three main strands of thought can be identified. The first is the deterministic vein ("hard"), which is focused on technology. Harrison et al. (2010) argue that a smart city is characterized by the three I's: *instrumented*, *interconnection*, *intelligent*. The second strand (the "soft" vein) emphasizes the importance of human capital. Florida (2003), for example, exposes the importance of the three T's in explaining the economic development of a city through the concept of a new geography of creativity: *tolerance*, *talent*, and *technology*. The third vision combines the "hard" and "soft" aspects and highlights the fundamental role played by the government and community. Albino et al. (2015) explains a smart city as a smart community of common or shared interests, whose members, organizations and governing institutions are working in partnership to use IT to transform their circumstances.

Furthermore, there is no consensus on what qualifies as the dimensions of a smart city. However, one of the most recognized and used models, the "Vienna Model" proposed by Giffinger et al. (2007), distinguishes six main smart categories: smart economy, smart people, smart governance, smart mobility, smart environment, and smart living. Cities performing highly in all these categories can be considered a smart city.

Moving to more practical ideas, new urban theories are shaping the structures of cities. In recent years, and especially during the COVID-19 pandemic, the 15 minutes city model proposed by Moreno et al. (2021) is growing in popularity. Multiple major cities around the world, with Paris (Bouveyron et al., 2015), London, and Helsinki (Piter et al., 2022) as the leaders, are designing and shaping their communities to meet the goal that is the foundation of this new urban planning theory: allowing people to access essential services and amenities by foot or bike in a very short time. Living and working near where services are provided can be considered an incentive to massively reduce the use of cars and consequently traffic congestion while adopting public transportation or ride-sharing options.

Whatever scientific contribution one considers, smart mobility is one of the main drivers of a city's smartness. Indeed, a smarter transportation framework must be developed in the smart city context to improve people's lifestyles and mitigate traffic and environmental issues affecting urban conditions. Several studies investigated which characteristics should be respected to make the mobility sector as smart as possible. Consider, for example, road safety management (Francini et al., 2014), accessibility, sustainability and innovation (Chen and Silva, 2021). Also, great attention was given to the use of new technologies (Battarra et al., 2017) and to innovations aimed at older generations (Boscacci et al., 2014).

However, as for the general definition of smart city, no univocal vision of the smart mobility concept was identified so far. Giffinger et al. (2007) highlight these main features to describe the mobility of a city, considering mainly the transportation and ICT sectors:

- local accessibility,
- national and international accessibility,
- availability of ICT infrastructures, and
- sustainable, innovative and safe transport systems.

Lombardi et al. (2012) propose considering logistics and infrastructure as the main factors behind the development and improvement of smart conditions in cities. More recently, Francini et al. (2021) published a review paper aiming at collecting the descriptions of smart mobility available in the literature and harmonizing them into a shared definition using a systematic literature review approach supported by a cluster analysis. According to their findings, a suitable definition of smart mobility is *"the result of a planning process which makes use of technological supports in the simulation phases, use and monitoring of individual and shared transport systems to ensure safety standards, functionality and sustainability"* (Francini et al., 2021, Section 4).

Eventually, by recalling the main challenges affecting urban environments and analyzing the various definitions in the literature, the concept of smart mobility can be clarified by examining three areas:

- *respect for the environment*: through the creation of efficient transportation systems that consider energy consumption, pollution, and environmental consequences, but also through improved planning and the efficiency of public transportation options (e.g., adopting real-time data analytics, machine learning in autonomous vehicles, sensors, data platforms, and software);

- *improvement of the economy*: y maximizing productivity and management; and

- *improvement of the society*: by increasing citizens' quality of life and reducing congestion, for instance, through car- and bike-sharing, resulting in a decline in citizens' frustration.

The transition to smarter and more environmentally friendly mobility patterns is becoming one of the most relevant aspects of urban policy, and many cities around the world are implementing smart solutions to project their city into the new era of urban transportation. Nevertheless, the commitment in this field varies significantly among cities; in addition, investments are often focused on different strands: technology, public transportation, and disincentives to car adoption. Moreover, the intrinsic characteristics of each city can shape decisions and the implemented measures. For this reason, in the last decade, greater attention has been placed on measuring cities' performance on smart mobility. Simple and composite indicators represent the most versatile instruments to compare cities in terms of transportation and its sub-aspects.

Chen and Silva (2021) collect and present one of the largest sets of indicators, including 49 items, to investigate interventions and the developments of the smart transport sector in English metropolises. Key aspects such as private, public, and emergency transport, on one hand, and accessibility, sustainability, and innovation in mobility on the other hand, are measured using detailed indices and a global index. A similar methodology and study scope are considered by Battarra et al. (2018), who examined Italy's 11 metropolitan cities, taking into account 28 mobility parameters in three categories: accessibility, sustainability, and ICT. A different vision is proposed by Debnath et al. (2014) in the creation of a transportation index for 26 world cities. A narrower view for smart transport is considered, combining 66 indicators measuring the implementation of ICT technologies in multiple mobility sub-systems (private, public, and commercial and emergency). Useful insights emerge evaluating the temporal implementation of smart measures as explored by Pinna et al. (2017) in the calculation of a smart mobility index for 22 average Italian cities. Significant heterogeneity in the implementation of smart solutions is present between northern and southern metropolises, and different growth patterns emerged over the time period considered.

The analysis of the differences among cities and the characteristics of the smartest ones can highlight best practices and possible paths to follow in the future. Battarra et al. (2018) show a positive relationship between investments in sustainability, ICT, and accessibility and performance in terms of smart mobility. Chen and Silva (2021) found that cities with higher scores on both private and public indices have the highest levels of accessibility and innovation and are characterized by higher populations and better economic performance. However, critical issues, representing possible room for improvement, can emerge even in the smartest urban areas. Aletà et al. (2017) show a dual and opposite situation in Spanish cities performing well on smart mobility (71% are above the target) while having poor results for the smart environment (only 23% are above the target).

4. Data on smart mobility in Milan

To investigate the pattern of the development of smart mobility in Milan, we collected data through the open database provided by the municipality of Milan (available at `http://dati.comune.milano.it/organization/comunedimilano`). Available data concern the 88 administrative neighborhoods of the city, namely, the NILs , which are the smallest spatial subdivisions of the municipality. The complete list of Milan's NILs is reported in the Appendix A.2.

We considered a set of variables that characterize smart urban mobility along three relevant dimensions: public transport means, sharing mobility means, and mobility infrastructures. All the considered variables refer to 2018. To control for potential scale effects that could generate bias in the values associated with each neighborhood, we further considered the population of each NIL registered on January 1, 2018. As defined by ISTAT (2016), the resident population is the number of persons habitually resident in the municipality, even if on the considered date they are absent because they are temporarily present in another municipality abroad. We use this variable as a weighting factor to create composite indicators. All the considered variables are weighted by the resident population and converted into per capita values.

In this section, the selected measures are briefly described. For public transport means we used the following variables:

- *Number of metro stops*: The number of metro stops in each NIL;
- *Weekly metro rides*: the number of weekly metro rides divided by the number of work days (Monday to Friday) and for Saturday and Sunday. Assuming a standard week, we multiply the number of weekly rides on working days by five and the number of rides on the other two days by one. For each station, the total weekly number of trips is calculated by summing the number of weekly rides of all routes passing through that station. For each NIL, the final value is computed by averaging the weekly trips of all stations belonging to the district;
- *Number of tram stops*: the number of tram stops in each NIL;
- *Weekly tram rides*: the number of weekly tram rides divided by the number of weekdays (5), and for Saturday and Sunday (see the explanation of the calculation of weekly metro rides above);
- *Number of bus stops*: the number of bus stops in each NIL;

- *Weekly bus rides*: the number of weekly bus rides divided by the number of weekdays (5), and for Saturday and Sunday (see the explanation of the calculation of weekly metro rides above);

- *Number of trolleybus stops*: the number of trolleybus stops in each NIL; and

- *Weekly trolleybus rides*: the number of weekly trolleybus rides by the number of weekdays (5), and for Saturday and Sunday (see the explanation of the calculation of weekly metro rides above).

Regarding sharing mobility means, we considered the following variables:

- *Number of GuidaMi stations*: the number of stations in each NIL;

- *Number of parking spaces GuidaMi*: the number of parking spaces for GuidaMi in each NIL. Each station has a different number of parking spaces; the variable is calculated as the sum of all parking spaces at each station;

- *Number of BikeMi racks*: the number of BikeMi racks in each NIL;

- *Number of BikeMi slots*: each BikeMi rack has a different number of spaces; the final variable is the sum of all spaces at each BikeMi rack.

Finally, for mobility infrastructures we used the following variables:

- *Number of recharging columns*: the number of columns for electric recharging in each NIL;

- *Number of bike racks*: the number of bike racks in each NIL;

- *Number of bike slots*: each bike rack has a different number of spaces; the final variable is the sum of all spaces at each bike rack.

The full list of considered variables is synthesized in Table 1, which reports the list of basic indicators and their descriptions. Note that the number of stops and the number of rides for each means of transportation have to be considered separately; hence, we considered four variables for the stops and four for rides.

Variable	Description
Metro/tram/bus/trolleybus stops	Number of metro/tram/bus/trolleybus stops in each NIL
Metro/tram/bus/trolleybus rides	Average weekly metro/tram/bus/trolleybus rides in each NIL
Parking spaces GuidaMi	Number of all GuidaMi parking slots in each NIL
BikeMi slots	Number of all BikeMi slots in each NIL
Recharging columns	Number of columns for electric recharging in each NIL
Bike slots	Number of all bike slots in each NIL
Population	Resident population in each NIL updated to 2018

Table 1: Description of the considered variables

Descriptive statistics for the considered mobility indicators are reported in Table 2.

Variable	Mean	Median	Std. Dev.	CV	Min	Max
Number of metro stops	1.02	0.00	1.43	1.39	0.00	6.00
Weekly metro rides	1503.00	0.00	1781.22	1.19	0.00	5510.00
Number of tram stops	5.67	1.00	8.88	1.57	0.00	42.00
Weekly tram rides	538.00	370.00	594.56	1.10	0.00	2753.00
Number of bus stops	13.14	10.00	13.87	1.06	0.00	68.00
Weekly bus rides	546.00	589.00	283.28	0.52	0.00	1175.80
Number of trolleybus stops	2.09	0.00	4.20	2.01	0.00	20.00
Weekly trolleybus rides	416.70	0.00	629.65	1.51	0.00	1981.00
Parking spaces GuidaMi	5.05	2.00	7.70	1.53	0.00	37.00
Number of BikeMi racks	92.34	0.00	149.11	1.61	0.00	777.00
Number of recharging columns	0.70	0.00	1.33	1.89	0.00	7.00
Number of bike racks	215.90	157.00	314.44	1.46	0.00	1874.00
Resident population	15855.39	14750	12944.49	0.82	2	62438

Table 2: Descriptive statistics of the considered variables

From Table 2, almost half of the sample variables report a median value equal to zero, suggesting a lack of specific services in the majority of the NILs. This is particularly significant for the number of metro stops, the number of trolleybus stops, the number of BikeMi racks, and the number of recharging columns. When analyzing the variability of the data, we find that the least heterogeneous variables are the weekly bus rides and the number of bus stops, which are characterized by a low coefficient of variation. This could indicate a wider presence of the bus services in the Milan area, with lower differences among neighborhoods compared to the other transportation services, such as the number of trolleybus stops, which shows the highest variability coefficient.

In Figure 1, we provide a spatial representation of the considered means of transport and infrastructure in Milan. This visualizes the presence and distribution of these resources across the municipal territory. We provide domain-specific maps for public transport (upper panel), sharing mobility (central panel), and mobility infrastructure (lower panel). Generally speaking, all three maps consistently show that Milan suffers from a deep concentration on mobility in the city's center, while the suburbs are not adequately covered. In the upper panel of Figure 1, the map shows a heterogeneous distribution of bus stops in almost all the NILs (e.g., the southern area is poorly covered). On the other hand, metro and tram stops are largely present in the city's center and have branches that move toward the suburbs, where they are sparse. Trolleybus stops reveal a particular pattern since they create a circular path around the city's center. Smart vehicles (central panel) are concentrated in the central NILs. However, the northern part of Milan shows a greater presence compared to all the other suburbs where they are almost absent. Also, the number of BikeMi stops is higher than the number of car-sharing stations. Finally, the bottom panel highlights a wider presence of bike racks in almost all neighborhoods and a prevalence of recharging columns in the central NILs.

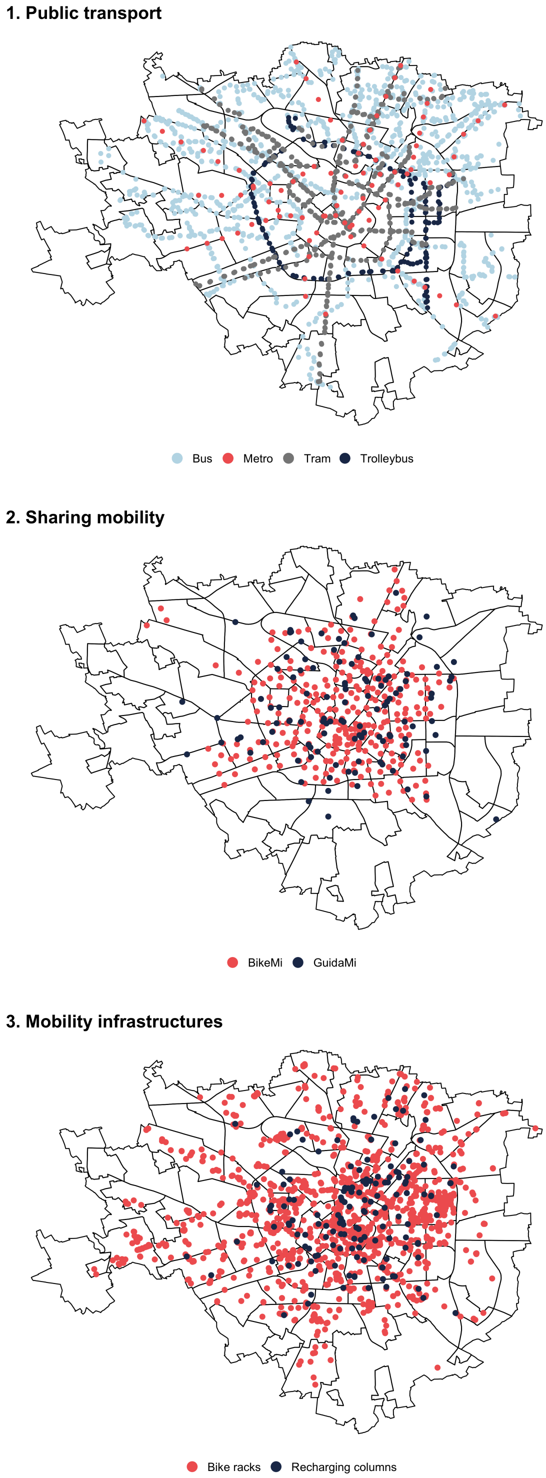

Figure 1: Spatial availability of pubic transport means (upper panel), sharing mobility (middle panel) and mobility infrastructures (lower panel) in Milan.

5. Statistical modeling

In this section, we depict the statistical process used to quantify the smart mobility degree of each NIL of Milan. We then group them into homogeneous groups with similar mobility levels.

5.1. Composite indicators

Composite indicators (Mazziotta and Pareto, 2013) are now the cornerstones of official statistics dealing with spatial measures of socio-economic well-being (consider the papers by Mazziotta and Pareto (2014, 2022) for the study of heterogeneity in well-being among Italian regions and by Mazziotta (2017) for the case of municipalities in southern Italy) and competitiveness (see, for example, the study by Scaccabarozzi et al., 2022, on municipal competitiveness, understood as municipality's ability to offer an attractive and sustainable environment for firms and residents to live and work). Here, we create a set of mobility measures using a composite approach to quantify the degree of mobility in the NILs. First, we choose and normalize a group of elementary indicators, computed as the ratio between the selected variables related to mobility and the 2018 resident population of each neighborhood. Second, we aggregate these elementary indicators using four composite indicators: the geometric mean, the mean of the rescaled values within the range 0– 1 (Mean 0–1), the Adjusted Mazziotta– Pareto Index (AMPI) and the Static Jevons Index (JJI) (Mazziotta and Pareto, 2017).

Let $j = 1,...,m = 12$, be the subscript of the elementary indicators, and let $i = 1,...,n = 88$ be the subscript for each NIL. Recall that the AMPI index is based on a min–max transformation of the original values such that the normalized values (y_{ij}) are constrained in the range 70 to 130. Denoting the mean with M_{yi}, the standard deviation with S_{yi}, and the coefficient of variation cv_{yi} of the normalized values y_{ij} for unit i, the composite index is given by the following formula:

$$AMPI_i^{+/-} = M_{y_i} \pm S_{y_i} cv_{y_i} \tag{1}$$

where the sign ± depends on the kind of phenomenon to be measured. In particular, when the composite index is *positive* — that is, increasing values of the index correspond to positive variations of the phenomenon — then AMPI^- is used. On the contrary, if the composite index is *negative* — or increasing values of the index correspond to negative variations of the phenomenon — then AMPI^+ is used. The previous formulas suggest that AMPI decomposes the score of each unit into two parts. The first part is M_{zi}, which represents the mean level of the indicator, while the second is $S_{zi}cv_{zi}$, often referred to as the penalty term, which penalizes the average for the units with unbalanced values of the indicators. The latter term has the objective to reward the units with a greater balance among the values of the indicators. To highlight those NILs with a particular and unbalanced presence of transportation services, we considered a negative penalty function defined by inverting the original polarity[2].

[2]Polarity of the elementary indicators is the sign of the relationship between the indicator itself and the phenomenon. When an indicator is positively related with the phenomenon of

The JJI for unit i represents the geometric mean of the index number of all the elementary indicators. The JJI is defined as follows:

$$JJI_i^t = \prod_{j=1}^{m} ((x_{ij}^t)/(x_{rj}^t) \cdot 100)^{1/m} \tag{2}$$

where x_{rj}^t is the reference value, for instance the average, and x_{ij}^t is the value of indicator j for unit i, at time t $\forall x_{ij}^t > 0$ (j=1,...,m; i=1,...,n; t=t_0, t_1).

Different features emerge comparing the approaches used in the calculation of each index. The main ones to be considered are the compensation and the substitutability among base indicators (Mazziotta and Pareto, 2022). These properties are relevant since each elementary indicator generally represents a specific dimension of the studied phenomenon. The overlap and compensation among them represent critical aspects to be considered in creating the index (Bacchini et al., 2020). The JJI is partially compensatory, as it is based on the geometric mean of the index numbers. It is a sensitive composite index due to the fact that it is based on a normalization (indicization), which gives implicitly weights according to the variability (Mazziotta and Pareto, 2018). The AMPI index is partially compensatory and enjoys the helpful quality of non-substitutability, meaning that all the elementary indicators used to compute it have all the same importance and a full compensation among them is not allowed (i.e., it is not possible to compensate the value of one indicator with that of another). Moreover, the AMPI is able to guarantee the spatial and time comparability of the units (Mazziotta and Pareto, 2018). It has simple and transparent calculations, is immediately usable, and it is easy to interpret the results. However, it seems that there is not a composite index that is universally valid for all areas of research; therefore, the index's validity depends on the strategic objectives of the research (Mazziotta and Pareto, 2014).

5.2. Influence analysis

Once the composite indicators have been computed, we implemented a leave-one-out influence analysis to assess its robustness when individually excluding each of the elementary indicators. Following the methodology proposed by Mazziotta and Pareto (2017) and (Scaccabarozzi et al., 2022), we compared the indices according to several descriptive statistics computed using the distances between the values of the indicators estimated, including or eliminating each of the underlying elementary variables. In general, we considered as robust an indicator that shows low variability and low average gaps when the sub-indices differ.

Let r_{ij} be the rank, or position, of the i_{th} NIL computed without the j_{th} indicator and let r_i be the rank of the i_{th} NIL computed using all the elementary indicators $j = 1, ..., m = 12$. The algorithm consists of dropping each j_{th} elementary indicator from the list of m base indicators and then re-calculating the in-

interest, it has a *positive polarity*; when it is negatively related with the phenomenon, it has a *negative polarity* (Alaimo et al., 2021) dex using the remaining $m-1$ indicators. At each iteration j, the algorithm computes for each i_{th} NIL the absolute difference (or shift) between its position in the full-index ranking and its position in the leave-one-out ranking, i.e. $d_{ij} = |r_{ij}\text{-}r_i|$ $\forall i = 1, ..., n = 88$. With $m = 12$ elementary indicators, for each aggregative indicator, the algorithm returns 12 vectors of shifts.

The sensitivity of each composite indicator is evaluated as follows. First, we computed the sample mean and the sample standard deviation for all the vectors of shifts. This step produced $m = 12$ averages ($\bar{X}$) and $m = 12$ standard deviations (S_X). Second, the above metrics are summarized by computing the corresponding sample averages, sample standard deviations and sample variability coefficients (i.e. the ratio between the standard deviation and the mean). Then, for each indicator, we obtained six descriptive statistics: the global average shift ($\mu_{\bar{X}}$), the standard deviation of the average shifts ($\sigma_{\bar{X}}$), the variability coefficient of the average shifts ($VC_{\bar{X}}$), the average standard deviations of the shifts (μ_{S_X}), their standard deviations (σ_{S_X}), and their variability coefficients (VC_{S_X}). To achieve the highest possible robustness, an indicator with a low degree of variability (i.e. low μ_{S_X} and low VC_{S_X}) and/or with a low degree of variability in the shifts (i.e. low $\mu_{\bar{X}}$ and low $VC_{\bar{X}}$) has to be preferred over the others.

5.3. Spatial cross-correlation analysis

This section is devoted to understanding the relationships between mobility and the land use of each NIL. Means of transport are generally designed to serve specific purposes of the population. We investigated the presence of a correlation between the smart mobility indices previously created and the presence of essential services (infrastructures) for the population. We collected further data for the city of Milan covering key aspects of the city, such as tourism, education, and health. In total, we considered seven variables aggregated by NIL, in addition to the area and the NILs' population density. The population density for each NIL was calculated as resident population divided by area, where the area is measured in square kilometers. To estimate mobility levels, we used the infrastructure information that was updated in 2018 or the latest version available. The infrastructure variables are listed in Table 3. The list includes the list

Variable	Description
Area	The area in KM^2 of each NIL
Population density	The population density of each NIL as resident population/area
Number of hospitals	The number of hospitals in each NIL
Number of hospital beds	The number of beds available in all the hospitals of each NIL
Number of schools	The number of high schools in each NIL
Number of school students	The number of students attending the high schools present in each NIL
Number of university campus or headquarters	The number of university campuses/headquarters in each NIL
Number of hotels	The number of hotels in each NIL
Number of hotel rooms or beds	The number of rooms/beds available in all the hotels of each NIL

Table 3: Structural variables used for spatial cross-correlation analysis

of variables that describe and quantify the socio-demographic and infrastructure features of the city that are not related to mobility, but that could be influenced by or affect municipal policy choices on enhancing the mobility of NILs. Specifically, we considered the area of neighborhoods; population density (2018 resident population divided by area); the number of hospitals and beds; number of schools, students, and university centers; and the number of hotels, rooms, and beds. Figure 2 presents the spatial distribution of the studied infrastructures. For high schools, the dimension of the dots depends on the number of attending students; for hospitals, it depends on the number of beds; for hotels, it illustrates the number of beds; and for universities, large dots represent the headquarters, while small dots represent the other campuses. The map shows that the infrastructures considered are mainly located in the city's center (i.e., Area C) and the northern neighborhoods. This is especially true for hotels, which are concentrated in the historic center and commuting areas. Schools and hospitals, on the other hand, are more widely distributed. Figure 3 represents the visualization of

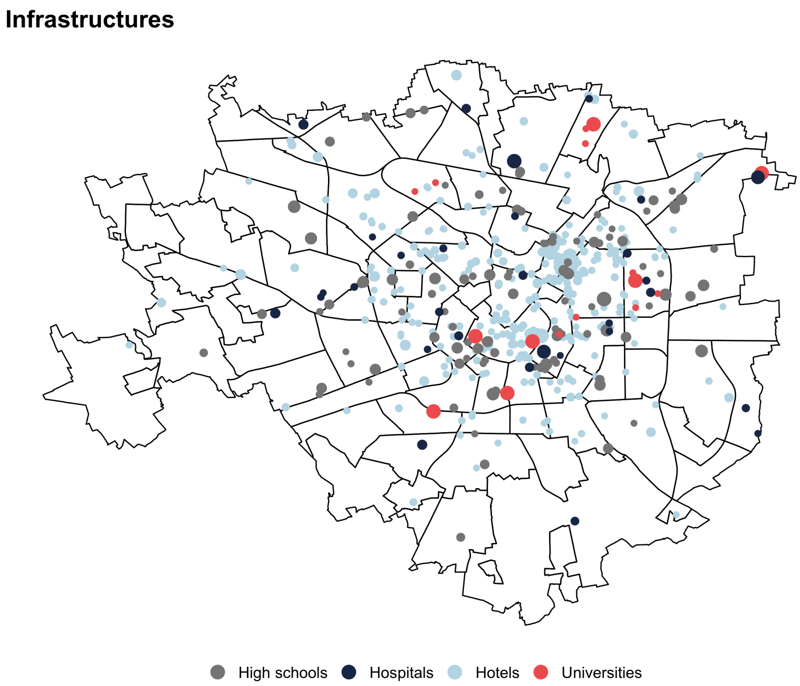

Figure 2: Spatial distribution of the studied infrastructures

the Population and the Population density of each NIL in Milan.

To further characterize the estimated smart mobility levels with respect to the territory of Milan, we quantified the spatial cross-correlation for each of the four composite indicators against a set of variables concerning the main socio-economic infrastructure of the city. The spatial cross-correlation analysis is based on the decomposition of the Pearson's linear cross-correlation index into its direct and indirect spatial components, as proposed by Chen (2015). Spatial dependence is measured by an inverse power decay function calculated using the distance between the centroids of each neighborhood. The author interprets Moran's spatial autocorrelation index (Moran, 1950) as a general case of the Pearson's linear statistic (Chen, 2013) and decomposes the latter into (1) an indirect spatial cross-correlation component measuring the indirect correlation be-

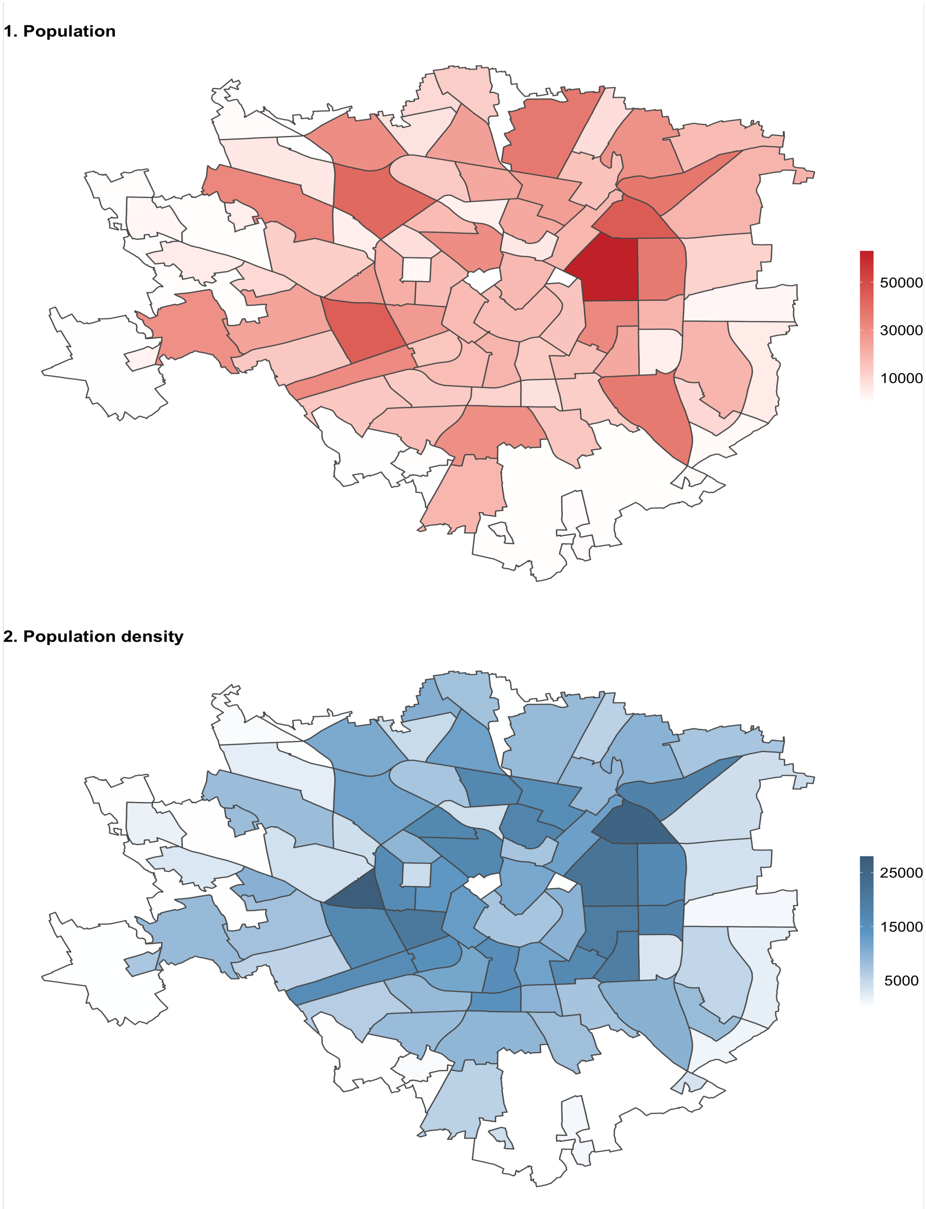

Figure 3: Spatial distribution of the population (upper panel) and its density (lower panel) in each NIL in Milan

tween variables X and Y through the spatial distances and other elements in a geographical system (i.e., the Spatial Cross-Correlation Index, or SCI), and (2) a direct spatial cross-correlation measure between X and Y , which is free of the spatial distance and spatial interactions between NILs (i.e., the Partial Spatial Cross-Correlation Coefficient, or PSCC). Following the notation proposed by Chen (2015), the decomposition is defined as follows:

$$R_0 = R_p + R_c, \tag{3}$$

where R_0 is the Pearson's linear correlation index, R_c is the SCI and R_p is the PSCC. The PSCC and the SCI can be interpreted as a direct correlation without a distance effect and an indirect correlation based on the distance decay effect, respectively. This decomposition has been used in various contexts, including mobility-related research. For example, in Jin et al. (2019), the SCI index is used as a measure of competition (positive sign) and complementarity (negative sign) between the presence of Uber cabs and public transportation in New York City. Other recent applications include the real estate market in Turkey (Moralı and Yılmaz, 2022) and the relationship between population fragility and COVID-19 in England (Nicodemo et al., 2020). While not indicating anything about the direction of causality between the relationships, the SCI and PSCC measures, as well as the Pearson's index, can give a broad indication of the criteria behind the choices made by municipal administrations in enhancing mobility and what might be the future drivers of mobility allocations. Indeed, we expect that where more infrastructure exists, the degree of mobility will be higher. In addition, a systematic mapping of key infrastructure with respect to the current mobility system is an essential tool for the design of strategic structural policies.

5.4. Cluster analysis

Cluster analysis techniques have become increasingly popular in applications related to smart cities, mobility, and urban studies. A research question of great interest concerns the identification of geographic patterns (e.g., groups of cities or groups of regions) partitioning the territory into homogeneous areas based on local mobility degree, demography, economy, and public services available to the community. Several studies can be cited. For example, consider the paper by Boscacci et al. (2014) which analyzes the relationship between urban attractiveness and the smart city concept (measured in various dimensions) across Italian provinces through a K-means clustering algorithm Arthur and Vassilvitskii (2006) in order to find differences and commonalities among provincial capitals. Or consider the paper by Mounce et al. (2020) on the role of governments in institutional, organizational, regulatory, and financial frameworks to support rural transport services in Europe. Once again, the authors propose using a K-means clustering strategy to identify distinct classes of institutional frameworks to support rural mobility. Alternatively, Balducci and Ferrara (2018) use a combination of PCA, hierarchical cluster analysis, and spatial autocorrelation to study the adoption of smart environmental policies in Italian provincial capitals. Finally, as an alternative to K-means, other methods such as latent class cluster analysis (Alonso-González et al., 2020) have been implemented to quantify an individual's propensity to use smart mobility solutions.

The goal here is to define internally homogeneous groups of NILs that exhibit similar smart mobility values while being distinguished and heterogeneous from each other. Cluster analysis is the most suitable tool to achieve this purpose. The cluster is performed by using as input the results of the sensitivity analysis described in the previous step. Indeed, the optimal aggregative indicator identified through the sensitivity analysis presented in Section 5.2 is used to group the city's neighborhoods according to the estimated smart mobility degree. For consistency with the literature presented above, we implemented a cluster analysis using the K-means algorithm with a number of groups varying from two to six and trying multiple random starting points. The optimal number of groups was selected by computing several clustering performance measures, such as the GAP statistic (Tibshirani et al., 2001), the silhouettes criterion and the majority rule-of-thumb for several indicators as proposed by Caliński and Harabasz (1974) and Krzanowski and Lai (1988).

6. Results

6.1. Composite indicators and influence analysis

Figure 4 represents the estimated value of each index for all 88 NILs in the city of Milan. The maps reveal two important findings about the overall degree

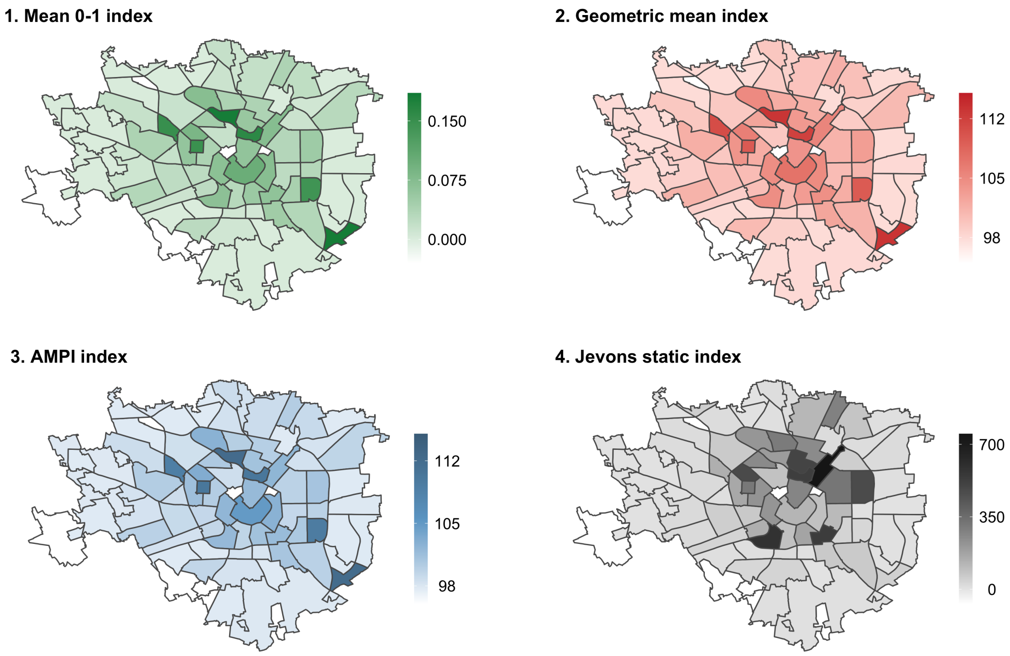

Figure 4: Estimated results of Mean 0-1 index (top left panel), Geometric mean (top right panel), AMPI Index (bottom left panel), and Jevons Index (bottom right panel) for Milan NILs. Values are reported in color scales of increasing intensity, i.e., larger ones are associated with more intense colors.

of mobility within the city of Milan. First, there is a strong similarity in the color intensities obtained from the geometric mean, Mean 0–1, and AMPI indices. The estimated values for the JJI, on the other hand, differ from the others. This is confirmed by the linear correlation analysis performed on the estimated values and reported in Table 4. In particular, a weak and non-significant correlation is present between JJI and the other indices. On the other hand, the correlation among the Mean 0–1, geometric mean, and AMPI indices is significant and close to 1. This suggests that the sensitivity analysis and cluster analyses performed with the first three indicators will be very similar and may deviate significantly from those obtained by considering the JJI. Second, all four maps are characterized by intense colors (high values) in the city center (i.e., in the limited traffic zone referred to as Area C) and in the districts where the primary mobility hubs are located (e.g., central station). This result first suggests a strong concentration and polarization of smart mobility in Milan toward the center, and infrastructural deficiency in the suburbs.

Index	Jevons	Mean 0-1	Geom. mean	AMPI
JJI	1.00	0.53	0.58	0.46
Mean 0-1	0.53	1.00	0.99	0.99
IMG	0.58	0.99	1.00	0.98
AMPI	0.46	0.99	0.98	1.00

Table 4: Pearson correlation of the composite indicators

The results of the sensitivity analysis for the considered indices are reported in Table 5.

Indices	$\mu_{\bar{X}}$	$\sigma_{\bar{X}}$	$VC_{\bar{X}}$	μ_{S_X}	σ_{S_X}	VC_{S_X}
JJI	2.298	0.907	0.395	2.317	0.536	0.231
Mean 0-1	1.309	1.140	0.871	1.973	1.398	0.709
IMG	1.468	1.249	0.851	2.091	1.474	0.705
AMPI	1.335	1.106	0.828	2.095	1.501	0.716

Table 5: Sensitivity analysis results

Comparing the variability coefficients and the standard deviations, the JJI performs very well, as it presents the lowest values both for the mean and the standard deviation. However, the global average shift ($\mu_{\bar{X}}$) and the average variability (μ_{S_X}) are the largest among those estimated. This lack of robustness of the JJI may derive directly from its construction method, which only considers index numbers and ignores the sample variability. The AMPI and the Mean 0–1 indices perform well in terms of the average shift (i.e., they show low average shift) while presenting slightly higher variability values. Overall, their performance seems to be equivalent. The IMG index exhibits estimates of the variability that are almost comparable with those of AMPI and Mean 0–1, but it also has a higher and more volatile average shift. To sum up, based on the correlation coefficients reported in Table 4, AMPI, Mean 0–1, and the geometric mean are equivalent (correlation close to 1) and have similar distributions on the map. However, the results shown in Table 5, show that (1) the JJI outperforms the others in terms of variability but not average shift, (2) AMPI and Mean 0–1 perform slightly worse than JJI, and (3) the IMG's performance is not satisfactory. Moreover, as previously stated in the literature on composite indicators, the AMPI index, compared with other non-compensatory indicators, satisfies some valuable statistical properties that make it a cornerstone of official statistics (i.e., space-time comparison, simplicity of calculation, easy interpretation of the results, robustness of the method, non-substitutability of the individual indicators). Thus, considering (1) the nearly perfect correlation between AMPI, IMG, and Mean 0–1; (2) the statistical properties of AMPI; and (3) the good performance of the JJI, our suggestion is to use both the JJI and AMPI indices as inputs of the K-means clustering algorithm. In particular, to take advantage of their potential in revealing the true patterns of neighborhoods, we suggest using them both individually and jointly and then comparing the resulting clusters.

6.2. Spatial cross-correlation with infrastructural features

In Appendix A.3 we report the Pearson's linear correlation, the SCI and the SPCC for all the pairs of composite indicators and structural variables. Reported values are sorted by increasing values of Pearson's index and show some interesting evidence:

1. In general, linear correlations are weak (range -0.24 to +0.31), but strongly depend on considered variables (economic infrastructures appear to be more relevant compared to schools and health facilities);

2. All the indicators are inversely correlated with area and population density. This means that larger and more densely populated neighborhoods have low levels of smart mobility, giving them the least coverage and making them the most deficient. Such neighborhoods are mainly suburban with some rural areas (see Figure 3). In contrast, central (more compact) NILs have better access to transportation services;

3. The presence of hospitals, schools, and universities seems to be unrelated to the degree of mobility. As shown in Figure 2, hospitals and schools are fairly widely distributed across the city. Thus, these infrastructures are present in both low- and high-smart-mobility neighborhoods;

4. The JJI shows an average positive correlation, but one that is much higher than the others, with the number of hotels and available rooms. As we will see in more detail in the cluster analysis, JJI sharply emphasizes commuting, tourism, and entertainment NILs, which are inevitably characterized by the presence of a high number of accommodations and restaurants (see Figure 2);

5. For both positively and negatively correlated pairs, the sign and magnitude are determined by direct spatial correlation (R_p). This indicates that the relationship between mobility and infrastructure is unrelated to distance between NILs and geographical factors (i.e., there are no spatial clusters). Thus, the correlation could be motivated by exogenous economic-social determinants;

Without attempting to include a causal link between the variables, we can nonetheless argue that Milan's current transportation system is oriented toward favoring the more compact central areas over the suburbs, and that neighborhoods with a higher degree of tourism benefit greatly from a good degree of smart mobility.

6.3. Clustering of the neighborhoods

Whether JJI, AMPI, or both are considered to create the clusters for the NILs, the criteria for selecting the optimal number of groups are consistent. Indeed, the majority rule of thumb suggests considering three or four groups, while both the silhouette and the GAP statistic suggest exactly four clusters. Therefore, we proceed to cluster the NILs by setting the number of potential clusters to four. Empirical results on the optimal number of groups are reported in Appendix A.1.

To avoid inconsistencies in the cluster results due to outlier values, we dropped from the analyses seven NILs[3] with a lower number of residents (i.e., ≤ 50 inhabitants) or containing large green areas (e.g., urban parks). Therefore, these districts will constitute a separate cluster that is not comparable with the others and that is labeled as an *outlier* group.

We performed and compared three K-means algorithms specifications: the first uses only the JJI index as a clustering variable (JJI clustering), the second uses only the AMPI (AMPI clustering), and the third combines both indices (JJI–AMPI clustering). The cluster analysis results are presented in the four maps of Figure 5.

The four clusters can be listed in ascending order of mobility level:

- **Low mobility**: suburbs and peripheral areas, characterized by deficient levels of mobility. Particularly, they are located in the southern and western parts of Milan or along the eastern border neighborhoods of the city;

- **Medium-low mobility**: composed of all the NILs with a large residential population but with few mobility services available. These are areas where people commute and live, which host a large number of offices and production activities;

- **Medium-high mobility**: include scientific university centers and former industrial areas; largely populated and wealthy neighborhoods;

[3] *Giardini Porta Venezia*, *Parco Sempione*, *Parco dei Navigli*, *Parco Agricolo Sud*, *Parco Bosco in Città*, *Cantalupa* and *Quintosole*

- **High mobility**: NILs where citizens commute to reach offices (JJI) or specific NILs characterized by a strong presence of a single mobility services (AMPI).

The JJI clustering effectively separates peripheral areas and suburbs from the historical city center, transit sites, and nightlife areas. The high-mobility group includes the main commuting points (Central and Garibaldi stations), the nightlife areas (Navigli in the southwest and Porta Romana in the southeast), as well as the Politechnical University area in the east. The medium–low cluster mainly coincides with the city center (e.g., the Dome) and some further inhabited areas (Viale Monza and Sarpi). The suburbs form a unique cluster surrounding the center of the city.

The AMPI-based clustering separates areas that are not well-discriminated by the JJI, such as the Linate airport area (southeast) or the new and highly coveted neighborhood of City Life (northwest). The algorithm groups them within the high-mobility cluster. Moreover, the AMPI identifies the city center more clearly than does JJI. In this case, the city center (medium–high mobility) coincides with Area C, which is the limited traffic zone adopted to improve the city's overall sustainability, extended to the commuting points and nightlife neighbors. The cluster associated with medium–low mobility includes all the university campuses and several inhabited areas. As in the JJI-based case, the AMPI separates the suburbs (with low mobility) and extends the middle-mobility NILs (i.e., the medium–low group becomes a larger area).

The JJI–AMPI cluster provides an excellent overview of the overall mobility as it inherits the useful properties of both single-index approaches. However, the result appears to be strongly dependent on AMPI's behavior, as it holds the high values of AMPI and JJI's low values. The algorithm clearly separates the city center from the suburbs, covering the entire peripheral areas of Milan, as in the JJI-based case. The city center is classified as medium–low, as in the JJI output. The medium–low cluster also includes some northern NILs, such as Bovisa and Bicocca, which are highly inhabited areas hosting several university campus and train stations. The JJI–AMPI algorithm separates into two clusters those NILs that were individually classified as high-mobility areas. In the combined scenario, the AMPI high-mobility clusters remain in the high-mobility group, while JJI's high-mobility NILs are now classified as medium–high mobility areas. Moreover, the medium–high group includes some other highly mobile neighborhoods and commuting points, whereas the high-mobility cluster includes NILs, such as *QT8* and *Tre Torri*, which are essential transit sites. The latter two NILs, together with *Portello*, were part of the Old Fair area of Milan.

The clustering results are consistent with those presented by Bernini et al. (2019), who use land-use variables (e.g., buildings, roads, green urban areas, etc.) in a network framework for community detection to identify groups of NILs with similar land-use mixes. The urban patterns they identify are summarized in four homogeneous groups or communities of neighborhoods. Considering the clustering based only on JJI, we notice that high-mobility clusters include NILs in the Community 1 area, while medium–high and medium–low mobility clusters

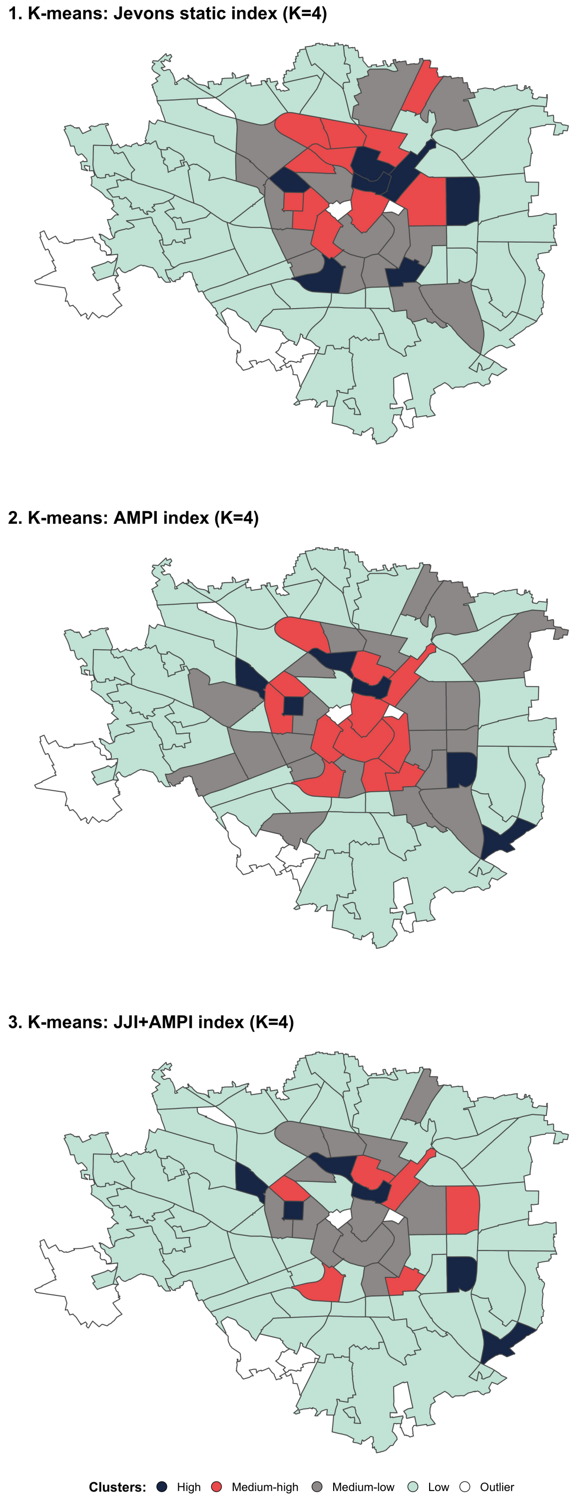

Figure 5: Results of the k-means algorithm with k=4 classes. Clusters obtained considering only Jevons Index (top panel), clusters obtained considering only AMPI Index (middle panel), and clusters obtained considering both AMPI and Jevons (bottom panel). The colors identify different clusters.

are spread among Community 1 and Community 3 areas. This fact is very significant since these NILs are characterized by a greater presence of buildings and industrial and commercial areas where it is reasonable to expect more mobility services. On the other hand, the low-mobility cluster fits in Communities 2 and 4, which are essentially characterized by green urban areas and agricultural areas. Such a marked overlap between the two results, however, is not observable when considering the AMPI-based clusters. For example, the high-mobility NILs are not concentrated in a single land-use cluster. Indeed, three of the top NILs for the AMPI index (i.e., *Farini*, *Ortomercato*, and *Tre torri*) are included in Community 3, *Porta Garibaldi* is in Community 1, *QT8* is in Community 2, and *Triulzo Superiore (Linate)* is in Community 4. Medium–high NILs are split in the Community 1 and Community 3 clusters. Also, medium–low mobility and low-mobility NILs are located in Communities 2 and 4. In general, there is a lower level of association between the AMPI cluster and the land-use cluster compared to the results observed for the JJI cluster. However, the AMPI index is capable of isolating some emerging NILs characterized by a specific mobility composition. Ultimately, considering the JJI–AMPI clustering, the majority of the NILs in the high, medium–high, and medium–low mobility levels fit in Community 1, while others are included in Community 3. The only exceptions are *QT8* and *Triulzio Superiore*, which showed high levels of mobility but are classified as Community 2 and Community 4, respectively, by Bernini et al. (2019).

Overall, both the spatial cross-correlation analysis and the K-means results are consistent. From a policy perspective, they both suggest that the current transportation system clearly favors the city center, composed of small neighborhoods with high tourist and commuting appeal, over residential neighborhoods located in more suburban areas.

7. Conclusions

In this paper we investigated the state of smart mobility in Milan in northern Italy at the district level using a data-driven statistical approach. We were interested in understanding whether the estimated smart mobility levels for the neighborhoods are related to social and economic phenomena, such as tourism or the presence of commuters from surrounding provinces, or whether it is guided by other urban development patterns.

Four composite indicators — the AMPI, JJI, geometric mean, and average of the rescaled values within the range 0–1 — were used and the results were compared. After estimating the mobility degree for each district, we performed a sensitivity analysis to the check the robustness of the variation in the elementary indices. The sensitivity analysis suggested that we use the AMPI and the JJI, as they were better-performing indices.

Furthermore, we studied the spatial cross-correlation between each composite indicator and a set of infrastructural features concerning health facilities, education, tourism, and size. The correlations suggest that touristic neighborhoods and the city's center enjoy a greater level of smart mobility compared to the peripheral areas and residential districts. Then, starting from the sensitivity analysis results, we used the AMPI and JJI to group the NILs according to their mobility degree using a K-means cluster algorithm that can identify homogeneous groups in terms of smart mobility.

The empirical results showed that, whether using each indicator individually or in combination, the cluster analyses provide meaningful results in grouping the neighborhoods. In particular, the AMPI and JJI were able to properly distinguish the main critical areas of the city, such as interchange hubs, university zones, the city's center, workplaces, and peripheral areas. Consistent with the suggestions provided by the spatial cross-correlation, the clustering results highlight substantial differences in terms of mobility within the Old Town (corresponding to the city's center), which is characterized by very high mobility levels, and the suburbs, showing very poor coverage of mobility services.

The results obtained are consistent with what is known about the evolutionary history of Milan over the last two centuries. Indeed, it is well known that the city has experienced long periods of demographic and urban growth without a real regulatory plan to govern its development (Rossari, 2020). Moreover, the great industrial poles that had once settled in the city's territory and that occupied large areas bordering the railway stations (e.g., *City Life* and *Bicocca*) gradually moved away. These factors forced the city administration to deal with the need to intervene with projects and programs, not only for the recovery of the territory, but also to rebalance socio-economic development, particularly in the most peripheral and disadvantaged areas. In the new Territorial Government Plan (Comune di Milano, 2019a), the goal is to reduce socio-economic imbalances, extend the development of each district, improve environmental conditions, and, in general, enhance citizens' quality of life by 2030.

Data and codes

All the results presented in this paper can be reproduced using R software. Codes are available at the following GitHub web page: `https://github.com/PaoloMaranzano/NC_MS_PM_PMC_MilanoMobility.git`.

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A. Appendices

A.1. Appendix 1: clustering metrics

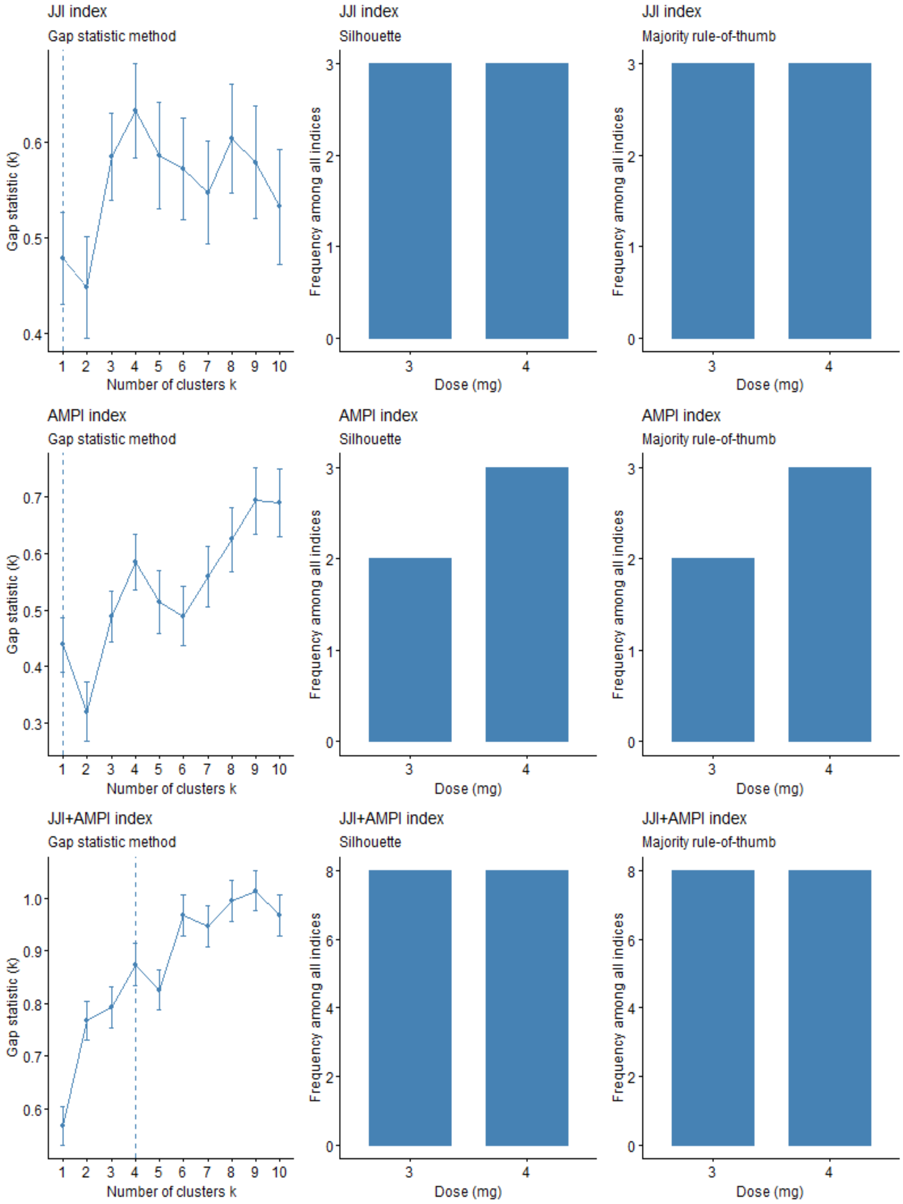

Figure 6: Clustering maps

A.2. Appendix 2: cluster results

IdNIL	NIL	JJI	AMPI	JJI + AMPI
1	DUOMO	Medium-low	Medium-high	Medium-low
2	BRERA	Medium-high	Medium-high	Medium-low
3	GIARDINI PORTA VENEZIA	Outlier	Outlier	Outlier
4	GUASTALLA	Medium-low	Medium-high	Medium-low
5	VIGENTINA	Medium-low	Medium-high	Medium-low
6	TICINESE	Medium-low	Medium-low	Low
7	MAGENTA - S. VITTORE	Medium-high	Medium-high	Medium-low
8	PARCO SEMPIONE	Outlier	Outlier	Outlier
9	GARIBALDI REPUBBLICA	High	High	High
10	CENTRALE	High	Medium-high	Medium-high
11	ISOLA	High	Medium-high	Medium-high
12	MACIACHINI - MAGGIOLINA	Medium-high	Medium-low	Medium-low
13	GRECO	Low	Low	Low
14	NIGUARDA - CA' GRANDA	Medium-low	Low	Low
15	BICOCCA	Medium-high	Medium-low	Medium-low
16	VIALE MONZA	Medium-low	Medium-low	Low
17	ADRIANO	Low	Low	Low
18	PARCO LAMBRO - CIMIANO	Low	Medium-low	Low
19	PADOVA	Low	Low	Low
20	LORETO	Low	Low	Low
21	BUENOS AIRES - VENEZIA	Medium-high	Medium-low	Medium-low
22	CITTA' STUDI	High	Medium-low	Medium-high
23	LAMBRATE	Low	Low	Low
24	PARCO FORLANINI - ORTICA	Low	Low	Low
25	CORSICA	Low	Medium-low	Low
26	XXII MARZO	Medium-low	Medium-low	Low
27	PORTA ROMANA	High	Medium-high	Medium-high
28	UMBRIA - MOLISE	Low	Medium-low	Low
29	ORTOMERCATO	Low	High	High
30	MECENATE	Low	Low	Low
31	PARCO MONLUE' - PONTE LAMBRO	Low	Low	Low
32	TRIULZO SUPERIORE	Low	High	High
33	ROGOREDO	Low	Low	Low
34	CHIARAVALLE	Low	Low	Low
35	LODI - CORVETTO	Medium-low	Medium-low	Low
36	SCALO ROMANA	Medium-low	Medium-low	Low
37	EX OM - MORIVIONE	Low	Low	Low
38	RIPAMONTI	Low	Low	Low
39	QUINTOSOLE	Outlier	Outlier	Outlier
40	RONCHETTO DELLE RANE	Low	Low	Low
41	GRATOSOGLIO - TICINELLO	Low	Low	Low
42	STADERA	Low	Low	Low
43	TIBALDI	Low	Low	Low
44	NAVIGLI	High	Medium-high	Medium-high
45	S. CRISTOFORO	Low	Low	Low
46	BARONA	Low	Medium-low	Low
47	CANTALUPA	Outlier	Outlier	Outlier
48	RONCHETTO SUL NAVIGLIO	Low	Low	Low
49	GIAMBELLINO	Low	Low	Low
50	TORTONA	Medium-low	Medium-low	Low
51	WASHINGTON	Medium-low	Medium-low	Low
52	BANDE NERE	Low	Medium-low	Low
53	LORENTEGGIO	Low	Medium-low	Low
54	MUGGIANO	Low	Low	Low
55	BAGGIO	Low	Low	Low
56	FORZE ARMATE	Low	Low	Low
57	SELINUNTE	Low	Low	Low
58	DE ANGELI - MONTE ROSA	Medium-low	Medium-high	Medium-low
59	TRE TORRI	Medium-high	High	High
60	S. SIRO	Low	Medium-low	Low
61	QUARTO CAGNINO	Low	Low	Low
62	QUINTO ROMANO	Low	Low	Low
63	FIGINO	Low	Low	Low
64	TRENNO	Low	Low	Low
65	GALLARATESE	Low	Low	Low
66	QT 8	Medium-low	High	High
67	PORTELLO	High	Medium-high	Medium-high
68	PAGANO	Medium-high	Medium-low	Medium-low
69	SARPI	Medium-low	Low	Low
70	GHISOLFA	Medium-high	Medium-low	Medium-low
71	VILLAPIZZONE	Medium-low	Low	Low
72	MAGGIORE - MUSOCCO	Low	Low	Low
73	CASCINA TRIULZA - EXPO	Low	Low	Low
74	SACCO	Low	Low	Low
75	STEPHENSON	Outlier	Outlier	Outlier
76	QUARTO OGGIARO	Low	Low	Low
77	BOVISA	Medium-high	Medium-high	Medium-low
78	FARINI	Medium-high	High	High
79	DERGANO	Medium-high	Medium-low	Medium-low
80	AFFORI	Low	Low	Low
81	BOVISASCA	Low	Low	Low
82	COMASINA	Low	Low	Low
83	BRUZZANO	Low	Low	Low
84	PARCO NORD	Low	Low	Low
85	PARCO DELLE ABBAZIE	Low	Low	Low
86	PARCO DEI NAVIGLI	Outlier	Outlier	Outlier
87	PARCO AGRICOLO SUD	Outlier	Outlier	Outlier
88	PARCO BOSCO IN CITTA'	Low	Low	Low

Table 6: Cluster results using Jevons and AMPI indices

A.3. Appendix 3: spatial cross-correlation results

Index	Variable	R_c	R_p	R_0
IMG	Area	-0.04	-0.20	-0.24
Mean01	Area	-0.04	-0.20	-0.23
AMPI	Area	-0.04	-0.20	-0.23
JJI	Area	-0.05	-0.17	-0.21
AMPI	Pop_density	0.06	-0.21	-0.15
Mean01	Pop_density	0.07	-0.17	-0.10
IMG	Pop_density	0.07	-0.13	-0.06
AMPI	N_Hospitals	0.03	-0.09	-0.06
AMPI	N_Schools_students	0.05	-0.10	-0.05
AMPI	N_Hospital_beds	0.02	-0.06	-0.04
Mean01	N_Hospitals	0.03	-0.07	-0.03
Mean01	N_Schools_students	0.06	-0.08	-0.02
Mean01	N_Hospital_beds	0.02	-0.04	-0.02
AMPI	N_Schools	0.06	-0.06	-0.01
IMG	N_Hospitals	0.04	-0.04	-0.01
IMG	N_Hospital_beds	0.02	-0.02	0.00
IMG	N_Schools_students	0.06	-0.04	0.01
Mean01	N_Schools	0.06	-0.03	0.03
JJI	N_Schools_students	0.06	-0.01	0.04
AMPI	N_Uni_headquarters	0.01	0.03	0.05
JI	N_Hospital_beds	0.02	0.03	0.05
AMPI	N_Hotels	0.05	0.00	0.06
Mean01	N_Uni_headquarters	0.01	0.04	0.06
JJI	N_Uni_headquarters	0.02	0.04	0.06
AMPI	N_Uni_campus	0.01	0.05	0.06
IMG	N_Schools	0.06	0.01	0.07
AMPI	N_Hotels_rooms	0.05	0.02	0.07
AMPI	N_Hotels_beds	0.05	0.02	0.07
IMG	N_Uni_headquarters	0.02	0.06	0.08
Mean01	N_Uni_campus	0.02	0.07	0.08
JJI	N_Hospitals	0.03	0.06	0.08
Mean01	N_Hotels	0.05	0.03	0.09
Mean01	N_Hotels_rooms	0.05	0.05	0.10
Mean01	N_Hotels_beds	0.05	0.05	0.10
IMG	N_Uni_campus	0.02	0.09	0.11
JJI	N_Schools	0.07	0.04	0.11
IMG	N_Hotels	0.06	0.07	0.12
JJI	N_Uni_campus	0.02	0.10	0.12
JJI	Pop_density	0.07	0.06	0.13
IMG	N_Hotels_rooms	0.05	0.08	0.14
IMG	N_Hotels_beds	0.05	0.08	0.14
JJI	N_Hotels	0.06	0.24	0.31
JJI	N_Hotels_beds	0.06	0.25	0.31
JJI	N_Hotels_rooms	0.06	0.26	0.32

Table 7: Spatial cross-correlation results.