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Methodological design for an Urban Inequality Indicator (UII) based on subjective bias

TESI DI LAUREA MAGISTRALE IN MANAGEMENT ENGINEERING INGEGNERIA GESTIONALE

Author: **Adrián Cantera**

Student ID: 276232

Advisor: Federico Bartolomucci

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Abstract

From previous existing processes, the extraction and representation of spatial data have often contributed to reinforcing existing inequalities and spatial injustices among citizens in urban environments. Despite the proliferation of measurements, thanks to smart city technologies and urban data platforms, there remains a considerable gap in how urban injustice is measured and visualised. The indicators, in general, are not capturing the multifaceted nature of urban inequality, as they analyse certain aspects of reality without considering a subjective dimension.

This research identifies a critical research gap: the disconnection between objective data and the cognitive biases that influence the interpretation of these results. Moreover, in the investigation field of this thesis, the focus is on how representations enhance understanding through their design choices. These design choices are key to providing municipalities with the perfect frame to clarify reality. Either the colour or the interactivy have an impact on the definition of new political decisions, if targeted to the correct segment of society.

To address these challenges, the present master's thesis develops the Urban Inequality Indicator (UII), a composite index specifically designed to identify spatial patterns of inequality across the 88 Nuclei di Identità Locale (NIL) in Milan. The methodology followed here introduces a novel approach by leveraging collected subjective bias into the indicator's design, achieved through citizen surveys. In addition, a comparative analysis was performed between arithmetic and geometric aggregation methods. The results indicated that a geometric model more precisely prevents the potential critical deprivation caused by large differences in values. With this method, the compensability between dimensions is prevented.

The main findings of the research indicate that urban injustice should not be considered as a static metric, but rather as a mutable variable within age cohorts. The statistical analysis carried out shows disparities between demographic groups. Moreover, by applying spatial autocorrelation techniques, specifically Local Moran's I, it was possible to identify clusters of inequalities.

In conclusion, the thesis demonstrates, with data and an extensive literature background, that by addresing cognitive bias representations based on this data supports inclusive and focused decisions. The final outcome, the Urban Inequality Indicator (UII), is proposed as a tool for municipalities to use to consequently reshape the cities led by real citizens' opinions. Is yet to become the new standard to alleviate inequalities.

Key-words: urban spatial data, cognitive bias, data representation, composite index, smart city, Milan.

Abstract in italiano

Nei processi esistenti in passato, l'estrazione e la rappresentazione dei dati spaziali hanno spesso contribuito a rafforzare le disuguaglianze esistenti e le ingiustizie spaziali tra i cittadini negli ambienti urbani. Nonostante la proliferazione delle misurazioni, grazie alle tecnologie delle città intelligenti e alle piattaforme di dati urbani, rimane un divario considerevole nel modo in cui viene misurata e visualizzata l'ingiustizia urbana. Gli indicatori, in generale, non catturano la natura multiforme della disuguaglianza urbana, poiché analizzano alcuni aspetti della realtà senza considerare una dimensione soggettiva.

Questa ricerca identifica una lacuna critica nella ricerca: la disconnessione tra i dati oggettivi e i pregiudizi cognitivi che influenzano l'interpretazione di questi risultati. Inoltre, nel campo di indagine di questa tesi, l'attenzione si concentra su come le rappresentazioni migliorano la comprensione attraverso le loro scelte di progettazione. Queste scelte di progettazione sono fondamentali per fornire ai comuni il quadro perfetto per chiarire la realtà. Sia il colore che l'interattività hanno un impatto sulla definizione di nuove decisioni politiche, se mirate al segmento corretto della società.

Per affrontare queste sfide, la presente tesi di laurea magistrale sviluppa **l'Urban Inequality Indicator (UII),** un indice composito specificamente progettato per identificare i modelli spaziali di disuguaglianza negli 88 Nuclei di Identità Locale (NIL) di Milano. La metodologia seguita introduce un approccio innovativo che sfrutta i pregiudizi soggettivi raccolti nella progettazione dell'indicatore, ottenuti attraverso sondaggi tra i cittadini. Inoltre, è stata effettuata un'analisi comparativa tra i metodi di aggregazione aritmetica e geometrica. I risultati hanno indicato che un modello geometrico previene in modo più preciso la potenziale deprivazione critica causata da grandi differenze di valori. Con questo metodo, si evita la compensabilità tra le dimensioni.

I principali risultati della ricerca indicano che l'ingiustizia urbana non dovrebbe essere considerata come una metrica statica, ma piuttosto come una variabile mutevole all'interno delle coorti di età. L'analisi statistica effettuata mostra disparità tra i gruppi demografici. Inoltre, applicando tecniche di autocorrelazione spaziale, in particolare l'indice di Moran locale, è stato possibile identificare cluster di disuguaglianze.

In conclusione, la tesi dimostra, con dati e un ampio background bibliografico, che affrontare le rappresentazioni dei pregiudizi cognitivi sulla base di questi dati supporta decisioni inclusive e mirate. Il risultato finale, l'Indicatore di Disuguaglianza Urbana (UII), viene proposto come strumento che i comuni possono utilizzare per rimodellare le città sulla base delle opinioni reali dei cittadini. Deve ancora diventare il nuovo standard per alleviare le disuguaglianze.

Parole chiave: dati spaziali urbani, pregiudizi cognitivi, rappresentazione dei dati, indice composito, città intelligente, Milano.

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1 Introduction

Since the dawn of time, humans have needed data to survive in our system. It is not surprising that, over the years and with the increasing complexity of societies, the extraction of this data has changed. With these advancements, the capacity for analysis has increased significantly. Now, the various datasets are not merely numerical values; they are the trigger for identifying a correlation with a problematic situation.

This research focuses specifically on a particular type of data points and the manner they influence other elements. The extraction and analysis of urban spatial data (data related to the shape and distribution of the cities) could facilitate the establishment of a direct correlation with the policy decision-making process (Rojas-Padilla et al., 2022). However, depending on how these datasets are transmitted (represented in this case), it may influence the result, potentially leading to either a deeper understanding or inaction due to poor interpretability or mistrust. Even when high levels of data literacy are present, the interpretation of spatial representations remains subject to inherent subjectivity and cognitive bias.

This thesis establishes the theoretical foundation for how urban data collection, processing, and visualization methods contribute to the identification of spatial inequalities and, by direct contact, in highlighting evidence-based policy decisions and city-planning. By bridging multiple dimensions to design the Urban Injustice Indicator (UII), this work pretends to bring back light on biased representations.

The key point of this study is that it is not only important the objectivity of the data frames, but also pivotal the influence it has the demographic profile of the observer. This is encompassed by analyzing different age groups, to extract a pattern. Understanding the representational biases is essential for urban planners to ensure that cities are shaped around the citizen's requests.

The existing literature often treats the indicators as mathematical outputs from the analysis. By, building the UII indicator with subjective bias it will put a precedent in the field putting the opinions at the center of the calculation.

By synthesizing perspectives from data ethics, geospatial analysis, and subjective social weighting, this thesis will end with static calculations to actionable results. Due to this interaction between classical calculation and urban subjective governance this study seeks to answer the following two core research questions:

RQ1: To what extent do perceptions of urban inequality and spatial justice diverge across different demographic age groups?

RQ2: How can dynamic data visualization strategies effectively represent these age-dependent disparities to facilitate inclusive urban policymaking?

2 Literature review

The assessment of urban inequality has expanded, now taking into account not only economic and physical factors but also spatial justice and the role of data-driven governance. The main challenge here is to design cities that can respond fairly to all these different aspects. With the development of the information technology, smart cities have started to use advanced data analysis tools, which allow local governments to carry out more complex studies. It is important to note that these technological advancements, have raised the alarms of all professionals, regarding data ethics.

This chapter examines the conceptual foundations and methodologies required to connect technical data extraction with citizens lived experiences. The central argument is that urban data does not objectively reflect reality; rather, it is shaped by methodological choices and cognitive frameworks. Data outputs may be influenced by modifications to extraction methods, parameters, conditions, and constraints, potentially resulting in biased interpretations of reality (Rose & Chang, 2023). The same dataset and its various representations can produce diverse outcomes depending on the age segment you ask. Even when urban forms are presented as neutral, the personal biases of data consumers often remain.

One of the most common form of seeing data, is orchestrated inside an indicator, to reflect a certain part of the reality. As many indicators, the tendency is to overlook subjective considerations.

This review examines how different age groups perceive their environment. Then, integrate these perspectives into a single index reflecting human bias. This indicator is the Urban Inequality Indicator (UII) that combines quantitative data with personal experiences, permitting policymakers with a thorough tool that captures the complexity of urban life. At the end of this review, it must be clear how perceptions can lead urban planning decisions, such as budget allocations for safety or community projects. The conclusions from this review guide the development of the indicator to integrate measurable data and diverse age group experiences.

The following sections present the key concepts needed to address the study's research questions. It would examine how various groups perceive their environment (RQ1) and how visual tools can help bridge these differences (RQ2).

Structuring the narrative, it begins by explaining the value of composite indicators in integrating diverse data types to provide a comprehensive view of society, safeguarding always the ethical part. It then addresses how personal bias can influence data representation and interpretation. The final section examines how the representations could influence policymaking .

Collectively with the literature review will support the development of a subjective indicator (UII), combining the natural mathematical rigor and the opinions of citizens.

2.1. Foundations of urban data and statistical modeling

The ultimate objective of data extraction is to interpret societal dynamics that are not yet empirically supported. However, the possession and the analysis of data should be always in the center of attention, to have a realistic calculation to portrait. The core objective passes always by the final representation. This final outcome allows researchers and stakeholders to visualize trends and uncover correlations that might otherwise remain uncover by poor analysis (Fernández-Castilla et al., 2020). Consequently, achieving a meaningful outcome requires a profound understanding of the technical and mathematical concepts, involve in the analysis.

Understanding this serves as a base to construct composite indicators that addresses technical requirements and subjective urban perception.

2.1.1. Spatial patterns and urban dynamics: a data-driven approach

For this data to generate real outcomes, it must consider the spatial dependences when analyzing the urban context. In this classification, the concepts of spatial correlation and spatial heterogeneity are defined:

- **Spatial association and autocorrelation:** these terms describe the degree to which variables, in this case urban spatial data points, are correlated. In this study, this refers to the distribution of specific metrics associated with Milan's *Nuclei di Identità Locale* (NILs, or local neighborhood units).

Applying this theory, it can be concluded that the positively correlated zones are due to a high degree resemblance between them (high values adjacent to high values). On the contrary, the negative correlation is due to the proximity of diverse patterns (Schuster-Olbrich et al., 2024) .When applied to neighboring clusters, this concept gives rise to spatial autocorrelation.

- **Spatial heterogeneity:** the non-uniform distribution of variables across an area. Analyzing heterogeneity is essential for understanding the abundance or scarcity of specific urban factors across the territory (Ju et al., 2025).

In the subsequent sections, the principal emphasis will be on the spatial autocorrelation between parameters, as its analysis can reveal heterogeneity in itself. Moreover, when analysing spatial data, attention should be paid to statistical inference, models, and functional forms to avoid potential misunderstandings (McMillen, 2003). The principle of parsimony, or Ockham's Razor (Gibbs, 1997), postulated in the 14th century suggests spatial data analysis can typically be explained by the simplest (least-dimension or least-complexity) model.

However, this should be treated carefully as some marginalized voices are hidden when simplification appears. Establishing the right balance between simple models and detailed ones is important.

Balancing these considerations ensures that spatial data analysis stays accessible as well as inclusive. A mixed method approach, as well as testing the sensitivity, could offer a comprehensive model on urban inequalities. Applying this, the integration of multiple data sources is a reality and will improve the robustness. Furthermore, the subjective part enhances the inclusiveness.

The literature highlights the importance of autocorrelation in urban analysis and the distinction between global and local indicators (Bivand & Wong, 2018).

- **Global indicators:** These measurements consider the entire dataset to identify general patterns. For instance, if analyzing regional income levels, a global indicator determines a spatial pattern of wealth that exists across the whole society. While it identifies overall behaviour, it does not pinpoint specific clusters. One of the most notable global indicators is Moran's I, calculated as follows:

$$I = \frac{n}{\sum_i \sum_j w_{ij}} \cdot \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \qquad (1.1a)$$

Where:

n: is the number of areas in the whole distribution

x_i*: is the actual value in the area i*

$\bar{x}$*: is the mean of all values*

w_{ij}*: is the spatial weight (1 if areas are neighbours, else 0)*

The functioning of this value calculation is as follows: a positive, relevant (near +1) value indicates clustering in the global view, while a negative (near -1) value indicates dispersion in the data around the area (Hartati et al., 2025). Values approximated to 0 are considered non-relevant. Another metrics, like Geary's C and Getis-Ord G, have a similar result as Moran's I, with some mathematical adjustments (Yamada, 2024).

- **Local indicators:** These correlate specific clusters with their neighbors to identify localized heterogeneity. They answer whether a zone is a "hotspot" (high-high), a "coldspot" (low-low), or an outlier (high-low or low-high). Luc Anselin formalised this through the Local Indicators of Spatial Association (LISA) (Anselin, 1995) . Given the indicator's nature, operating at a neighborhood level is perfectly suitable to underpin the council's intervention in affected areas. It is generally accepted that these indicators involved in this determination are variations of the previously exposed global metrics for the local cases in the spatial data. By identifying these localized hotspots, governments can make a more optimal redistribution of resources . For example, if a specific neighborhood is identified as a 'hotspot' in the dimension of low-income, councils may give priority to social programs or to build houses with lower rent prices, to address inequality within these clusters. Utilizing these tools, leverage the existing resources for concrete actions.

$$I_i = (x_i - \bar{x})\sum_j w_{ij}(x_j - \bar{x}) \qquad (1.1b)$$

Where:

A high value of I_i is related to hotspots (HH)

A low value of I_i is related to coldspots (LL)

Between those values, we find the outliers (LH) and (HL)

The difference between global and local perspectives is a key point in this thesis. Global autocorrelation gives a general statistical picture of Milan. However, it is a well-established fact, as evidenced in numerous cases, that the presence of a global autocorrelation can hinder the identification of possible clustering behavior. For that local analysis tools are needed to see how different demographic groups actually experience specific areas.

As said before, global indicators are useful tools in a bigger picture scale, to identify patterns without details.

However, when the goal is to address specific inequalities or to adapt policies to neighborhoods, local indicators are necessary. This metric reveals disparities at the street level and with the right analysis, lead to policy making .Thanks to the advancements in mathematics and to the engineering art of applying the knowledge into real-world applications, these dynamics are used more than just for descriptive purposes.

Through a mathematical analysis of clustering zones, the identification of stress zones leads to the identification of spatial justice or injustice, and the subsequent urban planning (Feitosa et al., 2024). The effective application of spatial analysis is essential for redefining cities into open environments for all citizens (Forde, 2024).

This is an essential part of comprehending urban dynamics. Recognizing the appropriate context for shifting between global and local perspectives enables planners to translate conceptual perspectives into practical urban planning, guaranteeing a comprehensive approach to urban inequality.

The study of these physical characteristics and their relation to municipal strategy is known as urban morphology. The study examines the physical characteristics of the metropolis (size and interconnection of streets, blocks of buildings…) and their relation to life and municipal strategic decisions. The objective of these last decisions is typically to determine how the territory's landscape should be expanded (Schuster-Olbrich et al., 2024).

On this field, it could be seen urban representations regarding city connectivity (Boeing, 2021) and even interactive platforms where it exposes economic factors in correlation with the resources distribution in the city of New York (Equity NYC, 2024).

Integrating all these measures allows us to discover new trends. One of the most interesting points to study is the presence of inequality hotspots. Here, various studies indicate that perceptions of these inequalities vary across observers (Kellogg et al., 2023).

For example, people aged 18 to 30 associate perceptions of inequality with limited access to the digital advantages cities offer. On the other hand, people over 60 perceive urban injustices. The latter focuses on access to health services. Given the various problems facing the city of Milan, it is interesting to conduct age-based studies to see inequalities with our own eyes.

Using Moran's I and LISA models, this study proposes conducting objective analyses while integrating people's subjective views. Only in this way will it be possible to detect the hotspots and cold spots present in each age group.

2.1.2. Why Data Extraction Matters for Cities

As previously discussed, the reality of data extraction is particularly relevant to urban areas, revealing the patterns of cities and the subsequent targets of specific problems.

Furthermore, the portrayed information possesses inherent meaning and implications in society. As in the paper written by Kitchin, data-driven decisions are being made to change urbanism, reflecting a neoliberal mentality. In this paradigm, citizens are seen as consumers and do not have a significant participation in the "smart city" decision-making (Kitchin, 2019).

In this context, spatial data points function as markers that require specific actions depending on their context. This allows researchers not only to monitor global efficiency-based trends regarding the management of urban populations (Kitchin et al., 2018), but also to go deeper into the uneven opportunities embedded in the landscape (Equity NYC, 2024). This analytical depth is essential to understand how different demographic cohorts perceive urban space (RQ1), as some beneficial actions for one group may represent a barrier for another.

One of the main reasons to extract information is to redefine past knowledge into future possibilities through predictive analytics. Data allows analysts to build robust tendencies and predictions based on lived experiences; the inference drawn from these longitudinal datasets can suggest the creation of sophisticated models to palliate complex structural problems.

A clear example of this is found in the management of critical infrastructure, such as the ageing of reinforced concrete bridges (An et al., 2025). In that specific project, the authors analyzed the corrosion tendency of bridge columns due to varying exposure conditions. Because existing models were not capturing the complexities of new datasets—particularly where non-uniform corrosion types appeared—random multivariate models came as a solution. Hence, the extraction of data is crucial to understanding the city.

However, it is imperative to note that raw data is merely that, data points in a spatial field. The critical process of transforming those sets into insights is inherently rooted in the human cognitive layer (Padilla et al., 2018). In this sense, urban data is not a neutral numerical value; it is an actual representation of the morphological and social shape of the city.

The application of theory and quantitative methods is compulsory; however, the interpretative dimension is a refined tool that ought to be use. Correlating risk-related land with existing racial segregation (Jesdale et al., 2013) or analyzing tree total area in urbanized US lands in relation to income—revealing that low-income areas often lack the environmental benefits found in wealthier districts (McDonald et al., 2021), are concepts that stray from purely mathematical analysis.

For that, even more important than extracting the data in a good way, is to recognise the social dimension of it. Only with this path can data visualisations help to fulfil equity goals in governments. (Nash et al., 2022).

This reflexive line of thought matches how different visualizations of strategies could be interpreted differently, depending on the direct observer (RQ1). Ensuring always that the frame used to translate data points into insights is inclusive and demographically sensitive (Matthew W. Wilson, 2016)

2.1.3. Statistical Frameworks: Composite Indicators, Normalization, and Aggregation Logic

When it is talked about the results of data representations or conclusions, it is always shown by the means of an indicator. Because spatial data has many dimensions, it is important to look generally at how composite indicators can bring these different aspects together to improve our understanding of urban phenomena (Lara & Rodrigues da Silva, 2020)

Composite indicators (CIs) are metrics standardized to compare and analyse diverse countries, overcoming local disparities by using other indicators. In general, CIs are aggregated metrics derived from smaller sub-indicators, thereby improving their interpretability (Vinkler, 2010).

This significant advantage, while easier to interpret, can be misinterpreted or misstated, so it is important to provide the corresponding documentation and explanation for each dimension and its treatment. (Wehbe & Baroud, 2024) Deprivation, injustice, or well-being are key elements in several studies (OECD, 2008) Moreover, this handbook specifies that indicators should be constructed following an organized set of steps. Specifically, for this study, the following steps will be adopted:

1. Developing a conceptual framework to establish a meaningful composite indicator.

2. Selection of data for analytical soundness and relevance.

3. Normalisation of data to ensure comparability.

4. Weighting and aggregation are consistent with the theoretical basis.

5. Conducting uncertainty and sensitivity analysis to validate the robustness of the indicator.

By complying with these steps, the methodology is made clear, which helps to make the composite indicator more transparent and reliable for this research.

An analysis of the aforementioned list shows that steps three and four are of particular interest. Data normalisation is a basic requirement for ensuring accurate data comparison. If the scale is not the same, the results will be incomparable. After that, data aggregation and weighting must be done in accordance with mathematical standards (OECD, 2008).

Taking the example of the HDI (Human Development Index) the normalisation and aggregation of three categories was applied: health, knowledge, and standard of living, following the steps outlined above.

When discussing specific methods of data aggregation, we must mention the geometric mean and the arithmetic mean.

There is no clear choice as to which is better or worse, but there is agreement on the advantages and disadvantages of each. This knowledge allows us to know when one or the other is more optimal.

Taking another example, such as Gross National Income (GNI), suppose that a country has a high value in one category but a very low value in another, such as life expectancy. The resulting arithmetic mean value will be a direct weighting of the two, which will result in a compensation towards a midpoint, giving a false sense of balance and equality. This is why, in composite indicator analysis relating to social data, a geometric mean is used to prevent this effect (Nations, 2025).

With this in mind, the question arise as: which method works better for urban spatial data?

To answer this, it is necessary to talk about compensability. As shown in the figure below, when data points are given certain weights, the arithmetic mean (an additive method) can end up treating values that are close together the same as those that are low, allowing a high value to make up for a low one. These are known as additive methods ((Esri, 2024).

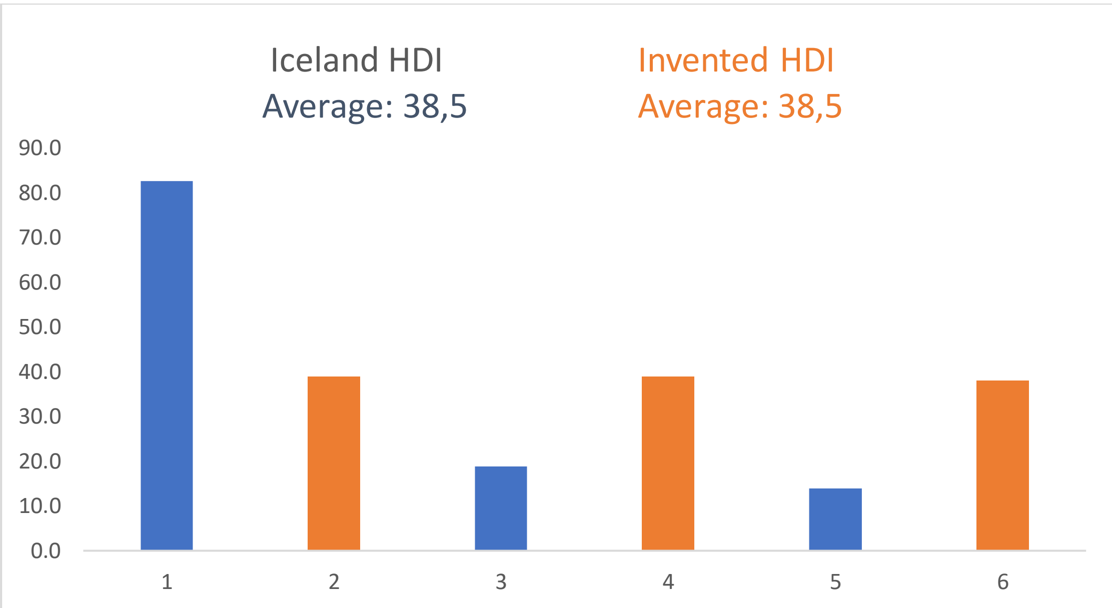


Figure 1: Comparison of how additive methods compensate high/low values

On the other hand, multiplicative aggregation strategies are non-compensatory, which means that a low or high value in one category does not get cancelled out by another value (Bruzzi et al., 2020).

The HDI example makes this clear: if a country has low life expectancy but high income and education, should it really be seen as equal to a country with moderate values in all three areas?

For multivariate analysis, the commonly used approach is to analyze the aggregation part with a geometric mean, because it puts the lower values as the ones with more importance for the index creation. In this way, the countries (or specimens under study) are not falsified by values that are much higher in only one category (Mariani & Ciommi, 2022).With this approach to indicator statistics, the standard deviation of the results is significally relevant, making the results better aligned with reality and giving greater weight to indices with less disparate values (Chakrabartty, 2024).

Another dimension of the construction of CI is the weighting theory. Schemes like AHP (Analytical Hierarchy Process) classify sub-indicators by their importance more effectively than Principal Component Analysis, because all the information is retained (Echebarria et al., 2025). Then the importance is expressed as a percentage of its actual contribution to the study.

For this study, the weighting scheme was built using subjective opinions collected from both online and in-person surveys with people living in Milan. This way, the composite indicator is based on what residents actually think and prioritize, making sure that the lived experiences are included in urban planning. This method gives a more subtle understanding than Principal Component Analysis (PCA), because it manifests the subjective voices of citizens.

By using these methods together, it becomes possible to construct an actual UII with a bias of resemblance.

2.2. Smart cities, data ethics, and inequality

As in a futuristic film, technology is gaining increasing power over human processes. In big cities, it is increasingly common to find a wide range of sensors and cameras monitoring citizens' movements. This in pursuit of the development and collection of data that allows the best redistribution of available resources. The influence of that data is, on paper, positive to improve safety and efficiency, but what if people feel continuously observed?

As previously discussed, technical data extraction constitutes a base for extracting data analysis. And also, the main concern is to connect these technical aspects with a critical discussion of the implications of data for social inequalities and data ethics.

When designing urban data studies, it is very important to incorporate ethical considerations to ensure fair treatment of the people behind the data, while also being rigorous about the technical implications. To take one example, misclassifying a neighbourhood as tense can mean extra effort is required to orchestrate risk mitigation strategies. Therefore, it is crucial to maintain ethical and technical rigour throughout the analysis to reduce the risk of misclassification and maintain confidence in the solutions proposed by smart cities(Lim & Taeihagh, 2019).

In this context, the investigation evaluates ethical risks associated with smart cities, mainly concerning surveillance and its relationship to urban inequalities (Wang et al., 2025).

Since the beginning, with Amsterdam among the leading smart cities in Europe, other cities have joined the revolution (Capra & Francesco, 1 C.E.) .The term "smart city" includes various concepts and definitions(Gracias et al., 2023).

From the analyzed papers, the definition of a smart city remains unclear. This may imply detrimental outcomes for policy makers trying to implement digital projects. The actual reason for setting the scope to the digital or technological part is that the papers investigating the definition of the matter converge in placing new technologies at the center of attention (Ismagilova et al., 2019). Studies similar to those by (Guo et al., 2017) point out the core significance of integrating the reality of communication devices across the city and how these solutions benefit urban morphology. But why is new technical progress vital to the discussion of digital cities (another name for smart cities)?

At the technological layer, the cities with this designation are characterized via integrating ICTs (Information and Communication Technologies) and data analytics into the urban environment to leverage hidden opportunities and raise overall wellbeing (Nastjuk et al., 2022). With this implementation, the towns are becoming more effective and efficient by monitoring infrastructure and sensing public spaces to obtain KPIs.

With these understandings, governments can align these purposes into "smart governance". The concept is directly a consequence of the technology implementation, just applying it to public services and basing decisions on evidence (Almulhim & Yigitcanlar, 2025).

Nevertheless, the definition is not free from criticism. The general awareness of the data provided by technology is a supposition of impersonality and apoliticism. However, studies have stated that the theory of a neutral implication of smart city policies is poorly supported. Instead, the neo-liberal and technocracy loopholes are evident (Kitchin et al., 2018) . Studies like the one mentioned before show that smart cities view people only as consumers and data points. This reductionist approach has a central role in reducing urban problems (Bibri, 2022).

This decision is not made without supervision. The role of citizens in new technology-based cities is under monitoring, and conclusions are determined based on the primary trend.

Many lines of investigation show that citizens are not taking an active part in the governor's field. As the paper by Rob Kitchin argues, the role of inhabitants in a civic context is key to understand the implications of ordinary people in these applications and representations (Kitchin, 2019)

As four identities are presented (Cowley et al., 2018), citizens behave normally as 'service users' or 'consumer users', not taking participatory positions in citizenship dynamics or planning for punctual issues in their public environment. It is not surprising that, in this field, many studies have been conducted to quantify human interactions with public services, such as consumer tendencies on weekdays (T. Yamada & Hayashida, 2020). This situation is leveraged by the (smart) cities, taking a position of stewardship, where the municipalities are deciding on behalf of their interest, just adding value from the fewer 'active citizen'(Kitchin et al., 2018).

The vast majority of citizens take a passive role in local participation. To delve deeper into the resources that authorities invest in researching citizen opinion, some studies present examples of action. This involves analyzing the digital footprints left by citizens on social media or directly asking for their opinion. These proactive behaviors on the part of local authorities go hand in hand with the low level of citizen participation that is generated if a direct approach is not taken. If you want data and you don't have it, you have to ask for it directly.

For this investigation, the conclusion came as this: smart cities are not just interconnected cities with a bunch of representations. The normative layer exposed in the review indicates that city governance is pointing towards a data platform.

As in the paper by (Jeong et al., 2020) based on the Korean smart city project, the future of cities is passing through integrated IoT devices across the land, all orchestrated via APIs. This summarizes the problem to only the ones shown on the platform, along with measurements, indicators, and metrics. This reductionist approach is dangerous because humans present data, and humans decide what to show. An ethical implication should be considered to avoid misjudgments or underrepresentation. (Philip Chen & Zhang, 2014)

It is particularly important to recognise, with respect to RQ1, that perceptions of urban inequalities in smart cities can be easily misinterpreted among diverse age groups (Beaunoyer et al., 2020). For instance, the paper on this field shows that, the same data representation or urban indicator might be interpreted by younger citizens differently to senior people. It could be indicating an acute need for digital infrastructure, but older adults are less critical with this subject and might prioritize other indicators, like healthcare or walkability (Schuster-Olbrich et al., 2024).

It is interesting to note this variation, as it can lead to the unintentional overrepresentation of certain age groups, while others are disadvantaged. This is particularly clear when automated platforms are used, as ethical review remains an issue in this area.

Therefore, reviewing these ethical implications must be a constant in the integration of tools of this type. Smart cities offer opportunities for improvement. However, we must avoid unconsciously governing for a specific group, whether defined by economic capacity or age.

By following these steps, it can be ensured that analyses maintain technical accuracy while accounting for the realities of all social and age groups. An inclusive and ethical approach can amplify inequalities and improve the design of the urban environment.

2.2.1. Ethical implications: algorithmic bias

Smart cities are not bad by nature; in fact, their solutions offer great benefits to control the entire city and improve its processes. However, it is important to highlight the ethical implications and the limits that must be adopted, so as not to violate the limits of privacy. These IoT control and measurement devices can generate tensions and surveillance sensations, of which any city must be aware and alleviate them as soon as possible.

Some challenges smart cities are encountering are the following:

- Surveillance and privacy issues
- Inequalities in the algorithm world

For the first point, the work by Ziosi (Ziosi et al., 2024) captures the exact concerns of this topic. In this paper, it is exposed that the implications of networked devices are "issues of control, surveillance, data privacy and security". By nature, smart cities inevitably present elevated levels of control across all aspects of people's lives. The combination of IoT devices (such as sensors or cameras) monitors the behaviour of the city's inhabitants, as was stated. The vast collection of data from different sources enables urban planners to understand behaviors, but it can violate privacy regulations. As the essay “The Moral Issues of Artificial Intelligence in Urban Planning” argues, AI is worsening problems of privacy and tracking by making automated decisions that violate individuals' right to be unseen. Cases like camera surveillance or facial recognition may violate these rights(Sanchez et al., 2025).

Normally, the models are precise, and with the proliferation of AI-based intelligence in urban dynamics, the results are more accurate. Nevertheless, the algorithms in society seem somewhat biased (Wang et al., 2025).

The Greenlining Institute defines these algorithms as algorithms which may yield unfair results, greatly satisfying one segment of society at the expense of others, or that directly engage in disparate treatment towards certain groups of people (Greenlining, 2020).

Before, in this passage, we discussed that the raw data is impartial, and this affirmation is partially true. When analysing algorithms, the data used is typically historical, and the decision on what type of data to store was not impartial or unbiased. These kinds of concerns are appearing in predictive models developed by police to prevent riots, crimes, or attacks in certain areas. Madison Cutler explains in this article that some American police stations have encountered problems when their predictive policing platforms correlate certain areas with criminality and fail to conclude that those areas need a reallocation of resources rather than a greater police presence (Madison Cutler, 2024)

The algorithms are not racist by themselves; the corrupt data may be. Moreover, the way these tools are developed, with an optimization approach, tends to serve wealthier, more developed classes rather than disadvantaged communities. So, questioning these smart city applications is fundamental to tackle potential uneven representation and to understand the urban reality (Lihua, 2025)

The analysis of this topic suggests that potential algorithms must create a system in which the search for equality is a primary asset. This chapter stands among the others, with a clear position into not taking for granted the outcomes of data analysis as the truth. As argue in this text, the reality could be shaped by the observant depending on their age but also could be misleading when not applying an ethical concern in the analyst.

2.2.2. RQ1: To what extent do perceptions of urban inequality and spatial justice diverge across several demographic age groups?

The way inequalities are seen is not equal for the vast majority of the society and this subjective perception should be studied and tracked to extract a pattern (Hajnal & Trounstine, 2014).

One example of subjective bias is when discussing data granularity. In a study by Oscar Nels, in collaboration with other investigators from the USA, they determined that a single-fitting model was not possible, as neurotic people tend to detect associations more readily, even when the granularity and the task mismatch (Oscar et al., 2017)

The subsequent references are based on surveys carried out in 26 communities in the USA, centered on the impact of specific politicians and their policies (Smith et al., 2023).

The analysis separated people according to political, racial, and economic backgrounds. The main findings suggested that communities with the least opportunities (lower rent per capita) report lower satisfaction than richer areas. This finding is not an outlier case, represent a real problem. This example manifests that the same reality could be felt in different ways, depending on the people asked.

The differences in perceptions are evident, and the sociocultural gap is a plausible explanation. However, centring the scope, many studies now point out that age differences assume a big role in molding how people see urban inequalities.

How people react to different spatial inequalities is crucial to understanding the sociological reality. When focusing only on age, younger people tend to focus on different factors than adults and senior citizens. This changes the valuation of the appreciation of urban injustice. (Beaunoyer et al., 2020).

For example, adults and elderly people find the accessibility of streets and the proximity of health services important. Studies show this exact behaviour, where seniors identify these aspects as the main contributors to uneven opportunities in the city (Patil et al., 2024). So, this group tends to prioritise practical, everyday issues that directly affect their independence.

On the other hand, younger users usually pay more attention to connectivity, rent prices, and a strong socio-cultural offer in the city. A lack of a fast internet connection or excessively high apartment prices are identified as main drawbacks of a smart city.

Due to these different priorities, policies are not beneficial for both groups at the same time. If investing more in improving digital infrastructure increases young people's satisfaction, the problem should also be addressed so that older people are benefited and listened to. This underscores the need for a multifunctional analysis to measure these inequalities, accounting for generational differences. Building a city where everyone feels heard should be the goal to follow (Urria et al., 2025).

Comparing studies, it is clear that adding an age variable to urban analyses makes the decisions made by municipalities fairer (Li et al., 2025). By examining how young and old people perceive cities, decision-making will clearly benefit. For this, the visualisation of these inequalities through maps is key to understanding how to do it. Based on these age ratings, decisions will be made using opinion data from the city under study.

In conclusion, addressing the problem from a multifactorial analysis perspective, focused on differences with age, allows us to understand social inequalities in a comprehensive way. Future societies must base their decisions on making cities balanced with citizens' needs. And that happens by including all opinions in the decision chain to increase veracity.

2.3. Mapping injustice: the spatial representation of inequality with a purpose

When mounting a compound indicator, it is important to keep in mind that these data must be interpretable. And no longer only interpretable urban data must reflect the different realities of citizens by age. Only in this way will it be possible to achieve clear interpretations and measures by the groups of influence and the municipalities.

The way these indicators are presented should make the specific perceptions and experiences of urban inequality visible. In the following section, the analysis of different styles will help clarify the literacy needed to understand the range of demographic realities more comprehensively.

2.3.1. The importance of spatial representation in inequalities and policy adoption

Dynamic spatial representations, such as interactive maps, dashboards, and layered visualizations, are essential for showing how injustices are distributed among different age groups in the city. By the use of tools like GIS, it eases the task to overlay different dimensions, which could lead to the identification of specific neighborhoods where certain age groups face more pronounced inequalities (Padilla et al., 2018).

For instance, mapping areas with low digital connectivity together with the distribution of young people permit the possibility to highlight districts that require investment in broadband technological services. In the same way, looking at the senior segment of the society, if we look at access to medical care and mobility in relation to where older adults are concentrated, it becomes clear where there are gaps in basic services and where to target interventions. It is important to note that the literature shows how the clarity, deep understanding, and interactivity of these tools have a direct impact on their usefulness for policy decisions (R. Zhang & Nie, 2025).

To change generalist policies to more inclusive ones, visual representation by age-groups obtains a clear importance (Saha et al., 2022) (Schloss et al., 2019b).

For this reason, the way these representations are designed and used is not just a technical matter, but a strategic choice that can have real consequences for urban equity and social justice.

The first question to be answered here is how data treatment leads to an interpretation of reality. The answer is not naïve; the model chosen may produce uncomfortable results, such as underrepresentation (Luo et al., 2025) or stigmatization of certain areas of the city (Tedeschi, 2024). But not only the model, also the way datafication in cities is distributed, shows an imbalance in the representation of people's problems.

It is important to clarify that the data limits are due to the fact that their coverage is not uniform throughout the city. This causes, for the most part, communities with fewer resources to be marginalised by the lack of representation. Nor is the solution to use more generic data batteries at the spatial level, since these can trigger simplistic conclusions that do not look at the real problems of the neighbourhoods.

The solution is to know this reality and carry out studies in which these data are subject to social and ethical considerations.

However, to put this into context, in the current Big Data society, information is widely available, and many studies are carried out to extract relevant data points.

As has been said, combining large sets of data with socioeconomic variables can yield a much more robust understanding of society and its inequalities than the current one. Always going through an exhaustive knowledge of the society under study (Wu et al., 2020).

Various dimensions, such as housing, mobility, and environmental exposure, have been studied. Mapping these inequalities is essential for identifying where public resources need to be adjusted.

For example, in the work of Brazilian researchers (Lara & Rodrigues da Silva, 2020) the approach was to use existing datasets to create a metric called the Pedestrian Crossings on Urban Streets (PeCUS) index. This index was designed to show how travel patterns have changed over time due to uneven, unplanned city growth. Without going into more detail about the use of technologies from smart cities, such as IoT surveillance or measurement sensors, the study identified more than 10 dimensions. The mathematical analysis showed that perceptions of inequality were linked to vulnerability and poverty, in addition to other variables such as age. The final step was to present these findings through graphical representations, which is a common outcome in many studies on urban inequalities.

Regarding another part of the urban context, access to green space is a great concern. Pallathadka (Pallathadka et al., 2022) ,after the COVID-19 pandemic, did a paper thesis in which they manifest two central concerns: *"(1) the relative racial vulnerability* *of Census Block Groups (CBG) and ZIP Code Tabulation Areas (ZCTA) to COVID-19 (2) green space distribution at CBG and ZCTA scale".*

The paper analyses America's distribution of green spaces in four states, grasping the idea that African American tends to be affected more by the pandemic due to the poor or null access to these public green spaces, exposing an endemic problem.

The revision of studies presents a wide range of analytical indicators for the specific division of the injustice. However, there are clear similarities in the expanded use of tools based on geographical representations.(Faka, 2025).

One of the most widely used software for spatial data analysis is GIS (Geographical Information System). Just giving a definition is hard to condense, since it involves many interactive factors. These systems are based on geographic references, and, according to the National Centre for Geographic Information and Analysis (NCGIA), the definition can include all software and procedures used to analyse and display georeferenced data. Mathematically, the model is based on coordinates in a Euclidean plane, using points, vectors, and polygons (Escobar et al., 2008). At this project, GIS tools were used to carry out all the studies and graphical interactions.

With this information, the technical and social aspects of these representations are addressed. The exposed point is that representing information through urban reality datasets is about making the actual conditions and the injustices they reveal visible.

In this regard, it must be cautious to avoid introducing unwanted bias into the collection and analysis part. Recognising the reality should inform analysts that bias considerations come in the following steps. As mentioned earlier, subjective evaluation should be conducted only after the data have been objectively collected and processed. The interpretation should always follow a careful and neutral gathering of information.

2.3.2. Interpretative bias present in urban representations

Metropolitan environments are, by their very nature, complex socio-technical systems, shaped by a wide range of socio-economic, environmental, and infrastructural patterns. It is well established in the literature that the shape of the cities is determined by multiple factors, rather than individual assessments done in specific environments.

In recent years, the way cities are understood has undergone a 180-degree shift due to advances in digital transformation. This has increased the availability of spatial data, enabling urban disparities to be mapped more effectively. In turn, this greatly benefits the traditional issues of dealing with geospatial data, such as mobility, accessibility, or injustice. These technological advances enable us to reach more accurate conclusions about the problems in urban society (Wu et al., 2020).

Putting the city of New York as an example, the adoption of new public transportation policies, guided by accurate geospatial mapping, it is no surprising to have an immediate impact in improving accessibility and reducing congestion in areas that have historically been underserved (Yi et al., 2025).

Such policy changes serve to illustrate the relevance of geospatial advances for the public and their direct influence on the quality of urban life.

Within this section dedicated to the theoretical background and literature review, the main objective is to extract and present the key findings related to interpretative bias present in visual representations. The following pages are intended to provide an overview of the existing forms of representation, with particular attention to how the selection of different approaches can enhance understanding for specific levels of literacy and for certain age groups within society. The intention is to clarify how these choices in visualization can influence the perception and interpretation of the data, as supported by the literature.

2.3.3. Mapping types

The key aspect to base this section is communicating urban spatial inequalities to stakeholders, from a perception of the city and drives new policies.

Studies show that multi-stakeholders' analyses are a must to understand the different literacy levels. In particular, the paper "Visualizing Urban Accessibility: Investigating Multi-Stakeholder Perspectives through a Map-based Design Probe Study" gives people diverse types of data visualization methods. Twenty-four representations were exposed in the investigation to determine how inaccessible is the area of Washington D.C

Conducted in two different experiments, the conclusions were, precisely, that the policy makers and department officials are more interested in going in depth about the task provenience and its implications (going into a high level). On the other hand, caregivers and mobility impairments (who we could consider citizens) were more focused on a low-level problem, wanting a solution rather than a multi-factor analysis of the underlying endeavor (Saha et al., 2022).

The literature suggests that design choices should prioritize maximizing data interpretability. Putting transparency as the main asset regarding data extraction and modelling in the whole processes, supports the idea that multi-variable representations are trustworthy.

To achieve that ultimate goal, it is important to apply specific design practises. The use of legends, the application of adequate and accessible colour palettes, and the incorporation of explanatory annotations help ensure an intuitive use of the representation. Thus, clear guidelines can be provided to those responsible for interpreting the data.

The literature presents the different typologies of maps in a collective society (Jeremy W. Crampton, 2010). Before going into detail about the best performative ones, regarding our scope, the outline of the most important portraits needs to be done (UNHCR, 2026).

- **Point map:** these are straightforward maps, specially used to point out specific locations in an area. With a quick look, you could sketch the density of a specific dimension of the concept under study. The points could also have pin icons, as people associate them with locations. When introducing the value of a variable, it is important to rename it to 'bubble maps'. The size of each bubble indicates the importance of that region to the analyses, perfect to compare the same variable in the whole country (Lewis Chou, 2019).
- **Line/street map:** especially interesting when the aim is to highlight a route or trends in the streets of certain cities.
- **Heatmap:** normally represented as a conglomerate or a mass divided by colours to differentiate high and low values (Tjaden et al., 2024).
- **Grid maps:** this interesting type of map divides the area into equally sized zones of interest. Used when no exact information is available.

- **Choropleth:** a combination of heatmaps and grid maps, is a representation in which defined areas (like cities) are coloured according to a colour scale or a progressive opacity/darkening of the same colour, depending on the data available. Taking Figure 3 as an example, the darker the blue, the better accesible is the part of the city. Normally, the legend indicates an interval in which the different tones are laid out.
- **Region map:** in this category, it encompasses all the versions of the same nature, but with different zoom levels. It is a map that shows information at the country/region/neighborhood level. It is mandatory to use a legend to see possible trends.

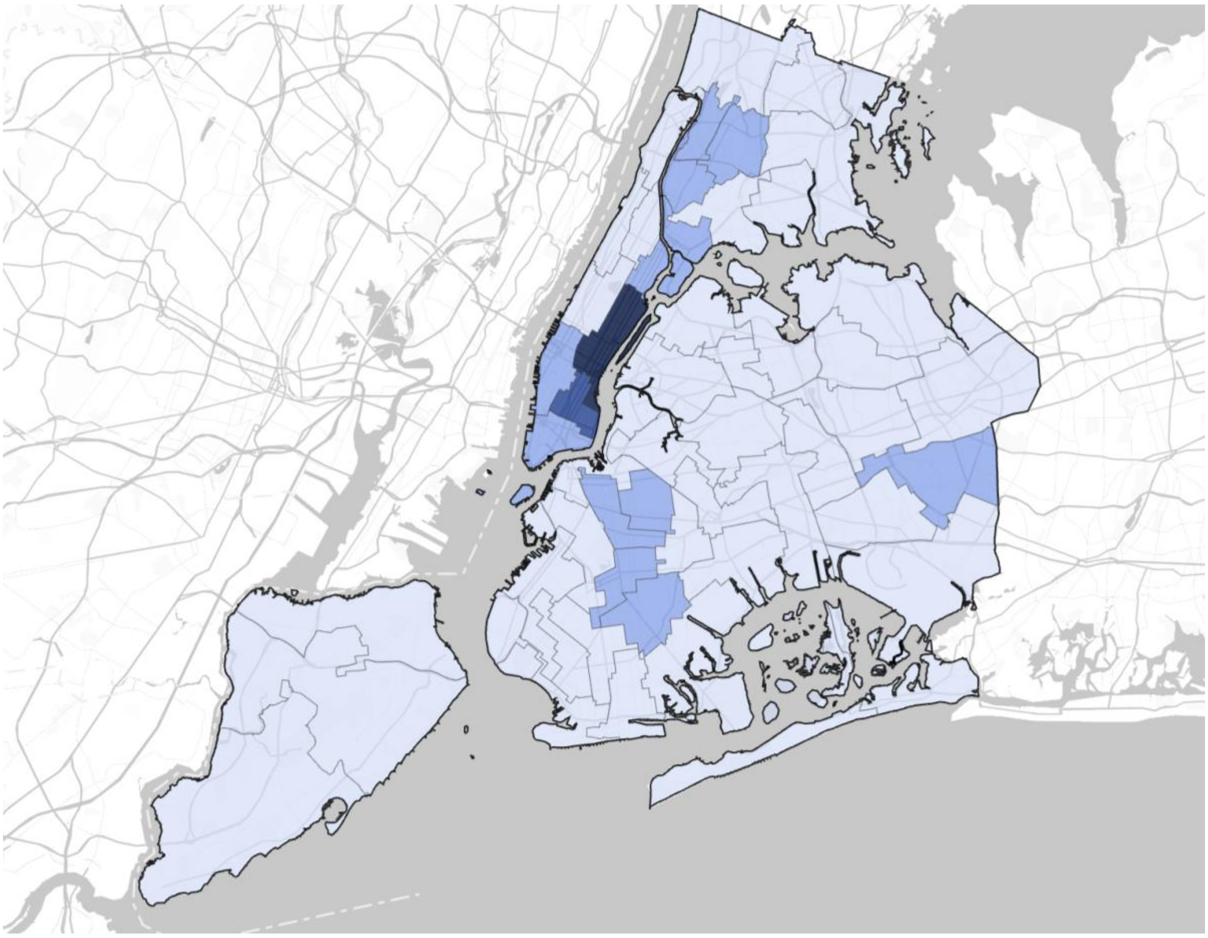


Figure 2: Example of a choropleth regional image from the NYC government representing the bus lanes density

2.3.4. Mapping interactions

Another dimension of the mapping theory is its interactivity. Web-tools which permits the adjustment of the information registered in the representations have intrinsic effects on the engagement and the understanding of the situation treated (Ataman & Tuncer, 2022)

To determine whether there is a meaningful improvement in understanding inequalities depending on this design option, we ought to review the literature.

Scientific experiments were carried out using both non-interactive and interactive tools to compare results across understandability and other dimensions. One of them is the one performed by Xexakis and Trutnevyte. The paper discussion went as follows: in terms of trust, involvement, and comprehension, the static representations were as good as the interactive ones, even if not better in some respects.

It needs to be said that the static representations were four, providing the same information as the one platform with the interactive tool. Even more interesting is that the conclusions regarding understanding were slightly worse for interactive tools due to the barrier to knowing their use, which affected the final assessment. According to the experiment, the plausible explanation for poor performance is the lack of literacy and the tool's mentally challenging nature, which aggregates many possible combinations to analyze (Xexakis & Trutnevyte, 2019).

Park and associates conducted another systematic literature review on the impact of data visualizations on the public health system. The study shows that representations play an important role in decision-making through overcoming the cognitive barrier to understanding the problem and providing more information with less effort (Park et al., 2022).

It is clear that interpretability ought to be sought, rather than integrating new tools. Attending to age-gaps groups discussed in this project, the associate difficulty for elderly people in the understanding of interactive web tools may be a key factor in democratizing the solution proposed at the end of the investigation (Rodríguez Parrado & Achury Saldaña, 2022).

However, it ought to be noted that not all the total number of technological advancements are keen on enhancing society (Selby & Desouza, 2019). It is a trade between clarity and interactivity. The idea is always to prioritize understanding over visual attractiveness considerations, in special when representing marginalized communities.

In this last paragraph lies the fundamental conclusion of this second part of the study of literature. Effective representation of social inequalities involves integrating the perspectives of diverse social groups. Considering this point, precise representations can be developed that serve as drivers of real decisions, aimed at improving people's reality.

2.3.5. Effective design while mapping data

Data visualisation has a wide range of powerful software-based graph makers, that transmits with an image the same information as lines of text. Humans know that we interpret images better than unformatted text.

This effectiveness depends in great scale of the choices the designer makes, such as in colour, gradient, granularity, interactivity… As a recurrent thought in this thesis, the neutral implication of these choices is no more than a lie.

The guide, prepared by the Urban Institute of Washington, interviewed a dozen professionals in the data world. They stated that “exhibiting empathy for the people and communities you are focusing on and communicating with should be the beacon for those working with data" (Jonathan Schwabish; Alice Feng, 2022). In this article written by Alice Feng & Jonathan Schwabish in 2021, they say that the wording, the order and the colour are choices that, without any harmful provenience, provoke an impact on society (Alice Feng; Jonathan Schwabish, 2021)

For that sake, choosing a good colour representation is the right path to demonstrate this commitment with communities, rather than engaging in segregation without knowing it. In the previous article, they gave an example of the MIT demographic dashboard. This pallete present some problems, but the one with more emphasis in the scope of this descriptive literature review of data visualisation of inequalities, is the use of a gradient of the color blue to identify various races present in their classes, as it is shown in Figure 4.

Gradual colors of palletes generally speak about higher values when it is darker and lower when it comes to the brightest parts of the scale. In this example below, the scale does not correlate with the normally assumed association, so the understanding of it is reduced. In addition to that, the associating of darkness with greater quantity could be a misleading point into people thinking, one groups segment is more represented than the other. This needs to be treated carefully.

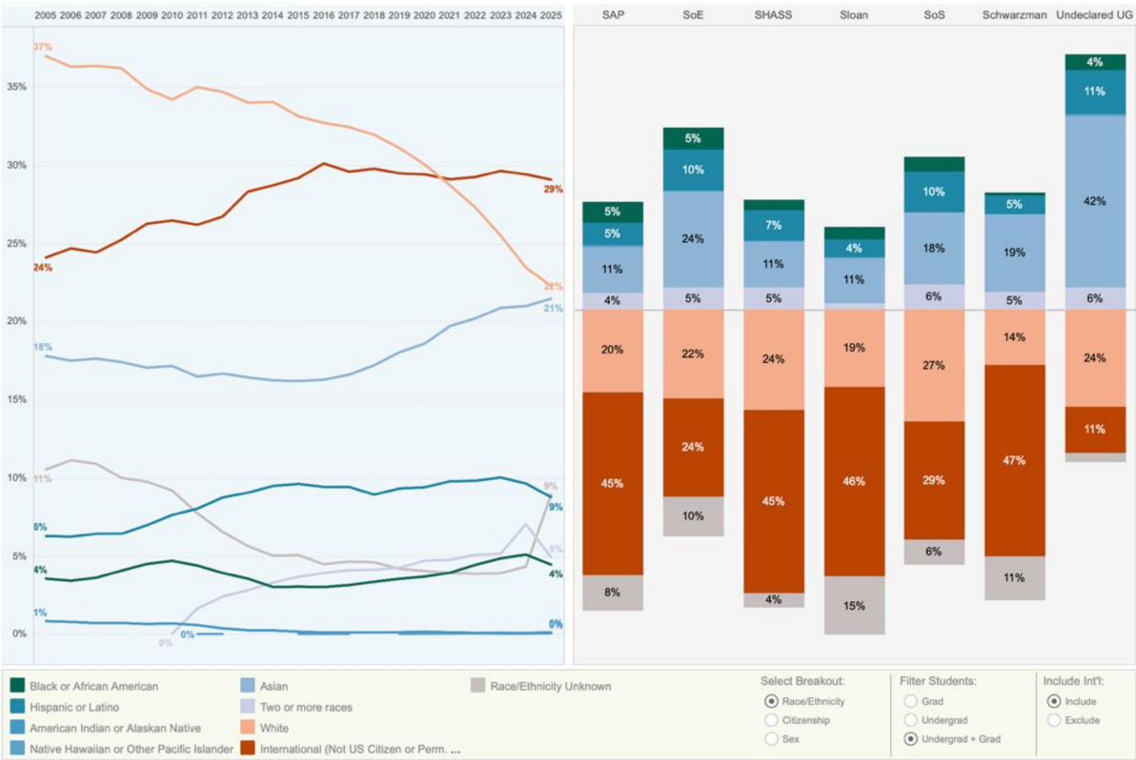


Figure 3: Screenshot of the demographic dashboard from the MIT

Following this line of thought, it is important to express what the work done by Schloss exposes to the world. (Schloss et al., 2019)

In this case, the fields analysed were intended to determine whether mapping with different opacities, contrast (including the background), and dark scales influences knowledge. The literature suggested that darker colours should be reserved for large quantities, but this experiment tested that using colour opacity changes (opaque-is-more bias) to determine the best option. In general, when opacity is absent, darker colours are directly associated with larger quantities, regardless of the background colour.

At the same time, the background needs to stay as white as possible to enhance a quicker comprehensibility in general cases; if the background is darker, a shadowing of the colors came as the best solution. It is also very beneficial not to select any background colours that might affect the opacity of the colouring parts of the portrait image.

But not only does it have to be considered the way colors resemblance us to a certain quantity, but importantly enough is also the pleasure they gave and the visual impact.

It is a debate in the academic arena about the use of the rainbow scale, commonly used for forecasting and other natural events. The name of this colorimetry style comes from the resemblance to a rainbow figure. The technical explanation is that it is related with the electromagnetic spectrum of visible colours, shown in Figure 5, (from lower to higher frequency).

Normally, in those events such as forecasting, the blue scale are associated with lower values of temperature, and the reds the other way around.

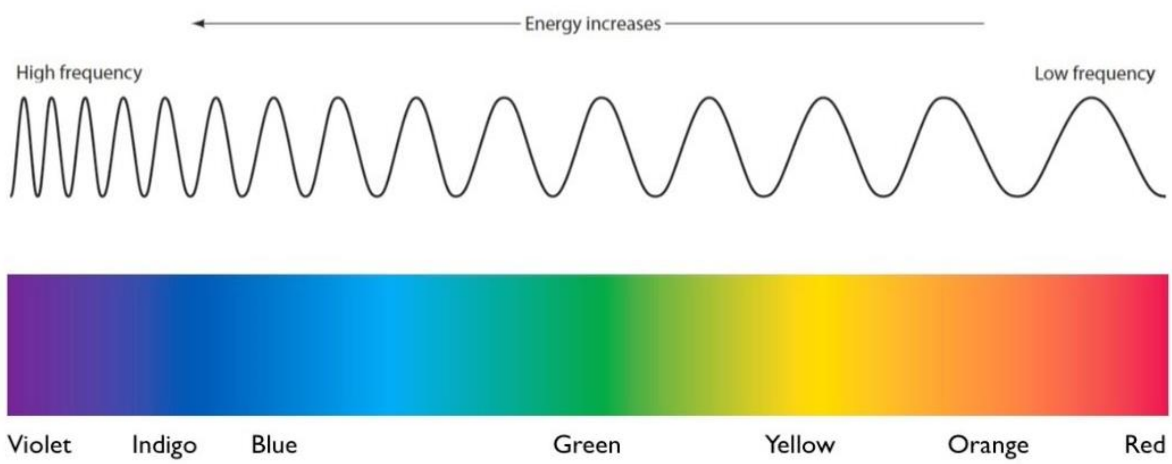


Figure 4: Electromagnetic visible spectrum

However, in those fields mentioned, there is a commonly accepted association created for the scale; in socioeconomical indicators, using choropleth representations, it is not intuitive at all. The presented representation lacks an explicit, straightforward ordering, and the middle values may create the illusion of value jumps and lead to confusions with other extreme colors (Golebiowska, 2019).

The image below is from another study by the same author and colleagues, which shows that the bordering effects these representations have (how clear jumps in values are) are not present in the other two representations at the right. So, the conclusion is that these patterns are not suitable to understand the tendencies and improve decision-making with them, they create false boundaries, and the usage of a legend is no negotiable (Gołębiowska & Çöltekin, 2022)

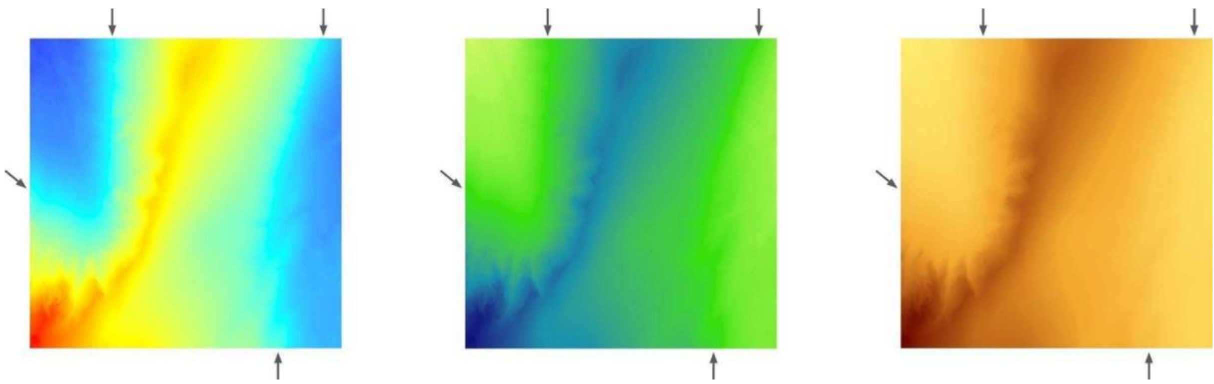


Figure 5: Golebiowska representation of a boundary effect from the rainbow scheme

Other dimensions, rather than the color, to leverage design choices in order to support the understanding, are data granularity and dimensionality.

Regarding data granularity, this concept concerns the level of detail to which data is reduced and the degree of exactitude it achieves. Normally, the level of detail has beneficial effects on the adoption of new strategies and on the efficiency of the process chain for which it is used. Studies like this one, conducted in the heart of smart city practices, inform readers that high-granularity data trades have an impactful role in social life, enhancing existing services (Palviainen & Kotovirta, 2025) However, the level of task requirements specification and the complexity of the analysis are factors to consider.

On the other way around, if there is not enough granularity in the data platforms, misleading outcomes might arise. Possible when investigating different granularities in geospatial information: as the sample size increases (country-size), the studies presented have more details than those with smaller samples (CAP-size). On the other hand, some studies argue that fine-grained information in some datasets cannot reveal the general trend of a process, due to individual statistical problems and storage limitations. (Diversification, 2025)

With respect to dimensionality, the narrative is very clear: the 2D representations on a Euclidean plane are better than 3D representations. The comprehension and the difficulty to understand the data, when the task under study is represented in a 3-D model, were more challenging to understand the concept behind the graph (Brandie M Stewart; Jessica Cipolla, 2009). As a general condition, representations adding 3D features negatively affect negatively in extracting information from them.

2.3.6. RQ2: How can data visualization strategies efficiently represent these age-dependent disparities to facilitate inclusive urban policymaking?

In this last section of the literature, we must focus on one of the most important aspects when defining the objective of this work. The question to be answered, aligned with the research question, is: How can data visualisation strategies represent these inequalities to improve policy development? This question, combined with the analysis of differences across age segments, addresses how to reflect this urban reality inclusively, while avoiding interpretability issues.

For this, the urban planners in charge of Milan can use a broad indicator that is tailored to the complex nature of social inequalities. Likewise, it can be corroborated in the literature that the indicators adjusted to an analysis by age bias and with subjective assessment can identify areas where greater investment is necessary in the improvement of the internet connection network. But the indicator used can also indicate that more resources should be allocated to another area to improve accessibility and medical services.

Having this indicator that points out so truthfully the inequalities given citizens' ages, the only thing missing would be to provide a platform for collecting that information, with graphs that promote understanding.

These platforms are increasingly recognised as important tools when it comes to representing these complex patterns. Interactive maps, control panels and the wide variety of colour combinations are important factors that increase the understanding of what is represented. However, it should be noted that a certain level of literacy is needed in these software platforms, so that they are used in the correct way.

All this happens by combining these visualisation strategies with empirical data, contrasted with opinions biased by age. The proposed evaluation methods to reach this point include conducting qualitative surveys of representative users or conducting audited tests. These methods help to work out a solution to improve understanding. These experiments in written literature have caused conclusions adaptable to this study.

An affected group are the elderly, who in general terms find more reluctance when it comes to using software infrastructures. Therefore, in addition to the information shown, the graphical interface must be intuitive and use simple graphics. The design choice should be carefully considered, as it can either reduce or widen the differences caused by age.

For example, Xexakis and Trutnevyte discovered that static representations often outperform complex interactive tools among older users or those less familiar with technology. On the contrary, younger people find a better solution in this interactivity.(Xexakis & Trutnevyte, 2019).

As the first fact limits the other, although young people have a greater understanding of these interactive technologies, this must be balanced with a common solution that favours everyone.

Therefore, the development of inclusive urban policies involves the use of inclusive communication techniques in representations. This does not mean that should be simple and static representations. The midpoint must be the objective, since the progress of seeing more complex variables represented should not be left behind.

To guide future decisions, these representations must include data focused on the particular needs of people; only in this way can technology be used to unblock issues related to urban reality.

2.4. Synthesis: towards a new indicator

Dealing with these research questions requires analysing the relationship between data representations and individual interpretations. As noted in the first research question, there are many individual interpretations to consider. The range of complexity it faces in analysing all the possible subjective biases motivates people to concentrate on one dimension. In this case, the age gap is the focus. However, it is interesting to see how the individuals' interpretive biases are evident when a data representation is near (Philip Chen & Zhang, 2014).

In the experiment conducted by Holder and Xiong, they reported a clear tendency. By nature, contestants find the easiest explanation for the problems shown in the provided charts rather than looking for structural factors to detail the real story up to the point they reached. These prejudicial cognitive though is what the authors called "deficit thinking". The study shows that there are some designs that aggregate the information, which promote this shortcut in more extent. As aligned with the second research question, these design choices could improve interpretability.

For example, when data dispersion is absent (e.g., bar charts that show all results at the mean rather than the tendency), they are more likely to promote this biased thinking. Trying to show the variability, with a jitter representation or by correctly labelling the legend (without classifying that could stigmatize certain social groups), appears to be the solution to prevent undesirable bias (Holder & Xiong, 2022).

With this last question, the study reached the point where perceptual bias can lead to a critical interpretation of the situation represented. The indicators created must be based on all this prior information to avoid errors to misreadings interpretations. People's biases when assessing the importance of the data portrait are key to targeting them for specific political matters. (Capozzi et al., 2021).

Since the scope of the thesis investigation was to examine the implications of individual interpretations in data visualisation platforms, the best way to fulfil that aim is to integrate all the investigated knowledge into the creation of a new indicator. With this indicator, the final objective is to analyse how data interpretation differs across observers (RQ1).

The literature clearly shows that perceptions of urban inequality and spatial justice differ across demographic groups. This also relates to the changes in personal preferences that occur as people get older. At different stages of life, priorities change, and this also applies to urban reality.

As already seen in this thesis's analysis, younger people tend to view access to housing and the presence of public spaces that meet sociocultural requirements as the greatest sources of inequality. On the contrary, older people, with more health problems, value in a city the presence of parks, hospital centres and avenues that allow walking. This variation, as has been seen, leads to differences in how urban reality is perceived and, consequently, in how municipalities should allocate public resources to improve these situations.

In smart cities, these differences can be magnified. Massive urban data can benefit political decision-making, but if not combined with an age-based assessment, they can be seen as fair and effective by one age cohort, but as insufficient or even exclusive by another. As they are experience-based valuations, the decisions should be communicated carefully. If not, the result is misinterpreted or overlooked if the analyses address only the priorities of the dominant group.

This is where dynamic data visualisation strategies come in. In the previous section, we saw how interactive dashboards, customisable maps, and multimodal data platforms are effective at representing disparities. However, for older adults, simple and high-contrast graphics should be used, with clear navigation, to improve access and understanding. Although for younger users, interactive interfaces are the ideal choice for representing social inequalities, the literature emphasises that understanding should be the priority above all.

Only with the incorporation of a dynamic visualisation and a conscious design of the public's knowledge gap is it ensured that urban inequalities are communicated in a transparent and inclusive way. This will allow all efforts to represent the different social realities to translate into personalised and coherent decisions

Thanks to this summary, the key findings of the literature review are observed. It shows how the literature provides answers to both research questions and, at the same time, emphasises the importance of continuous research.

3 Methodological design of the Urban Inequality Indicator (UII)

After the literature review, the practical part of this thesis is the creation of an indicator to highlight inequalities in the city of Milan, while maintaining the structure established in the literature review.

The idea came about when identifying a gap in the theoretical part. Studies analyze the problem by focusing on one dimension of urban reality (health, environment, access to public services…). However, there are a few indicators to unite various dimensions to fulfil a metric.

Composite indicators, such as the HDI, as commented on in the literature review, are in line with the idea behind this thesis. Nevertheless, the clear inspiration is the Multidimensional Poverty Index (MPI), which they put together three parts of the society. This human development report studies the effect of poverty around the world, equally weighing the three categories. As seen in the subsequent Table 2, the categories are stablished to nurture the indicator as much as possible with relevant data.

DIMENSIONS	SUB-DIMENSIONS	WEIGHT
HEALTH	Nutrition Child mortality	1/3
EDUCATION	Years of schooling School attendance	1/3
STANDARD OF LIVING	Cooking fuel Sanitation Drinking Water Electricity Housing (infrastructure state) Assets (from the house)	1/3

Table 1: Dimension of the MPI index

The MPI (Multidimensional Poverty Index) indicator shows, on the web page where it is hosted, a design decision that theory applied to colourimetry supports using a scale from the same colour, from darkest to brightest.

The example below is from the country of Chad (UNDP, 2025). It needs to be said that the theory of always putting darker colours in higher quantities is not met. However, as it is a global indicator and the legend is specified, the understanding is regulated.

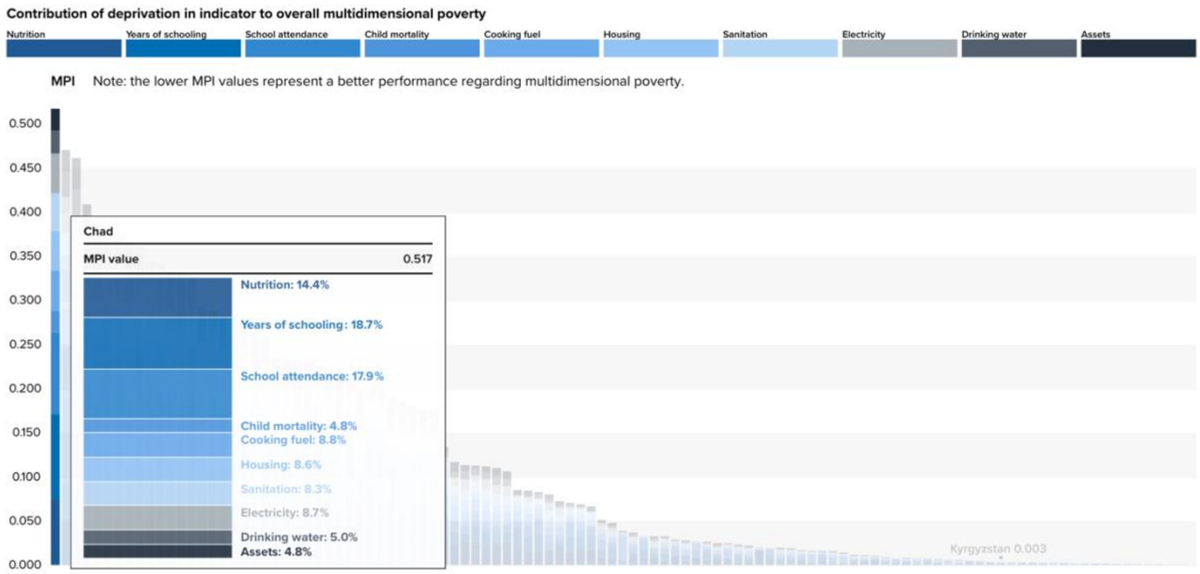


Figure 6: MPI Chad index

Here, it should be noted that the objective of the final visual representation is, in more detail, to align with both research questions. As specified, the objective of revising all the literature related to this was to provide a clear path for preparing a variety of representations that reflect these age-gap differences. How is it going to be done?

First, in the review, it was clarified that the senior population was more focused on health and accessibility concerns, in contrast with the housing and socio-economic principles defended by the younger generation. The idea in this thesis is to prove whether there is such a difference between what is said on paper and. By surveying the population of Milan and forcing them to quantify the relative importance of these factors to them, we could extract the information and reflect the reality of these people in different representations. By that, the thesis of the first research question would be reinforced, seeing exactly to what extent the interpretative biases are different for diverse age groups.

Secondly, regarding the second question, the design choices were made in the interest of interpretability for both segments of society. It is a fact that literacy in interactive web tools is enhancing in the vast majority of people. Nevertheless, finding a middle way to satisfy all was the solution.

Point out that design choices based on interpretability do not demean the adoption of policies. A multifactorial indicator is going to be created, expressing clarity to leverage the existing data sets to find solutions to existing problematics. The adoption of policies targeted by age groups is maintained because all options preserve the best practices for doing so.

Having this in mind, the indicator index and its subsequent representation on a platform will be specified.

3.1. Objective design: A mixed-method approach

To understand the index's global structure, we need to answer this question: Why is a mixed-method design used?

On one hand, we have the quantitative method of extracting the data and building the scores for each of the zones under study, to next aggregate all the scores into a single index value. With that, the weighting part is normally an equally distributed metric, as specified in the Table 1. Here is where the subjective part comes in.

The weighting will be determined through a survey asking people in Milan for their on-field opinions on different dimensions. For that, a set of questions will be specified and passed to a group of people from Milan, or at least that the have been working or studying in Milan in recent years. With that, the conclusion may arise: how do people view the city? And different outcomes should be analyzed to portray how data importance is not objective. It depends on the lenses you have.

3.2. Phase 1: defining the dimensions of inequality for Milan:

As stated at the beginning of the project, the city chosen as the focus of the study was Milan. The reasons were abundant; first, proximity. Also, the department from the Politecnico di Milano supporting this thesis, Tiresia, encourage to focus the lens on this city, due to the knowledge of the city from the tutor revising this thesis, the grade of guidelines potentially given would be much higher regarding the results.

Another reason is the city's complexity. In the book by Jones, he analyzed the evolution of various European cities from the years 2009 to 2016. The case of Milan is similar to cities like Copenhagen or Manchester, which are set around the gentrification problem, impacting radically on lower social groups, making renting or buying a house nearly impossible (Jones, 2018) . The European tendencies set in

Milan have created a problem of segregation, where scholars are pointing out that what descendants inherit from their working-class families is changing the shape of the neighborhoods.(Marcińczak, 2016) .With that and other factors such as globalization or inequalities, the gap between rich and poor citizens is extending at a vertiginous pace.

Specifically, in Milan, these tendencies are displacing lower-income groups to the outskirts of the metropolitan area (Lelo et al., 2018).

So, with that being said, Milan served as an example of an European approach addressing challenges of social integration and accessibility for the majority of its inhabitants. For that reason, Milan, by its appropriateness and social disparities, came as a good candidate for the following study

3.2.1. Framework definition (Economic, Educational, Sociodemographic, Health, Living Environment).

The first part of this experimental application was defining the dimensions of the index. Milan is a metropolis with more than one million inhabitants and, as a big European city, the inequalities in the urban distribution are a present state. To determine the categories, exhaustive research on indicators and examples in urban reality was conducted. The idea was to create a single metric to highlight the injustice and then portray each subdimension to understand the pattern and gain a more detailed view of the problem. This index was born as the Urban Inequality Index (UII).

The economic and housing issues are recently receiving significant attention due to rising prices (Loberto, 2019) and the quasi-inexistent affordability for low- and middle-income households, resulting in prices five times higher than salaries (Bricocoli & Peverini, 2024). Making it a city for richer people. Many are the representations that include this aspect, treating it as a clear indicator of the unjust spread of wealth and the inequity of opportunities (Francesco Andreoli, 2014)

Regarding the world of sanitarian concerns and around the public well-being of people in their neighbourhood, several are the indicators and representations exist about pollution ,(Quality Index Project, 2025), temperature risk maps (Bacci & Maugeri, 1992) or access to green spaces (Capolongo et al., 2025).

Another tendency observed is the movement of citizenry from cities to the headquarters LEF, 2025). These patterns of emigration and immigration are of particular interest when considering the integration processes of cities, often resulting in densification or, in some cases, gentrification. This is especially relevant when analysing equity in the most densely populated zones. In the specific context of Milan, existing studies support the thesis that a high concentration of immigration is often found in districts where the infrastructure remains in an outdated state (Igor Costarelli, 2017). For the purposes of this project, high immigration rates have been associated with a negative impact on the final indicator. It is important to clarify that no discriminatory or racist criteria were applied at any stage of this sub-dimension analysis.

Lastly, not least important, but yes, the one less populated with representation studies is the educational part. Here, studies are relating the states of the infrastructures and local reality with the perception of inequality in the Italian field (Orazio Giancola & Adamo Lo Cicero, 2025). Also of interest is the level of education in the zones under study(Cordini et al., 2019).

Integrating these five dimensions should be enough to identify the whole reality of Milan's inequalities, seeing which are the zones with the best relationship with these indicators, divisional parts.

3.3. Phase 2: Data collection and justification:

In this section, the objective is to clarify, for each set, which subcategories are selected to form the indicator. As said before in this text, the weighting scheme will be determined by the survey, dividing people's perceptions by age. However, in this first approach, is going to be equiprobable the weight for each of the sorts present (20% to each). Then the different age-based weights will be applied.

3.3.1. Definition of each sub-dimension

The Table 2 expose the groups defined and the four metrics selected for each of the big picture categories. The justification of each selection and the traceability of data extraction is remarked.

Dimension	*Indicator Code*	*Indicator Description*	*Year*	*Unit*	*Polarity*
ECONOMIC	ECO_1	Income higher than 55.000 euros a year	2023	Euros	-1
ECONOMIC	ECO_2	Total number of worker that are contributing to the state/total population	2023	Number	-1
ECONOMIC	ECO_3	Cost of the rent in the zone	2025	Euro/m2	1
ECONOMIC	ECO_4	Cost of the houses in the zone	2025	Euro/m2	1
EDUCATIONAL	EDU_1	Number of universities nearby (neighbors' estimation)	2025	Number	-1
EDUCATIONAL	EDU_2	Number of schools (from 3 to 15 years old)	2025	Number	-1
EDUCATIONAL	EDU_3	Number of people with some kind of studies	2025	Number	-1
EDUCATIONAL	EDU_4	State of the infrastructures	2021	Number	1
SOCIODEMOGRAPHIC	SOC_1	Population density	2024	Number	1
SOCIODEMOGRAPHIC	SOC_2	Immigration rate	2024	Number	1
SOCIODEMOGRAPHIC	SOC_3	Bar, restaurants, third sector establishments presence	2024	Number	-1
SOCIODEMOGRAPHIC	SOC_4	Number of buildings in depraved conditions per NIL	2024	Number	1
HEALTH	HEA_1	Number of pharmacies per zone	2025	Number	-1
HEALTH	HEA_2	Number of beds of public hospitals per CAP population (adjusted to NIL)	2023	Number	-1
HEALTH	HEA_3	Danger of heat in each of the zones	2024	Number	1

HEALTH	HEA_4	Pollution in the zone	2025	US AQUI (PM 2.5)	1
LIVING ENVIRONMENT	LIV_1	Index of green spaces en each of the zones	2024	Number	-1
LIVING ENVIRONMENT	LIV_2	Percentage of the population of each NIL, that uses public transport	2021	Number	-1
LIVING ENVIRONMENT	LIV_3	Nils that are hotter in July	2024	Number	1
LIVING ENVIRONMENT	LIV_4	Percentage of population of each NIL, that uses bike or walks	2024	Number	-1

Table 2: Definition of categories and subcategories for the UII

Before scrutinizing the reasons for each subdimension, it is necessary to explain the importance of the polarity number for the indicator construction.

When aggregating the diverse parts of an indicator, as the cases exposed before of the HDI or the MPI, it is crucial to determine the direction of its proportionality.

Normally, it seeks a direct proportionality, which is called positive polarity. When a quantity of that value is increasing is related to an improvement in quality of life (Pareto, 2023)

The other way around occurs when having a negative relation in the polarity. Figure 7 express exactly this inverse proportionality. The main goal is to have all the dimensions in the same order and with the same polarity. As this index is used to highlight stress zones of inequalities in the urban area of Milan, the polarity is inverted in the positively defined variables, so as to have a metric that, when a high value is exposed, is due to a negative factor (inequalities and spatial inequity seen as an unpleasant factor). So, the explanation should be centered on why an indicator is considered positive or negative. The figure 7 express exactly this inverse proportionality

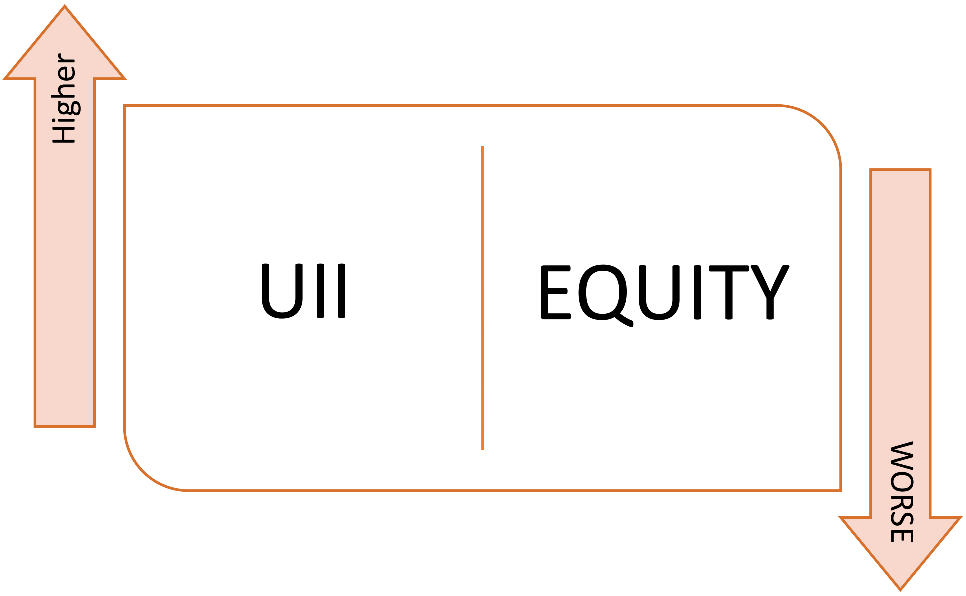


Figure 7: Proportional relation of the UII

As general rule:

- **Direct dimensions:** variables whose increasing value relate to deprivation of socio-economic rights. These variables receive a +1 polarity
- **Inverted dimensions:** contrary to general thought, when they provide positive outcomes or advantages for a specific group of people. These variables receive a -1 polarity

Another remark that ought to be made is the level of granularity of data collection. The analysis of the thesis is centered in the "*comune*" area of Milan, corresponding to the capital city of Milan (not including its metropolitan area). In paper studies published like this one talking about foreign companies in the Milan domains, we could see that division (Egidio Riva, 2014). This area is divided by 88 NILs (*Nucleo di Identità Locale*), corresponding to the minimum possible sub-division provided by the internal territorial government, according to historic records and urban division patterns. This image representation has the division neighborhoods used for the whole analysis extracted from the storage datasets in the "*Comune di Milano*" (Nuclei d'Identità Locale (NIL), 2025) and represented with the program QGIS-LTR.

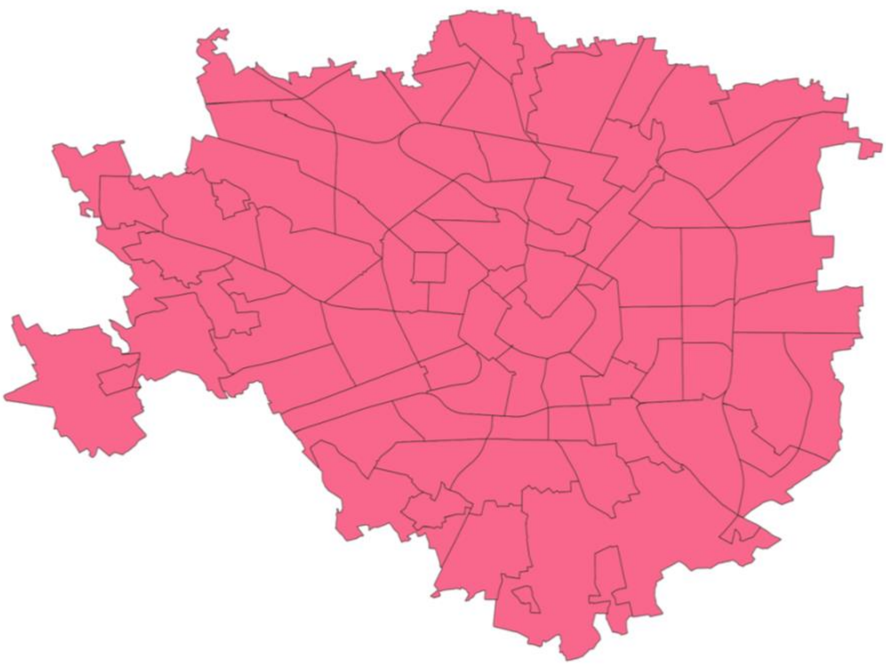


Figure 8: Representation of the 88 NILs in the city of Milan

As a concern in this study, data approximation was avoided to the extent possible to ensure truthful data. When approximations were performed, it would be indicated and how it was interpreted. For that sake, the specification of the postal code or CAP ("codice di avviamento postale") and the "municipi" number were used to leverage more existing data. Moreover, the importance of knowing exactly how many people is in each NIL is notable *Table specification of population, NILs and municipal numbers* located in the first appendix, all this information.

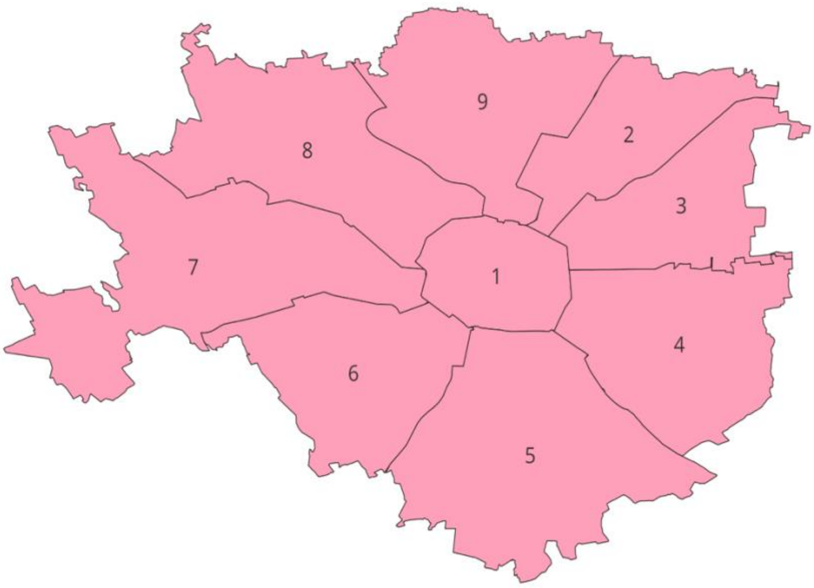


Figure 9: Representation of the 9 *municipi* of Milan

For each of the measurements there are four sub-categories. For each measurement a 20% of the final result (all the same weight). Then for each sub-category, the corresponding percentage assigned to each of them is 25% from the previous result (20%), being a 5% in the global final index. This is obviously, for the generalist case when there is no bias in the quantification.

In the next chapter is going to be defined the granularity of the data and the reference sites where it was extracted.

3.3.2. Granularity and calculations

Economical dimension:

For the economical part the sub-categories are:

- **Income higher than 55.000 euros a year:** this information was extracted from the ISTAT (*Istituto Nazionale di Statistica*) web page in the trimestral report about the contributors to the state in each of the 38 CAP numbers in the city centre of Milan. The report (ISTAT, 2025) exposes the whole population divided in different stages. For the inequality indicator a minimum wage of 55.000 euros a year, was set to determine the limit from which a salary is considered high (well above the mean income per family (*An Expat Guide to Milan: Housing, Jobs, Culture, and More*, 2025). Here the absolute value of people was not considered as the number of people in this district have its importance. A division with the actual population for each CAP was performed.
    - **Objective:** determining the number of "rich" income inhabitants
    - **Polarity:** the people in a zone having more money, is a positive effect in their stability. Considering this metric as positive, the polarity is inverted.

$$ECO\_i_{adj} = \frac{ECO\_i}{Tot\_population} \qquad (2.1a)$$

- **Total number of workers that are contributing to the state:** here it was seen from the last reference table from ISTAT (ISTAT, 2025) the number of working people in each zone. As the first category, the comparison with the total population is crucial to determine the actual proportion of workers in the zone.
    - **Objective:** seeing the employment rate
    - **Polarity:** studies shows that lack of employment is related to a burden in the economic development (Gupta et al., 2024). Considering this metric the other way around, is positive and so the polarity is -1.

- **Cost of buying/renting a house:** the portal *inmobiliarie* has a large dataset of information regarding the prices of real state. The division of data, as seen in its website (Inmobiliare IT, 2026) is a middle road between the NILs division and the postal code one. With 38 defined zones, the adjustment was done by a clear exploration and manual rearrangement of zones, putted together in the *Economic indicator data ECO_3 and ECO_4* table, where the CAP and the zones are correlated to have a comparable field.
    - **Objective:** determine the problem of accessing the real estate market.
    - **Polarity:** as discussed one of the main problems or gentrification is the affordability problem of the houses in European cities. For this reason, this metric should be in positive polarity as more implies worst for the people.

Educational dimension:

Even though this field is debatable about its direct relation with inequality in cities, there is evidence to set that the measurements of inequity opportunities and achievements have to do with the level of education (Ferreira & Gignoux, 2014) .

- **Number of universities/schools nearby:** analyzing the proximity of universities to the neighborhoods. In this field the data from the part of (Unità Open Data, 2025), bring this information. Here, as the availability of education is not tied to belonging to the NIL itself, a neighborhood estimation has been performed to place greater weight on zones near university locations. More information available in the Table in the appendix A *Universities count per neighborhood* and *Schools distribution across Milan*.
    - **Objective:** determine the accessible proximity to universities and schools.
    - **Polarity:** this metric should be inverted as; more presence of centers determines an advantage in displacements. Polarity of -1

- **Background level of studies:** The pattern of regulated formation could imply a higher level of perceived inequity. The information for this indicator was obtained from the open data from the commune of Milan, and the pivot table is specified in the last part of the document *Level of studies in the city of Milan*
    - **Objective:** determine the level of knowledge of the whole area
    - **Polarity:** this metric should be inverted as; more presence of knowledge determines an advantage in opportunities. Polarity of -1

- **Infrastructures state:** normally the state of the educational infrastructure and their surroundings determine the security and equally distributed version of education. In the table it is shown the count of damages in the buildings *Infrastructural state* it is summarized, as a large data set of the ambient of schools is gather in this part of the website. (Unità Open Data, 2024)
    - **Objective:** portrait the care of buildings in the city of Milan
    - **Polarity:** this metric should be presented as is with a polarity of +1.

Sociodemographic dimension:

In this category, we are including an equal distribution of social concerns, population change and redistribution across the field. Studies show the clear relation of migratory movements and density with a decrease in the broad distribution of resources and with social implications, like this one done in Cape Town, suggesting the utilisation of these metrics to have a more distributed city (Scheba et al., 2021).

- **Population/Immigration density:** The data tracked are from the commune dataset, which exposes movements at the neighbourhood level. For this part, an adjustment has been made. The density analysis should be applied to the area under study, so a correlation with the area of each factor is specified in the tables. *Population density in the city of Milan Immigration rate*
    - **Objective:** show the density in the NILs.
    - **Polarity:** as related studies before exposed shows, the more population per area present, the more the lifestyle is burden. For that, the polarity should be +1

- **Third sector services present:** from this part of the urban reality, we could glance the number of establishments, including bar, restaurants, cafés… *Thrid sector services per ID_NIL*
    - **Objective:** study the proximity of this third sector services
    - **Polarity:** it should be -1, because the existence of these businesses equips the zone with a better lifestyle completeness.

- **Living buildings in deplored state:** from the available data set (Unità SIT e Toponomastica, 2024) could be seen the level of security of the zones and how the quality of this kind of buildings is related to the perceived safety in this districts (Garcia et al., 2024).
    - **Objective:** count the number of buildings in this state to set the attractiveness of each NILs.
    - **Polarity:** it should be +1, because the existence of this number of buildings is subjected to a poor perception of the quality of life.

Health dimension:

Uniting in this context the availability of hospital and health related resources, with possible danger the urban design of Milan is doing on people, the dimension is set.

- **Number of pharmacies/hospital beds nearby**: the access to the health sector is something relevant when analyzing equal opportunities. As the study perform in the metropolitan areas of Iran determined relation with the equally distribution of opportunities, the dimension sustains. (Chavehpour et al., 2019). The data were extracted from (Unità Open Data, 2025)

  - **Objective:** extract the density per inhabitant of these services.
  - **Polarity:** these two metrics ought to be inverted, so a polarity of -1 is mandatory

- **Danger of heat health problems:** this is based on a study and the data recollected by the Milano central offices, attending the risk of heat wave (Unità Open Data (calore urbano), 2024) The result is an index that set the risks as a function of vulnerable groups in the zones. The data is supported by the European SPOTTED group project and it is available here *Heat wave index*
  - **Objective:** determine the hazard for each NIL, attending to the heat wave risk
  - **Polarity:** as it has a bad effect in the health the high values of this indicator, the polarity is positive.

- **Pollution in the zone:** over the years the measurements on pollution in the city of Milan were no other than outrageously high. News like this from studies done in October 2025 (WantedInMilan, 2025) spotted Milan as one of the worst urban areas, regarding pollution of PM2.5. However, measurements of data have been recollected, with a AQI (Air Quality Index) historic of nearly 2025 moderate values on health (between 50 to 100) (Aqui, 2025).
  However, a metric was taken in the moment of study, as it could be seen in the table *Pollution AQI measurement*. The values were all considered hazardous to health and equally distributed. For that reason and considering the scientific consensus on classifying Milan as a bad city for smog, it was decided not to

consider one zone of Milan better or worse than others in this category, as this could be misleading to users. This is an endemic problem, due to its location and industrial development, of the whole city, when values are low in the totality of the region, and so for the other extreme values. To that extent, all the NILs have the same value for this sub-indicator.

- **Objective:** setting that the pollution is not a problem of a single neighborhood, is a problem of the whole city.
- **Polarity:** as it has a bad effect in the health the high values of this indicator, the polarity is positive.

Living environment dimension:

In this section, we focus on green spaces distributed across the city and on public transport or other modes of communication, in terms of the predisposition of the inhabitants to use them.

- **Green spaces availability:** Zhang develop in it work a revision of availability and accessibility of urban green space (UGS) in New Zealand, extracting diverse tendencies related with deprive areas and ethnics (Y. Zhang et al., 2024). For this reason, the index available of the city of Milan, exposes a reality in urban inequity. From the data set present in *Green space index* the corresponding number is a system of measurement develop by the Milan headquarters, referring to the quantity of considered green spaces, located in each of the NILs.

- **Objective:** appreciate the quantitative value of the parks and vegetative areas in the city.
- **Polarity:** in a city context the presence and availability of green spaces is something considered with good effects; however, it has a despaired distribution across areas (Bwanbale Geoffrey David, 2025) This sake, provoke a -1 polarity for our index.

- **Public transport usage and walkable and cyclable reality:** the number of people using the public transport services is a notable indicator of good accessibility services, as well as people walking or going by bike. Milan is a plane city, with not many slopes, perfect to practice this transport method and in the eyes of municipalities to reduce the pollution levels (The Guardian, 2025). The utilization of these methods of transportation is crucial so as to understand possible inequalities, that governments should put focus on (Bokhari & Sharifi, 2024). More details are shown in the table *Public transport usage and Walkability and bike usage*
    - **Objective:** expose the pattern of the people living in zones of Milan , whether they are eventual users or common ones
    - **Polarity:** normally for the living environment, the effects of reducing traffic and using other transports, are beneficial, so the index should be inverted for our scope.

- **Hotter urban islands:** from the same study performed by Spotted, we get the other metric to shed light on the heat island phenomenon. This is produced when the surroundings are buildings, streets and concrete based sites, rather than green spaces. This causes energetical problematics, to cool down the spaces, and precocious deaths provoke by this extreme conditions (Hibbard et al., 2017). The table located at *Hottest NILs* gives a better view of the category calculation.

- **Objective:** show the tendency regarding the urban heat islands, to target policies towards ending their effect.
- **Polarity:** for our indicator the bad effects proportional metrics have a normal positive polarity.

3.3.3. Data cleaning, normalization, and aggregation

After exposing the subdimensions, it is time to describe how the corresponding preparation and calculation of the UII were performed. The tool used for the calculations was Excel. With its features, Excel is a great tool for small datasets. Normally, data rows had no more than 88 (the number of NILs), and if the datasets were larger, pivot tables and other functions were used to extract the counts of the corresponding metrics.

- **Excel formulas used:** XLOOKUP, MAP, SUMIF, COUNTIF, MIN & MAX

The last one was utilized to determine from the whole population of data, which was the ordering in a 0 to 1 scale (in the work, was reshaped from 0 to 100). As in the example's tables, that could be seen in the *Appendix A*, the scaling for each of the NILs was done. This is a method well used in many indicators worldwide, like the HDI (Herre, 2023). The method used is based on comparing the minimum and maximum values of the set analysed and then extract an scale from 0 to 1. Because the UII is an indicator of inequalities, a high value in this calculated index is associated with a bad outcome (a more-is-worse understanding). For that, the min-max normalisation should be direct for categories considered as "bad-if-higher" (in this case, with a positive).

$$Normalized_{value\_bad} = \frac{(actual_{value} - min_{value})}{(max_{value} - min_{value})} * 100 \quad (2.1a)$$

For the "good-if-higher" variables under study the normalization should be inverted (polarity -1), so as to have in the same scale and in the correct theoretical mindset.

$$Normalized_{value\_good} = \frac{(\text{max}\_value - actual_{value})}{(max_{value} - min_{value})} * 100 \quad (2.1b)$$

The min-max normalization is really helpful in these composite indicators, as it does not classify all the values in an equally distributed scale but also includes the distances between values. Normally, the relative position normalizers do not reflect these actual distance. This is particularly important: having a normalization method that considers the actual distance between values rather than just ranking them, accounts for a reliable result.

For example, if three values are the mean rent prices in a certain zone: 1.000, 1.100, and 2.000 euros, the ranking results with **relative position** metrics will be: 0, 50, and 100. With our method, the results will be 0, 10, and 100; with this, the tendency of the values is preserved and is not lost in the normalization step. In the Table 4, another example shows that the extreme values are always 0 and 100, but the distances are respected and not equally distributed.

RENT PRICES	PERCENTRANK.INC	MIN-MAX
1.000,00 €	0,00	0,00
1.100,00 €	25,00	10,00
1.500,00 €	50,00	50,00
1.900,00 €	75,00	90,00
2.000,00 €	100,00	100,00

Table 3: Normalization methods comparison

After this normalization, we aggregate all the sub-indexes into one metric, to then aggregate it to the whole final index value calculation. This two processes are done by a **Geometric Mean formula**. As we discussed in the theoretical part of this document ***Error! Reference source not found.*** the geomean is the well-accepted form of calculating the mean value in the indicator construction world. The use of a degree-root prevents the cannibalization of the standard deviation of results, giving higher values to sets that are more evenly distributed, rather than to those with high variability.

The only problem to highlight is that the values treated as 0 in the min-max normalization should be converted to 1, because otherwise the calculations will cancel out and the index value will return 0. So, a constant value of 1 is added to all values to avoid this mathematical issue, while maintaining the distribution as-is.

$$GM_{eachsubindex} = \sqrt[4]{x_1 * x_2 * x_3 * x_4} \;\; (2.2a)$$

Where:

⇒ xi is the value of each of the five dimensions, different four subdimensions

For the global calculation, when there is the geomean of all the categories, the final calculation is like this:

$$GM_{eachsubindex} = \sqrt[5]{y_1 * y_2 * y_3 * y_4 * y_5} \ (2.2a)$$

Where:

⇒ yi is the value of each of the five dimensions index calculation

At the end, the result is 88 different number indicators, for each of the NILs presented in the city of Milan. Thanks to all the calculations, it could be extracted the values impacting more and less to the final inequality outcome. In the final Appendix B, it is specified the results with the importance of each of the dimensions *Final index calculation with the weight of each of the sub indicators*.

3.4. Phase 3: Survey design

Now, with the final outcome of the UII, each NIL has a result with an equal weight. The clear scope of this thesis is to understand the pattern of inequality, but more in detail, how different age-groups are appreciating the inequalities and the degree of importance of each of the subdimensions. For that, we have conducted a survey asking people in Milan the following questions and defining a new weight.

Here it is the survey reference (Adrian, 2025).

After some brief control questions to classify the surveyed by age, the following questions were designed to ask about the perception of well-being of the different factors.

⇒ ***City well-being:*** *In this section, we will analyze the impact of key factors on your perception of inequality. Inequality manifests itself as disparities in available opportunities, determined by the presence or absence of a specific factor. The relevance of these factors in your perception of one area of the city over another is the measure we are looking for. We are not asking you about the situation in your neighborhood, but how much you believe each aspect contributes to inequalities between neighborhoods.*

When asking about the five categories in general:

⇒ *In your opinion, how much does each of these aspects influence inequality between different neighborhoods in Milan? Scale:*

- *1 = Not at all important*
- *2 = Not very important*
- *3 = Quite important*
- *4 = Very important*
- *5 = Extremely important*

When asking about each of the four sub-categories of the previous categories, this question was repeated for all:

⇒ *In this last section, it will be important to determine which sub-dimension is most important for each dimension. When voting, consider the following scale.*

- *1 = Not at all important*
- *2 = Not very important*
- *3 = Quite important*
- *4 = Very important*
- *5 = Extremely important*

After the questions the results were obtained by age, and the reshape was indeed done.

3.5. Phase 4: Integrating subjective data into the composite indicator.

After the survey, the critical mass of 47 respondents was concentrated in Milan. 80% of the people who filled out the assessment were actually living in Milan or coming there to work or study every day. For that, the survey is justified to be targeted at the city's residents; hence, conclusions about the city's specific nature are possible.

Normally, in the first calculations the weight of each of the indicators conforming the final UII, is set at an equally distributed percentage between the five of them (20%). However, with the survey, some tendencies could be interpreted from the results. In the below commented *Table 4* we could see some general similarities in the first two age gaps. Interesting enough, is the difference regarding the gap over 60 years old, where the living environment, the socio-demographic and the health dimensions are more equally distributed than the other two sections of the society. The economical category is important in the three of the stage divisions, being over 2% more principal to younger and adult segments.

Needs to be said that all the percentages shown here accounts to a 100%, meaning that the final result is complete.

	18 TO 30	30 TO 60	OVER 60
ECO_INDEX	22,32%	22,06%	20,19%
EDU_INDEX	18,97%	18,91%	17,31%
HEA_INDEX	16,96%	16,91%	20,19%
SOC_INDEX	20,98%	20,63%	21,15%
LIV_INDEX	20,76%	21,49%	21,15%
TOT_RESULT	**100,00%**	**100,00%**	**100,00%**

Table 4: percentages of weight asked to Milan's inhabitants

A general agreement of the survey is that the educational part is not so interesting regarding the establishment of a inequality metric.

To widespread exactly the analysis in its completeness, we need to go in depth in the valuation of each of the four sub-dimensions for the five intermediate indexes of the UII. In this case detailed in Table 6, the sub-indicators are indicating how spread is that above number in Table 4. Gathering all the four numbers for each age cohort, we will get the calculated importance.

For example, if I have a index value calculation for all the economical sub-dimensions, I will apply this percentage to this number out of 100. By summing all the four, I will get a value out of 100, to then do the same, but aggregating all the index for an age group.

	18 TO 30	30 TO 60	OVER 60
ECO_INDEX_1	25,07%	24,92%	26,25%
ECO_INDEX_2	19,89%	20,54%	22,50%
ECO_INDEX_3	28,61%	27,27%	25,00%
ECO_INDEX_4	26,43%	27,27%	26,25%
EDU_INDEX_1	26,13%	23,27%	22,54%
EDU_INDEX_2	23,90%	27,35%	28,17%
EDU_INDEX_3	27,43%	26,94%	26,76%
EDU_INDEX_4	22,54%	22,45%	22,54%
HEA_INDEX_1	26,55%	25,00%	26,03%
HEA_INDEX_2	27,59%	25,86%	23,29%
HEA_INDEX_3	20,34%	22,84%	24,66%
HEA_INDEX_4	25,52%	26,29%	26,03%
SOC_INDEX_1	21,93%	22,46%	20,25%
SOC_INDEX_2	27,91%	25,72%	30,38%
SOC_INDEX_3	23,07%	23,91%	21,52%
SOC_INDEX_4	27,09%	27,90%	27,85%
LIV_INDEX_1	26,73%	25,09%	28,05%
LIV_INDEX_2	30,93%	26,52%	26,83%
LIV_INDEX_3	18,62%	22,22%	20,73%
LIV_INDEX_4	23,72%	26,16%	24,39%

Table 5: Percentage of the Milan's inhabitants for each sub-dimension

In here each of the four, in non-bias case, should have a weight of exactly 25%. Nevertheless, is not the case at all. Some arrangements are that the Nils hotter due to the global warming and the urban decisions (LIV_INDEX_3), the population density (SOC_INDEX_1) and the active people in the zone (ECO_INDEX_2), have a lower percentage across all the age segments. Then we could see some comments regarding tendencies, such as younger and older people being more preoccupated with the immigration rate (SOC_INDEX_2) or the two youngest parts of the inhabitant field considering more crucial the rent prices in the inequality measurements than 60+ people (ECO_INDEX_3).

Moreover, the senior population has greater concern when evaluating inequalities, health-related indicators, and the living environment. With these results, which are similar to those analyzed in the literature review, it can be concluded that subjective and age-based lenses for seeing inequalities in cities exist. So, exposing this project to differentiate those realities is supported by truthful data.

The survey reflects how people view the same reality. Choosing their lenses directly could prompt municipalities into building specific policies to attract those sectors and enhance their view of the city. In the following parts of the thesis, it will be explained how the different representations were carried out, with which tools, and the final outcomes that were unearthed.

4 Platform development

As the scope of the project is to discover the under covered bias of the inequalities interpretation, several graphics were done regarding the survey performed and escalated to the weighting system produce by it.

4.1. Conceptual and programming design

Having the analysis part and all the calculations perform it is time to portray these outcomes into real maps. The literature shows that, in the end, maturity considerations should be taken into account when deciding the final outcome. Supporting a middle-ground approach between interactivity and statistical outcomes emerges as the final solution to enhance interpretability.

Many studies indicate that composite indicators are represented with color scaling applied to the relative indicators. The choropleths maps are the one chosen by many composite indicators to show the results, when referring to geospatial datasets (Choropleth Maps, 2023). The tools selected to perform the representation are a mix of ArcCIS tools and python libraries.

The concept of the design it is detailed up to the NIL level. The whole design should be planned around the *Figure 8* and The colorimetry should be a scale from a certain color, from darkest to brightest, since it ranges from 0 to 100 and does not justify a change of color for a given value.

From the official website of the municipality of Milan, the archive shapefile (.shp) was obtained. This archive is an GIS generated file, where all the polygons of the NILs are present. From this part, we are now in the position to start uniting the indicators calculation with each of the NILs and sketching the images. In the Annex B it could be encountered the repository of the whole coding methods followed by the repository where the representations are *Importing instances* for the code

```
import geopandas as gpd
import pandas as pd
import folium
import branca
import mapclassify as mc

# ── 1) Load your data
# Load your Milan shapefile
gdf_shp = gpd.read_file("/Users/adriancantera/Library/CloudStorage/OneDrive-
PolitecnicodiMilano/Thesis/Thesis_Code/Data_Milano/REAL_NIL/NIL_WM.shp")
# Sort by NIL alphabetically
gdf_shp.sort_values(by="NIL", inplace=True)
# Load Excel with indicators
df_excel = pd.read_excel("Milan_indicator_index.xlsx", sheet_name="Reference_table_2", engine="openpyxl")
# Sort by NIL alphabetically
df_excel.sort_values(by="NIL", inplace=True)

# ── 2) Clean join keys to avoid mismatches
df_excel['NIL'] = df_excel['NIL'].astype(str).str.strip()
gdf_shp['NIL'] = gdf_shp['NIL'].astype(str).str.strip()

# ── 3) Merge
gdf_merged_2 = gdf_shp.merge(
    df_excel[['NIL',
'FINAL_INDICATOR_INJUSTICE','ECO_iNDEX','EDU_iNDEX','HEA_iNDEX','SOC_iNDEX','LIV_iNDEX']].rename(
        columns={'FINAL_INDICATOR_INJUSTICE': 'indicator',
                'ECO_iNDEX': 'eco_index',
```

```
            'EDU_iNDEX': 'edu_index',
            'HEA_iNDEX': 'hea_index',
            'SOC_iNDEX': 'soc_index',
            'LIV_iNDEX': 'liv_index'}
    ),
    on='NIL', how='left'
)

# ── 4) Ensure WGS84 (lat/lon) for web maps
if gdf_merged_2.crs is None:
    # set your source CRS if you know it, then convert
    # gdf_merged_2 = gdf_merged_2.set_crs("EPSG:32632")  # example for UTM32N
    pass
gdf_merged_2 = gdf_merged_2.to_crs(epsg=4326)

# Optional: simplify geometry to reduce file size (tune tolerance)
gdf_for_web = gdf_merged_2.copy()
gdf_for_web['geometry'] = gdf_for_web.geometry.simplify(0.00003, preserve_topology=True)
```

B.1. Building the representation

```
import folium, branca, mapclassify as mc
import geopandas as gpd
import pandas as pd
import numpy as np

# Base Map
center = gdf_for_web.geometry.unary_union.centroid
m = folium.Map(location=[center.y, center.x], zoom_start=12, tiles=None)
folium.TileLayer('cartodbpositron', name='Base (fixed)', control=False).add_to(m)

#  Shape of the NILS
outline_style = {
```

```
    'fillColor': 'white',
    'fillOpacity': 0.0,
    'color': '#333333',
    'weight': 1,
}
folium.GeoJson(
    gdf_for_web.geometry,
    style_function=lambda x: outline_style,
    name='Milan Outline (Fixed)',
    control=False,
    interactive=False,
    tooltip=False
).add_to(m)


# Creation of a function to add layers and legends
def add_layer_and_legend(map_obj, gdf, field, layer_name, colors, n_classes=4, show=False):

    gdf_local = gdf.copy()
    gdf_local[field] = pd.to_numeric(gdf_local[field], errors='coerce')
    vals = gdf_local[field].dropna()
    vals = vals[np.isfinite(vals)]

    vmin = float(vals.min()) if vals.notna().any() else 0.0
    vmax = float(vals.max()) if vals.notna().any() else 1.0
    if vmin == vmax and vals.notna().any():
        vmin = vmin - 0.5
        vmax = vmax + 0.5
        if vmin < 0 and vals.min() >= 0: vmin = 0

    classifier = None # Force equal interval by default

    # Create the Colormap
    if vals.empty:
        cmap = branca.colormap.LinearColormap(colors=['#d3d3d3', '#d3d3d3'], vmin=0, vmax=1).to_step(n=2)
        cmap.caption = "Sin datos"
```

```
        cmap.index = [0, 1]

    elif classifier:
        bins = [vmin] + list(classifier.bins)
        cmap = branca.colormap.LinearColormap(colors=colors, vmin=vmin, vmax=vmax).to_step(index=bins)
        cmap.caption = f"{layer_name} (Quantiles)"
        cmap.index = [round(x, 2) for x in cmap.index]

    else:

        cmap = branca.colormap.LinearColormap(colors=colors, vmin=vmin, vmax=vmax).to_step(n=n_classes)
        cmap.caption = f"{layer_name} (Equal Interval)"
        cmap.index = [round(x, 2) for x in cmap.index] #

    # Define the style function
    def style_fn(feature):
        val = feature['properties'].get(field)
        if val is None or not np.isfinite(val):
            return {'fillColor': '#d3d3d3', 'color': 'black', 'weight': 0.8, 'fillOpacity': 0.7, 'fill': True}
        # Compara float vs float (¡correcto!)
        return {'fillColor': cmap(val), 'color': 'black', 'weight': 0.8, 'fillOpacity': 0.95, 'fill': True}

    tooltip = folium.GeoJsonTooltip(
        fields=['NIL', field], aliases=['NIL:', f'{layer_name}:'],
        localize=True, sticky=True, labels=True
    )

    # Adding the style_fn to the folium GeoJson layer
    layer = folium.GeoJson(
        data=gdf_local[['NIL', field, 'geometry']].to_json(),
        style_function=style_fn,
        tooltip=tooltip,
        name=layer_name, show=show
    ).add_to(map_obj)

    # Create the HTML
```

```
    legend_html = f"""
      <div style="font-weight:800; margin-bottom:12px;">{layer_name}</div>
      {cmap._repr_html_()}
    """

    return layer, legend_html

# Adding each of the layers and legends

# FINAL_INDEX_LAYER
final_colors = ['#FEFDE7','#FCFABB','#FAF68F','#F8F363','#F5EE27','#F4EC0B',
                '#C8C109','#9C9707','#706C05','#444203']
final_layer, final_legend_html = add_layer_and_legend(
    m, gdf_for_web, field='indicator', layer_name='Final Injustice Index',
    colors=final_colors, n_classes=3, show=True
)

# SOCIAL sub-index
social_colors = ['#f7fbff','#deebf7','#c6dbef','#9ecae1','#6baed6',
                 '#4292c6','#2171b5','#08519c','#08306b']
social_layer, social_legend_html = add_layer_and_legend(
    m, gdf_for_web, field='soc_index', layer_name='Social sub-index',
    colors=social_colors, n_classes=3, show=False
)

# ECO sub-index
eco_colors = ['#fff7ec','#fee8c8','#fdd49e','#fdbb84','#fc8d59','#ef6548','#d7301f','#990000']
eco_layer, eco_legend_html = add_layer_and_legend(
    m, gdf_for_web, field='eco_index', layer_name='Eco sub-index',
    colors=eco_colors, n_classes=3, show=False
)

# HEALTH sub-index
health_colors = ['#f7fcf5','#e5f5e0','#c7e9c0','#a1d99b','#74c476','#41ab5d','#238b45','#005a32']
health_layer, health_legend_html = add_layer_and_legend(
    m, gdf_for_web, field='hea_index', layer_name='Health sub-index',
```

```
    colors=health_colors, n_classes=3, show=False
)

# Livelihood (si existe)
liv_colors = ['#f7fbff','#deebf7','#c6dbef','#9ecae1','#6baed6','#4292c6','#2171b5','#084594']
livelihood_layer, livelihood_legend_html = add_layer_and_legend(
    m, gdf_for_web, field='liv_index', layer_name='Livelihood sub-index',
    colors=liv_colors, n_classes=3, show=False
)

# EDUCATION sub-index
edu_colors = ['#fff5f0','#fee0d2','#fcbba1','#fc9272','#fb6a4a','#ef3b2c','#cb181d','#99000d']
education_layer, education_legend_html = add_layer_and_legend(
    m, gdf_for_web, field='edu_index', layer_name='Education sub-index',
    colors=edu_colors, n_classes=3, show=False
)

# Control from layers
folium.LayerControl(collapsed=False).add_to(m)


# ===== 3) CSS and JS for legends =====
legend_css = """
<style>
#legend-container{
  position:absolute; bottom:14px; left:14px; z-index:9999;
  background:rgba(255,255,255,.95); color:#222;
  padding:8px 12px; border-radius:8px; box-shadow:0 2px 10px rgba(0,0,0,.15);
  max-width: 500px;
  min-width: 440px;
  font-family: system-ui,-apple-system,Segoe UI,Roboto,Ubuntu,Helvetica,Arial,sans-serif;
  font-size: 13px;
}
#legend-container .branca-colormap {
  width: 100%;
  margin: 0;
```

```
}
#legend-container .branca-colormap span {
    height: 12px !important;
}
#legend-container .branca-colormap ul {
  list-style-type: none;
  padding: 0;
  margin: 2px 0 0 0;
  width: 100%;
  display: flex;
  justify-content: space-between;
}
#legend-container .branca-colormap li {
  font-size: 10px !important;
  text-align: center;
  white-space: nowrap;
  flex-basis: 0;
  flex-grow: 1;
}
#legend-container .branca-colormap li:first-child {
  text-align: left;
}
#legend-container .branca-colormap li:last-child {
  text-align: right;
}
#legend-container .branca-colormap-caption {
  font-size: 11px;
  margin-top: 4px;
}
</style>
"""
m.get_root().html.add_child(folium.Element(legend_css))

# Exporting layer names for JS
map_name         = m.get_name()
final_jsname     = final_layer.get_name()
```

```
social_jsname     = social_layer.get_name()
eco_jsname        = eco_layer.get_name()
health_jsname     = health_layer.get_name()
livelihood_jsname = livelihood_layer.get_name()
education_jsname  = education_layer.get_name()

# Dictionary of legends in JS
legend_js = f"""
<script>
 setTimeout(function() {{
  var map = {map_name};

  function ensureLegendContainer(){{
   var c = document.getElementById('legend-container');
   if(!c){{
    c = document.createElement('div');
    c.id = 'legend-container';
    c.style.display = 'none';
    map.getContainer().appendChild(c);
   }}
   return c;
  }}

  var layers = [
   {{ layer: {final_jsname},      legend: `{final_legend_html}` }},
   {{ layer: {social_jsname},     legend: `{social_legend_html}` }},
   {{ layer: {eco_jsname},        legend: `{eco_legend_html}` }},
   {{ layer: {health_jsname},     legend: `{health_legend_html}` }},
   {{ layer: {livelihood_jsname}, legend: `{livelihood_legend_html}` }},
   {{ layer: {education_jsname},  legend: `{education_legend_html}` }}
  ];

  function keepOnly(activeLayer){{
   layers.forEach(function(o){{
    if(o.layer !== activeLayer && map.hasLayer(o.layer)) {{
     map.removeLayer(o.layer);
```

```
    }}
   }});
  }}

  function updateLegendFor(activeLayer){{
   var c = ensureLegendContainer();
   var entry = null;
   if (activeLayer) {{
    entry = layers.find(function(o){{ return o.layer === activeLayer; }});
   }}
   if (!entry) {{
    entry = layers.find(function(o){{ return map.hasLayer(o.layer); }});
   }}
   if(entry){{
    c.innerHTML = entry.legend;
    c.style.display = 'block';
   }} else {{
    c.innerHTML = '';
    c.style.display = 'none';
   }}
  }}

  map.on('overlayadd', function(e) {{
   keepOnly(e.layer);
   updateLegendFor(e.layer);
  }});
  map.on('overlayremove', function(e) {{
   updateLegendFor(null);
  }});
  updateLegendFor(null);

 }}, 100);
</script>
"""
m.get_root().html.add_child(folium.Element(legend_js))
```

```
# Save and show
m.save('milan_injustice_map_def.html')
print("Saved: milan_injustice_map_def.html")
m
```

B.2. Spatial analysis code

```
# ── Imports
import geopandas as gpd
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from libpysal.weights import Queen, KNN, lag_spatial
from esda.moran import Moran, Moran_Local
from esda.geary import Geary
from esda.getisord import G, G_Local

# Optional: FDR multiple-testing correction
try:
    from statsmodels.stats.multitest import multipletests
    HAS_SM = True
except Exception:
    HAS_SM = False

# ── 0) (OPTIONAL) Start from your merge result
# gdf_merged_2 = ...  # your object after merging indicator by NIL

# Keep only rows with a valid indicator and geometry
gdf = gdf_merged_2.dropna(subset=['indicator', gdf_merged_2.geometry.name]).copy()
gdf = gdf.reset_index(drop=True)

# Ensure projected CRS for contiguity (or distance) operations
```

```
# If your layer is EPSG:4326, pick a projected CRS for Milan (e.g., EPSG:32632 or 25832)
if gdf.crs is None or gdf.crs.to_epsg() in (4326,):
    gdf = gdf.to_crs(epsg=32632)

# Target variable as a numpy array
y = gdf['indicator'].values.astype(float)

# —— 1) Build spatial weights (Queen contiguity, row-standardized)
w = Queen.from_dataframe(gdf)
w.transform = 'R'

# Handle islands (areas with no neighbors): attach 1-NN links so every NIL has at least one neighbor
if w.islands:
    print(f"Found {len(w.islands)} island NIL(s). Adding 1-NN links to ensure connectivity.")
    w_knn = KNN.from_dataframe(gdf, k=1)
    w = w.union(w_knn)     # combine contiguity and kNN
    w.transform = 'R'

# —— 2) GLOBAL INDICATORS
# Moran's I
mi = Moran(y, w, permutations=9999)
# Geary's C
gc = Geary(y, w, permutations=9999)
# Getis–Ord G
g_global = G(y, w, permutations=9999)

print("\n=== GLOBAL SPATIAL AUTOCORRELATION ===")
print(f"Moran's I: {mi.I:.4f}  p-value (perm.): {mi.p_sim:.4f}")
print(f"Geary's C: {gc.C:.4f}  p-value (perm.): {gc.p_sim:.4f}")
print(f"Getis–Ord G: {g_global.G:.4f}  p-value (perm.): {g_global.p_sim:.4f}")

# Store global results for reporting
global_results = {
    "moran_I": mi.I, "moran_p": mi.p_sim,
    "geary_C": gc.C, "geary_p": gc.p_sim,
    "getis_G": g_global.G, "getis_p": g_global.p_sim
```

```
}

# —— 3) LOCAL INDICATORS
# Local Moran's I (LISA)
lisa = Moran_Local(y, w, permutations=9999)
# Local Getis–Ord Gi*
gi = G_Local(y, w, permutations=9999)  # Z-scores and p-values

# Benjamini–Hochberg FDR correction for multiple testing (recommended)
if HAS_SM:
    reject_lisa, p_lisa_fdr, _, _ = multipletests(lisa.p_sim, alpha=0.05, method='fdr_bh')
    reject_gi,   p_gi_fdr,   _, _ = multipletests(gi.p_sim,   alpha=0.05, method='fdr_bh')
else:
    reject_lisa = lisa.p_sim < 0.05
    p_lisa_fdr = lisa.p_sim
    reject_gi   = gi.p_sim   < 0.05
    p_gi_fdr    = gi.p_sim

# Quadrant mapping for LISA:
# 1 HH, 2 LH, 3 LL, 4 HL  (Anselin, 1995)
labels = np.array(['NS','HH','LH','LL','HL'])
lisa_sig = np.where(reject_lisa, lisa.q, 0)  # 0 => NS
lisa_labels = labels[lisa_sig]

# Attach results to GeoDataFrame
gdf['moran_I']     = mi.I
gdf['moran_p']     = mi.p_sim
gdf['geary_C']     = gc.C
gdf['geary_p']     = gc.p_sim
gdf['getis_G']     = g_global.G
gdf['getis_p']     = g_global.p_sim

gdf['lisa_Ii']     = lisa.Is
gdf['lisa_p']      = lisa.p_sim
gdf['lisa_p_fdr']  = p_lisa_fdr
gdf['lisa_cluster']= lisa_labels  # 'HH','LL','HL','LH','NS'
```

```
gdf['gi_z']        = gi.Zs
gdf['gi_p']        = gi.p_sim
gdf['gi_p_fdr']    = p_gi_fdr
gdf['gi_sig']      = reject_gi

# ── 4) QUICK DIAGNOSTIC PLOTS (optional)
try:
    import mapclassify as mc

    # Choropleth of the indicator
    ax = gdf.plot(column='indicator', cmap='viridis', scheme='Quantiles', k=5, edgecolor='white', linewidth=0.2,
legend=True, figsize=(8,8))
    ax.set_title('Indicator by NIL (Quantiles)')
    ax.axis('off')
    plt.show()

    # LISA cluster map
    cluster_colors = {
        'HH':'#e41a1c','LL':'#377eb8','HL':'#4daf4a','LH':'#984ea3','NS':'#bdbdbd'
    }
    gdf['_color'] = gdf['lisa_cluster'].map(cluster_colors)
    ax = gdf.plot(color=gdf['_color'], edgecolor='white', linewidth=0.2, figsize=(8,8))
    ax.set_title('Local Moran’s I clusters (FDR 5%)')
    ax.axis('off')
    plt.show()

    # Gi* hotspots/coldspots (z-scores)
    # Significant only
    gdf['gi_class'] = np.select(
        [ (gdf['gi_sig']) & (gdf['gi_z']>0),
          (gdf['gi_sig']) & (gdf['gi_z']<0) ],
        ['Hotspot (+)','Coldspot (–)'],
        default='NS'
    )
    gi_colors = {'Hotspot (+)':'#d73027', 'Coldspot (–)':'#4575b4', 'NS':'#bdbdbd'}
```

```
    ax = gdf.plot(color=gdf['gi_class'].map(gi_colors), edgecolor='white', linewidth=0.2, figsize=(8,8))
    ax.set_title('Local Getis–Ord Gi* (FDR 5%)')
    ax.axis('off')
    plt.show()

except Exception as e:
    print("Plotting skipped:", e)
# LISA counts
lisa_counts = gdf['lisa_cluster'].value_counts().rename_axis('LISA').reset_index(name='n')

# Gi* classes (after you created gi_class)
gi_counts = gdf['gi_class'].value_counts().rename_axis('Gi_class').reset_index(name='n')

print(lisa_counts)
print(gi_counts)

# Top HH by local Moran's statistic
top_HH = (gdf[gdf['lisa_cluster']=='HH']
          .sort_values('lisa_li', ascending=False)[['NIL','indicator','lisa_li','lisa_p_fdr']].head(10))

# Top hotspots by Gi* z-score
top_hot = (gdf[gdf['gi_class']=='Hotspot (+)']
           .sort_values('gi_z', ascending=False)[['NIL','indicator','gi_z','gi_p_fdr']].head(10))

# Export for the thesis appendix
with pd.ExcelWriter('milan_local_clusters.xlsx') as xl:
    lisa_counts.to_excel(xl, sheet_name='LISA_counts', index=False)
    gi_counts.to_excel(xl, sheet_name='Gi_counts', index=False)
    top_HH.to_excel(xl, sheet_name='Top_HH', index=False)
    top_hot.to_excel(xl, sheet_name='Top_hotspots', index=False)

print("Saved: milan_local_clusters.xlsx")

summary = pd.DataFrame({
    'Moran_I':[gdf['moran_I'].iat[0]], 'Moran_p':[gdf['moran_p'].iat[0]],
    'Geary_C':[gdf['geary_C'].iat[0]], 'Geary_p':[gdf['geary_p'].iat[0]],
```

```
    'Getis_G':[gdf['getis_G'].iat[0]], 'Getis_p':[gdf['getis_p'].iat[0]],
    'LISA_HH':[int((gdf['lisa_cluster']=='HH').sum())],
    'LISA_LL':[int((gdf['lisa_cluster']=='LL').sum())],
    'LISA_HL':[int((gdf['lisa_cluster']=='HL').sum())],
    'LISA_LH':[int((gdf['lisa_cluster']=='LH').sum())],
    'Gi_hotspots':[int((gdf['gi_class']=='Hotspot (+)').sum())],
    'Gi_coldspots':[int((gdf['gi_class']=='Coldspot (–)').sum())]
})
summary.to_csv('milan_spatial_summary.csv', index=False)
summary

# ── 5) SAVE RESULTS
out_cols = ['NIL','indicator',
            'moran_I','moran_p','geary_C','geary_p','getis_G','getis_p',
            'lisa_li','lisa_p','lisa_p_fdr','lisa_cluster',
            'gi_z','gi_p','gi_p_fdr','gi_sig','geometry']

out_path = "milan_nil_spatial_stats.gpkg"
gdf[out_cols].to_file(out_path, layer='nil_stats', driver='GPKG')
print(f"\nResults written to {out_path}")

# LISA Low–Low clusters (FDR-significant)
ll = (gdf[gdf['lisa_cluster']=='LL']
      .sort_values('lisa_li', ascending=False)[['NIL','indicator','lisa_li','lisa_p_fdr']])

# Gi* coldspots (FDR-significant)
cold = (gdf[gdf['gi_class']=='Coldspot (–)']
        .sort_values('gi_z')[['NIL','indicator','gi_z','gi_p_fdr']])

print("LISA LL clusters:\n", ll)
print("\nGi* coldspots:\n", cold)

with pd.ExcelWriter('milan_LL_coldspots.xlsx') as xl:
    ll.to_excel(xl, sheet_name='LISA_LL', index=False)
    cold.to_excel(xl, sheet_name='Gi_coldspots', index=False)
```

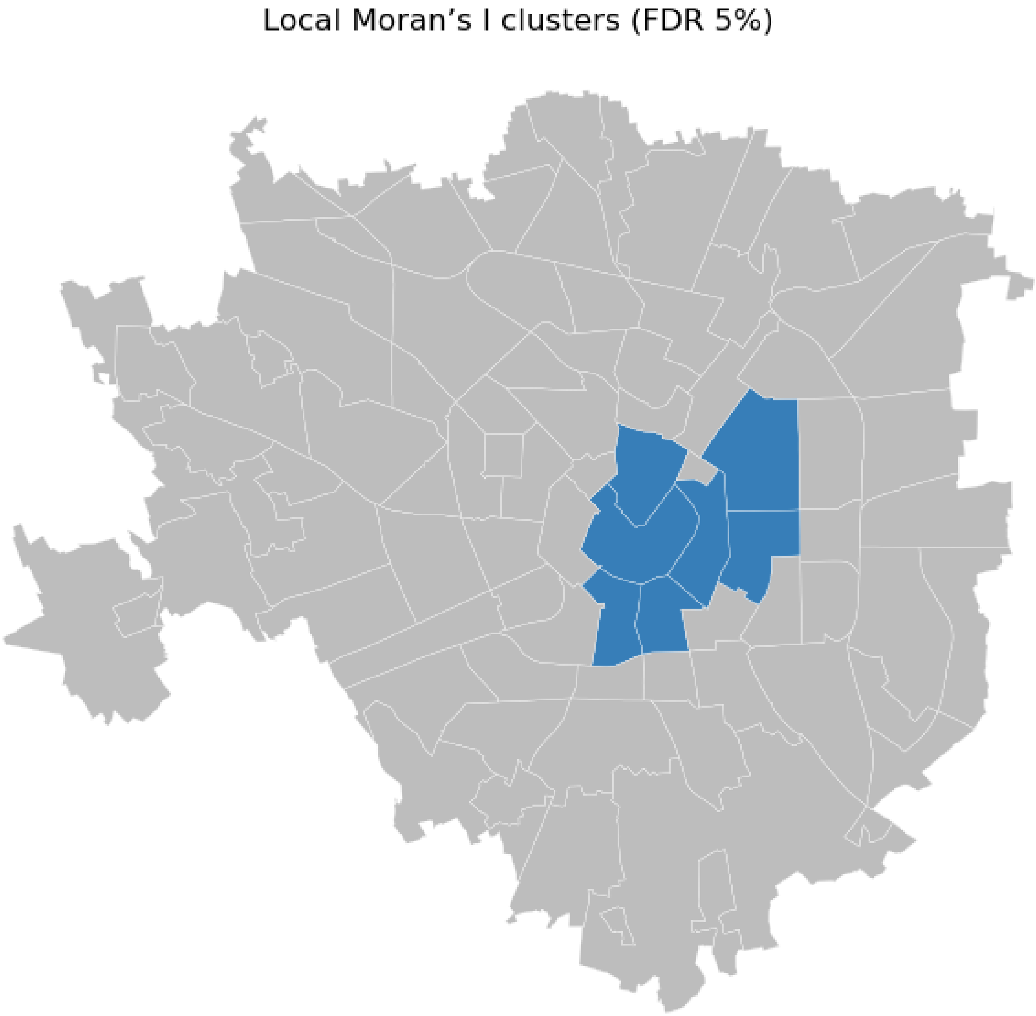
B.3. Final UII calculation

NIL	ECO_INDEX_AR	EDU_INDEX	HEA_INDEX	SOC_INDEX	LIV_INDEX	UII	UII_ARITMETIC
1	73,35	34,33	71,01	20,29	53,08	**54,65**	**50,41**
2	64,12	51,32	69,30	28,26	53,98	**55,33**	**53,40**
3	64,12	45,53	62,75	25,27	34,21	**48,58**	**46,38**
4	66,50	41,42	61,70	34,75	52,84	**52,89**	**51,44**
5	66,50	51,37	63,91	32,67	50,38	**54,40**	**52,97**
6	66,50	54,60	69,16	32,78	49,76	**56,31**	**54,56**
7	73,35	57,38	80,26	37,74	51,80	**63,13**	**60,11**
8	64,12	67,63	61,90	25,00	52,33	**56,32**	**54,20**
9	52,76	55,52	78,30	17,18	52,31	**55,12**	**51,21**
10	52,77	51,87	85,19	33,36	49,02	**58,93**	**54,44**
11	52,76	64,55	90,73	32,38	45,62	**64,08**	**57,21**
12	52,76	59,41	88,37	51,71	47,09	**64,22**	**59,87**
13	50,67	64,44	82,33	48,64	51,29	**62,07**	**59,47**
14	49,29	69,19	57,15	36,96	45,95	**53,02**	**51,71**
15	45,19	49,98	68,57	26,85	54,54	**50,82**	**49,03**
16	50,30	50,03	84,48	58,30	43,68	**60,84**	**57,36**
17	55,42	65,28	80,04	39,59	52,52	**61,06**	**58,57**
18	39,59	52,76	77,57	29,64	38,60	**51,11**	**47,63**
19	27,77	57,43	90,16	68,81	40,77	**64,25**	**56,99**
20	45,79	70,60	97,75	60,56	42,00	**74,52**	**63,34**
21	55,42	58,80	96,29	40,40	50,72	**70,23**	**60,33**
22	51,39	36,22	79,59	41,79	50,27	**54,97**	**51,85**
23	39,59	58,12	77,48	53,38	54,03	**58,51**	**56,52**
24	39,59	73,86	75,37	34,15	53,72	**58,73**	**55,34**
25	63,90	54,41	92,55	51,83	51,65	**68,65**	**62,87**
26	62,89	53,70	94,26	42,67	50,92	**68,64**	**60,89**
27	56,46	49,76	91,29	29,90	50,86	**63,02**	**55,65**
28	62,89	60,99	90,53	64,12	48,81	**69,56**	**65,47**
29	63,90	70,12	76,82	32,71	46,19	**60,90**	**57,95**
30	47,58	57,24	77,80	37,71	49,17	**56,33**	**53,90**
31	47,58	67,63	75,21	31,80	43,49	**56,08**	**53,14**
32	52,85	63,49	75,90	27,83	40,29	**55,21**	**52,07**
33	47,58	66,67	81,24	60,43	52,09	**63,73**	**61,60**
34	52,85	52,42	76,79	28,73	42,99	**53,67**	**50,76**
35	47,58	57,33	83,37	49,76	40,77	**59,24**	**55,76**
36	48,69	67,18	80,80	53,91	47,97	**62,09**	**59,71**

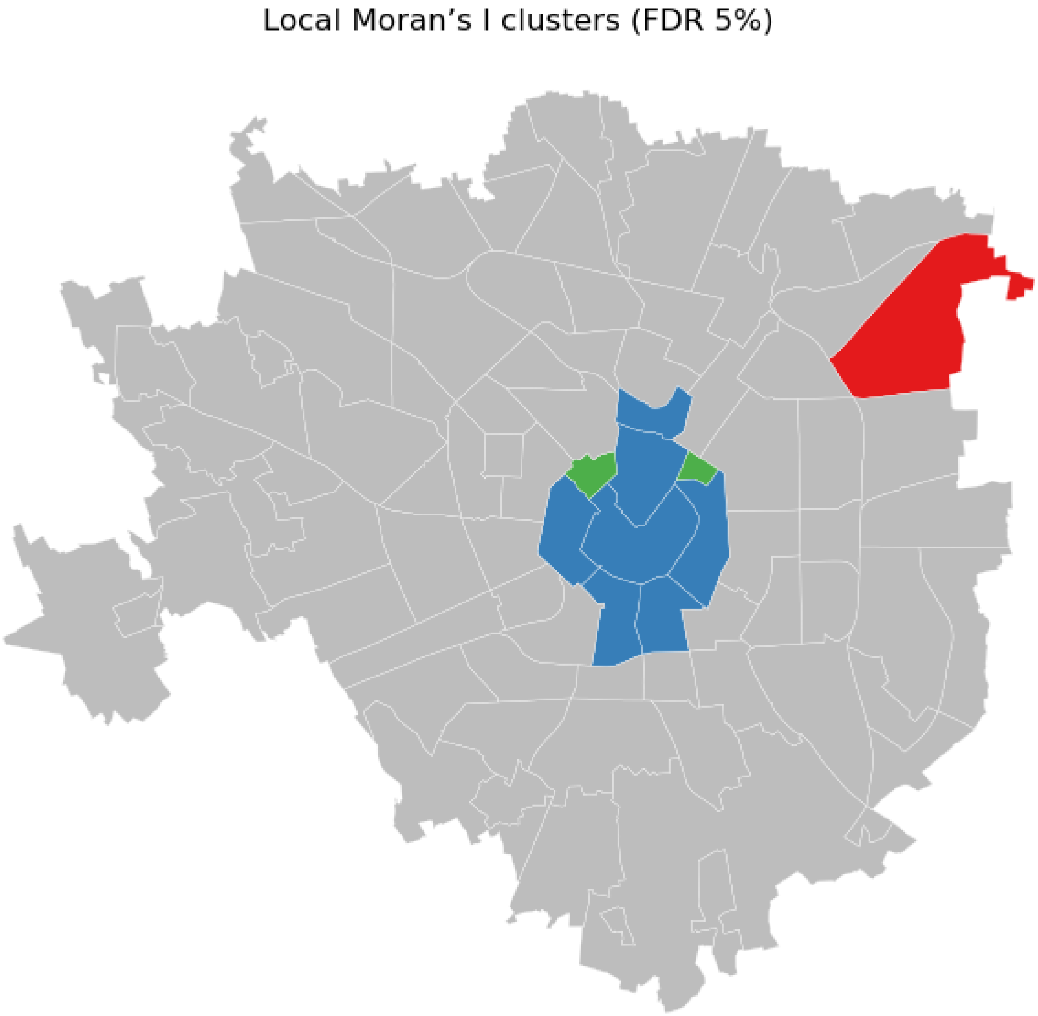
37	48,69	63,47	82,96	48,10	56,64	**62,64**	**59,97**
38	48,69	62,32	80,12	39,24	55,94	**59,88**	**57,26**
39	48,69	48,79	75,83	26,60	56,76	**54,13**	**51,33**
40	56,43	52,97	77,00	29,84	61,93	**58,25**	**55,63**
41	56,43	62,64	78,50	34,70	48,27	**58,76**	**56,11**
42	56,43	48,51	81,25	39,11	44,57	**57,19**	**53,97**
43	48,69	60,53	88,52	46,88	48,12	**63,35**	**58,55**
44	55,92	55,85	85,05	21,78	47,32	**58,54**	**53,18**
45	55,92	56,15	81,26	42,18	50,41	**59,80**	**57,18**
46	56,43	60,64	81,01	37,71	43,39	**58,97**	**55,84**
47	56,43	55,82	75,09	25,90	67,47	**58,96**	**56,14**
48	56,43	58,30	79,64	35,04	45,00	**57,82**	**54,88**
49	50,48	58,22	88,92	49,48	46,07	**63,53**	**58,63**
50	56,19	56,43	88,64	34,87	53,31	**63,13**	**57,89**
51	50,48	58,63	93,44	43,75	55,01	**67,43**	**60,26**
52	51,52	43,91	88,94	45,27	48,08	**61,15**	**55,54**
53	51,52	57,61	78,36	31,20	46,71	**56,02**	**53,08**
54	45,53	60,95	79,60	31,44	58,55	**58,39**	**55,21**
55	45,53	60,67	81,34	37,71	50,02	**58,30**	**55,05**
56	53,88	57,72	73,02	36,52	40,49	**54,28**	**52,33**
57	42,95	66,53	98,99	68,47	44,64	**77,37**	**64,32**
58	51,47	61,53	88,15	48,16	55,65	**65,03**	**60,99**
59	56,70	67,20	79,03	27,18	61,72	**61,56**	**58,37**
60	46,11	50,28	77,01	30,79	58,12	**55,22**	**52,46**
61	53,88	59,38	74,88	37,38	49,44	**56,84**	**54,99**
62	53,88	64,00	68,68	28,68	55,49	**55,95**	**54,15**
63	53,88	66,62	66,67	29,94	53,06	**55,76**	**54,03**
64	46,11	59,29	81,28	34,31	58,10	**59,10**	**55,82**
65	46,11	57,83	80,75	38,45	43,92	**56,66**	**53,41**
66	42,95	60,87	76,20	29,17	33,54	**52,09**	**48,55**
67	51,47	62,65	81,64	32,78	57,43	**60,47**	**57,19**
68	56,70	61,80	87,00	39,36	53,35	**63,78**	**59,64**
69	52,14	60,64	86,75	31,84	49,47	**61,18**	**56,17**
70	44,68	59,78	90,55	41,27	53,94	**64,12**	**58,04**
71	49,91	53,87	85,32	58,04	49,26	**62,56**	**59,28**
72	49,91	69,55	76,47	33,49	56,54	**59,83**	**57,19**
73	59,63	65,89	67,57	27,98	56,85	**57,46**	**55,58**
74	59,63	62,43	68,65	31,53	38,26	**54,18**	**52,10**
75	59,63	65,71	68,01	38,62	78,28	**64,12**	**62,05**
76	59,63	59,70	76,80	47,64	50,64	**60,34**	**58,88**
77	55,81	60,88	80,25	41,78	41,36	**58,86**	**56,02**
78	52,14	61,56	76,47	39,18	48,36	**57,61**	**55,54**
79	55,81	59,20	90,36	72,69	46,49	**69,50**	**64,91**
80	52,28	67,74	85,34	54,10	42,66	**63,99**	**60,42**

81	59,63	63,51	70,68	31,67	44,89	**56,08**	**54,08**
82	52,28	61,12	82,29	49,24	40,48	**60,14**	**57,08**
83	52,28	61,68	80,48	46,91	41,71	**59,30**	**56,61**
84	52,28	62,90	75,63	27,34	34,39	**53,93**	**50,51**
85	48,69	64,20	75,00	25,08	69,18	**59,65**	**56,43**
86	56,43	64,54	49,63	25,10	64,60	**53,95**	**52,06**
87	45,53	54,76	75,00	24,93	63,55	**55,74**	**52,75**
88	46,11	66,63	61,91	25,17	52,70	**52,44**	**50,50**

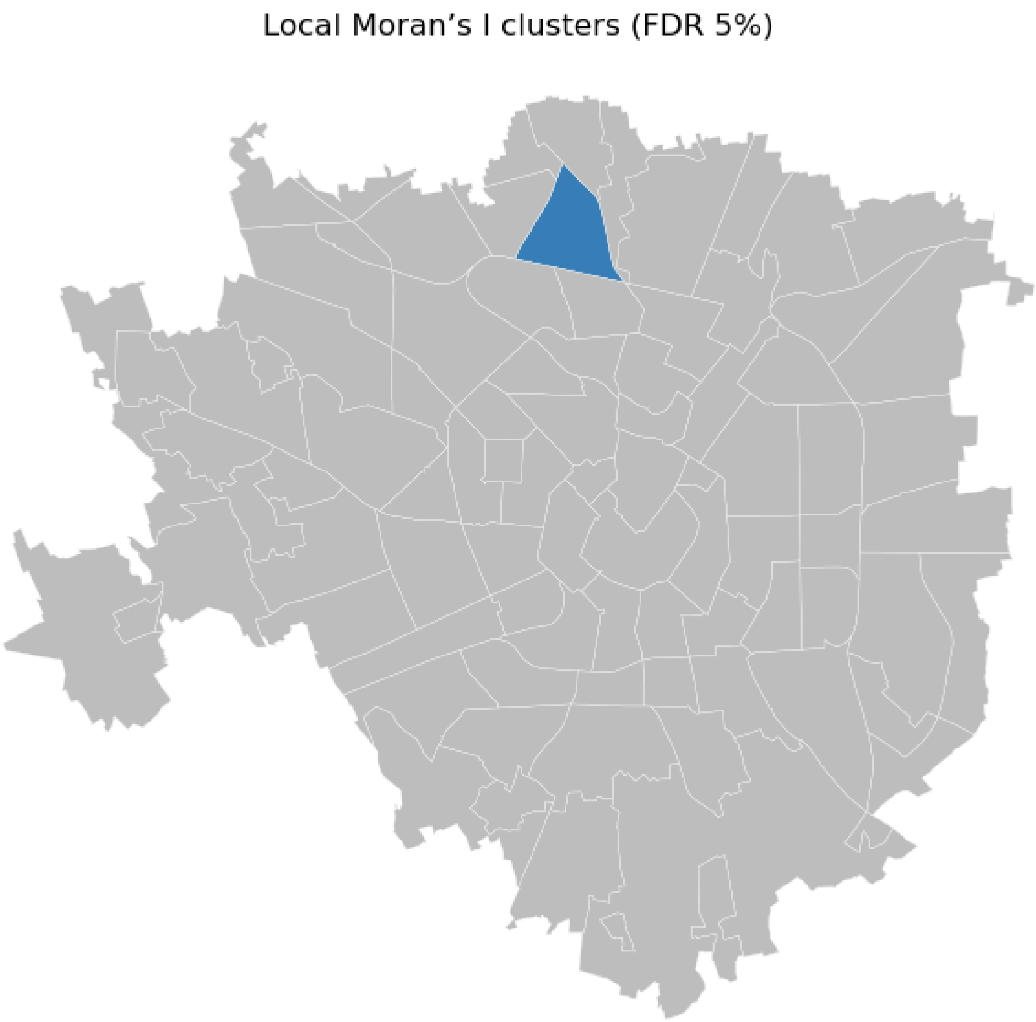
B.4. Image representation of the educational global and local calculations



B.5. Image representation of the socio-demographic global and local calculations



B.6. Image representation of the living environment global and local calculations



GitHub repository. Hence, here a brief description of the main ideas is going to be performed.

From the section *Importing instances for the code* the key comments are that the polygons are merged with their corresponding indicator number, just by sorting them attending to the ID of each of the NILs, something fixed for all the areas, even if they change slightly in their real names. The numbers are always constant. Also, it is a well-known practice to validate if the web maps are using the standard WGS84 to have the same base in the latitude and longitude measurements.

Advancing next to the representation part located in *Building the representation* a folium library was used in order to recreate the interactive map. This library is an intermediary between the python and CSS coding with the Leaflet dynamical JavaScript mapping resources (GitHub Folium, 2025). The Leaflet conglomerate a wide range of resources from open sources to permit user-friendly representations, being the most used tools for interactive mapping (Volodymyr Agafonkin, 2025).

The coding concept was to create six overlaid representations of the final indicator and the five sub-indicators. This was done to understand the whole reality with the six images. The only interaction of the user is the selection of the map that it is going to see, with a bottom logic, the layers are hidden and shown, depending on the selection. This is done by the viewer in the upper-right zone, where a legend is displayed. People just need to choose what layer of representation they want to see. However, we are not just showing a single glimpse of reality. For that reason, a landing page was created to integrate all the different representations, as shown in Figure 9. In total, we have 4 interactive visuals: one for the generalist case of equally weighted indicators and three for the specific age group.

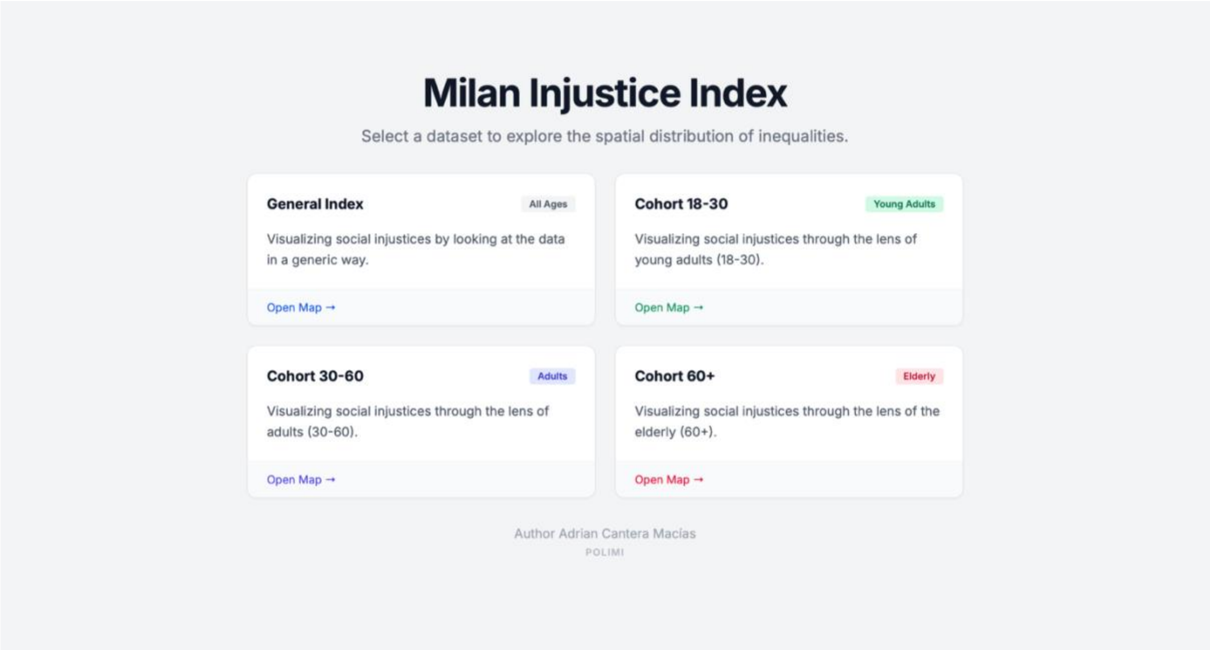


Figure 10: Landing page of the final platform

When a person opens one of the four visuals, it is chosen as the primary image and the final indicator UII because it is the composite indicator, and users should see it first to gain context for the representation.

For each layer, a scale was defined to include it in the legend. For all indicators, the data were divided into three segments: low perception of inequality, medium perception of inequality, and high perception of inequality.

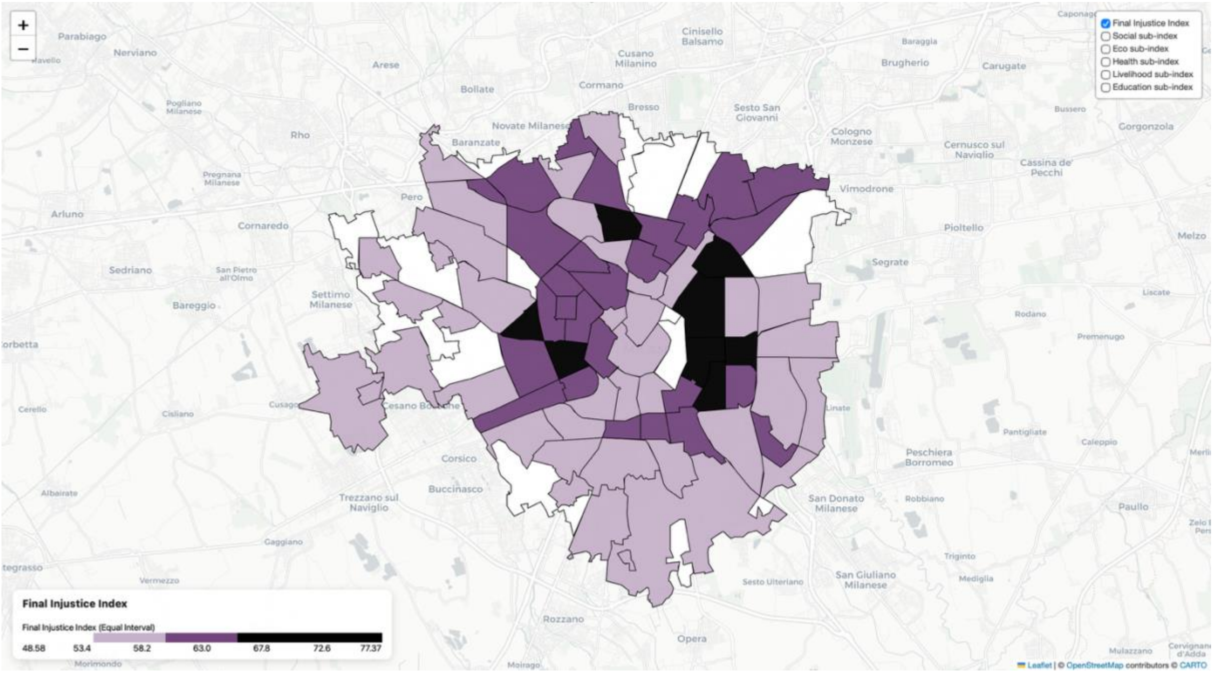


Figure 11: Final representation from the Python code integrator

The rest of the coding specifications are detailed in the last part of the coding structure talking about the spatial tests *Spatial analysis code.*

The global and local calculations were done, including Moran's, Geary's and Gettis-Ord G. The analysis includes the calculation of the hot-spots and the cold-spots of the principal indicator. With that, the spatial pattern is defined.

5 Results and discussion

Representing the inadequate distribution of urban and political resources, it is a practice in the core heart of the human being. Enhancing people's lives should be an objective many cities pursue. With the power of the web tools available, the present thesis work was able to represent the voice of the inhabitants of Milan, showing their order of preference in the matter under study. The following results are the discussion that needs to be opened, to overcome the people's necessities

5.1. The Urban Inequality Indicator (UII): Final results

For the first part of the results, testing the methods used seems like an optimal idea. The test examines how it influences the mathematical weighting of the data. This sensitivity analysis will compare the results from using an arithmetic mean (favorable to compensating) with those from a geometric mean (which, by multiplying its values, could be conditioned by a present disparity factors) in the last calculation part. We could see in the table in Annex B *Final UII calculation* .

Before comparing and identifying unbalanced NILs, the whole process included several design decisions to enhance comprehension of the problem.

When describing each sub-dimension's four factors, in this part, an arithmetic average was estimated independently for each zone. Following the HDI's great example, the arithmetic mean is used here to have a compensation. Here, it is interesting to compute the average of the four factors, without giving certain values more importance than others (as in the geometric mean).

For example, if a zone is not accessible by bus or metro, it could be accessible by bike or walking. Another example could be in terms of the living environment: the same zone could have a high immigration rate, but the population density is not particularly high. So, for that reason, if a geometric is applied, the result would be eclipsed by a single factor, a high or low factor and would not reflect the full reality of that category.

After this clarification, we are going to concentrate on the last calculation part, when aggregating all the sub-dimensions into the construction of the final index result. In this part we are comparing the result with a compensating approach and with a tendency approach, to see the distribution of the inequalities across the area. It is interesting to analyze whether some zones have an equally distributed inequality, or whether it is due to a really low value in one of them.

In this context, the first comment to be made is that all the results are compared to a normal scaling system from 0 to 100, from least to most uneven distribution of equal resources.

The lowest value in terms of inequality is the same in both, the NIL corresponding to the number 4 (*GIARDINI P. TA VENEZIA*) with a number below 50. The central aspects provoking this high and short ranges of values are known and it is bi-causal:

⇒ **Economic dimension:** There are a few values below the 50th value line; this is due to the fact that the gentrification problem is present in all European capitals, the prices of rent are at a shockingly elevated site and the possibility of buying a house is nearly zero, with the salaries available. In the quantification part, the method used was a MIN-MAX approximation, so values near the top value are close to it, reflecting the reality of the city. For that sake, knowing that all the prices are concentrated all together, even areas with lower prices do not have extremely low values. If these areas were given really low values in the indicator, we would not be reflecting the reality of Milan.

⇒ **Pollution decision:** early in this document, it was stated that the pollution variable of the health indicator, was set at the maximum in all the areas. Since, the method used with the geometric mean is beneficiating the considered as "bad values" (reflecting more inequality), this propulses the sub-indicator in higher values. This decision, was not personal was based in data available and explain in the section *Health dimension:*

Having this facts clear, we could compare the two distribution, to identify unbalanced neighborhoods.

Regarding the high-inequity numbers, the zone number 20 (*PADOVA - TURRO - CRESCENZAGO*) present a good value in the economic and living environment scale, however the others were above or way above the mean, so in the arithmetic example the number was hidden by others. On the geomean representation, the value state as one of the top ten uppermost grades. Something similar materialized in number 52 (*PORTA MAGENTA)* . In this specific cases, the presence of a disparity in the way inequalities are distributed is a fact. At the other site of the scale with lowest inequity numbers, happened another interesting factor with number 10 (*PORTA GARIBALDI - PORTA NUOVA*), where numbers were similar.

Nevertheless, as we want to penalize the presence of inequalities, in the geomean outcome it has a value in the middle of the distribution rather than being one of the bests NILs.

Identifying a tendency for the unbalance distribution, the information showed the clear prevalence of areas of the city with greater access to green spaces, to have less inequalities values. These zones are also associated with fewer gentrification problems. However, these districts are far from the city center. But this differences in the categories reflect a not uniform distribution of inequalities.

The city center is another area where the numbers are lower, due to the significant difference in the availability of leisure services and accessibility to public transport (metro, trains, buses…) compared to other areas.

Apart from this specific cases, the rest have an overall distributed inequality across all the categories. In the figures below specified, the comparison could be made.

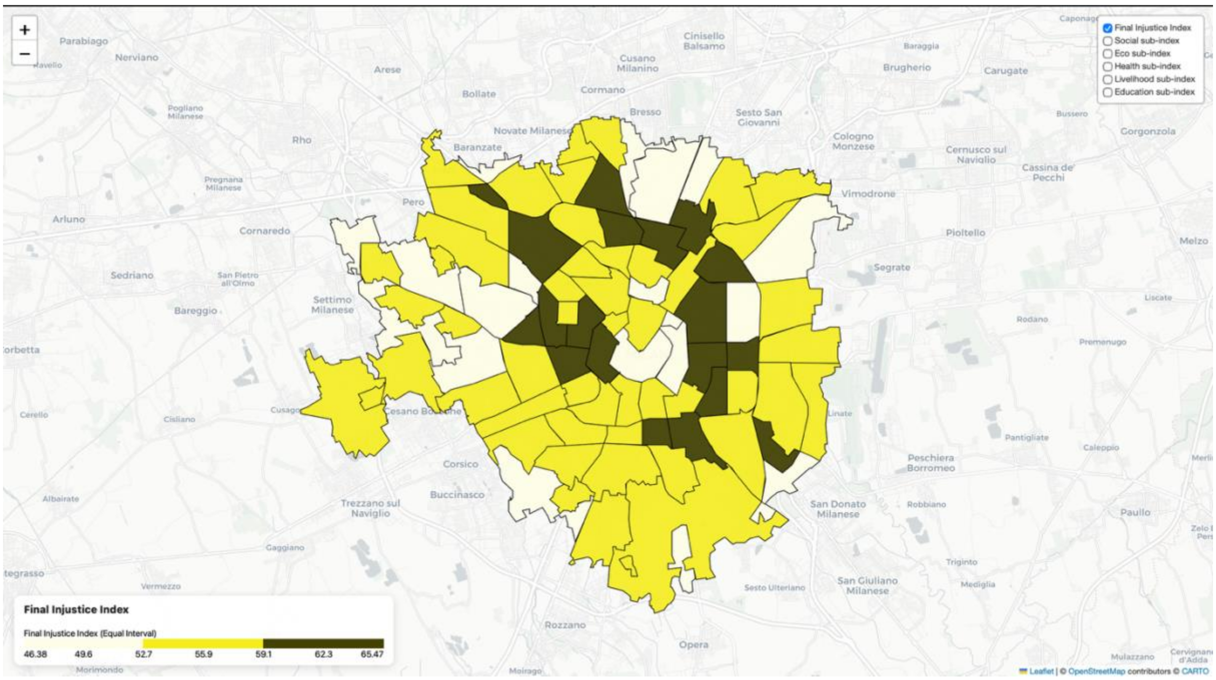


Figure 12: Arithmetic approach for the final UII

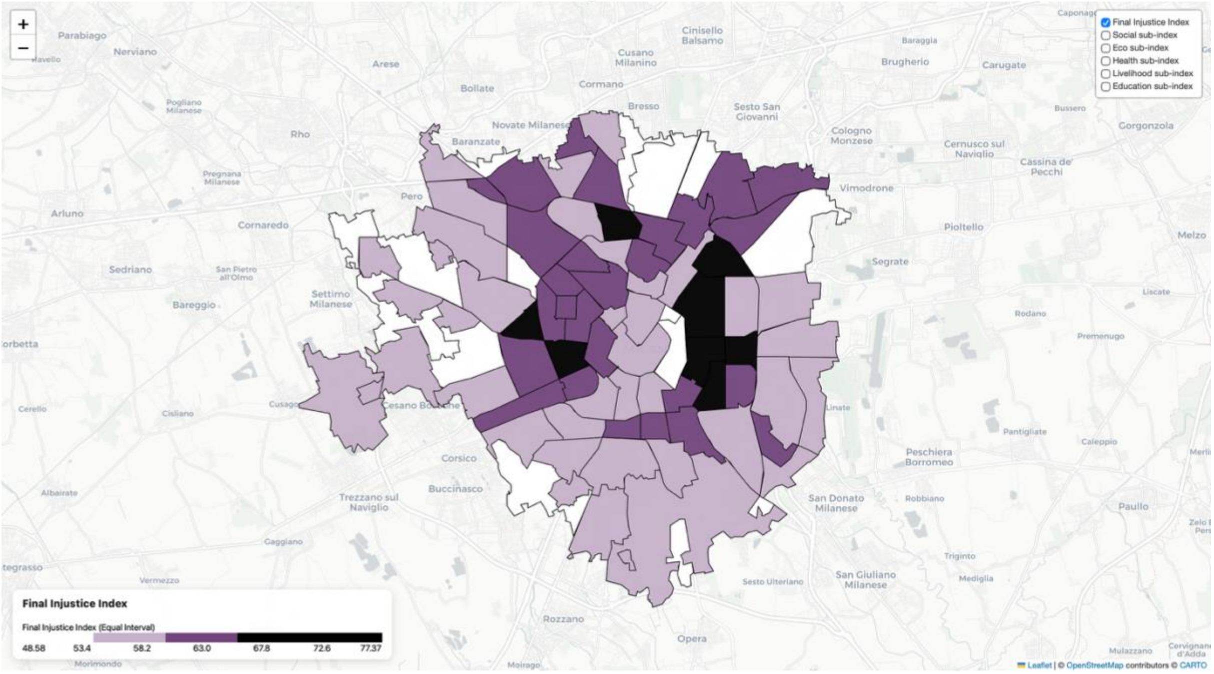


Figure 13: Geometrical approach to the final UII

As a matter of fact, the worst ranked and the best ranked NILs, are specified here in the Table 7 for the geometrical case.

NIL	NIL NAME	UII VALUE
3	GIARDINI P.TA VENEZIA	48,58
4	GUASTALLA	52,89
14	NIGUARDA - CA' GRANDA - PRATO CENTENARO - Q.RE FULVIO TESTI	53,02
15	BICOCCA	50,82
18	CIMIANO - ROTTOLE - Q.RE FELTRE	51,11
19	PADOVA - TURRO - CRESCENZAGO	64,25
20	LORETO - CASORETTO - NOLO	74,52
21	BUENOS AIRES - PORTA VENEZIA - PORTA MONFORTE	70,23
25	CORSICA	68,65
26	XXII MARZO	68,64

28	UMBRIA - MOLISE - CALVAIRATE	69,56
34	CHIARAVALLE	53,67
51	PORTA MAGENTA	67,43
57	SAN SIRO	77,37
58	DE ANGELI - MONTE ROSA	65,03
66	QT 8	52,09
79	DERGANO	69,50
84	PARCO NORD	53,93
86	PARCO DEI NAVIGLI	53,95
88	PARCO BOSCO IN CITTA'	52,44

Table 6: Best and worst valuated zones of Milan urban area

In this case, this comparison method confirms a main asset: the city of Milan generally shows high levels of inequity across all the dimensions studied. The standard mean will not compensate for such a high disparity across dimensions. However, to follow the well-established indicator construction method applied in all the papers studied, the geomean calculation would be maintained.

To expand the knowledge, the engineering tools and methods could give us a better understanding of the results and confirm how it structures the field.

5.2. Spatial analysis: Identifying hotspots and colds pots of inequality.

As stated, before in the beginning of the document, the complexity of the urban representations requires of some statistics, to identify some kind of inclinations in the results. Since it is important to determine the actual behaviour of the surrounded zones of a NIL, the next calculations are performed under the basis of global and local indicators. The tests were done to the general injustice indicator, already stated as the geometrical one. For the sub-indicators, only if big patterns were identified comments were done.

5.2.1. Results for the general UII case

Global spatial structure: using the coding structure located at the end of the document *Spatial analysis code* the results show a statistically significant positive spatial correlation (*Moran's I: 0.1422 p-value (perm.): 0.0154*). This means that the contiguity-based calculations determine that neighbourhoods next to each other tends to be the of the same nature (in this case with results of the UII). The positive denomination, put the base of clustering analysis.

The zones are not randomly or checkered-wise (high UII values near low UII values) distributed, they are showing located problematics tendencies. Geary's findings corroborate the idea, although the power is moderate in this calculation (*Geary's C: 0.8299 p-value (perm.): 0.0185*), the value propose that the touching NILs are some kind of similar to each other. This two first measurements indicate us, with the low and high values in each side, that the pattern of the city is not extremely determined by big blocks of high values and low values.

The p-values are lower than 0.05, so the results are factual and the final conclusion should be: Milan's NILs have a clustering behaviour without being a clear division in two zones, is distributed in small clusters of inequalities around the city.

Local spatial structure: this analysis identifies specific local trends, including how low and high values are distributed relative to one another.

The adjusted Local Moran's detects a Low-Low (LL), cluster located at Brera and an outlier Low-High (LH) in the east of the image. So, in other words, there is a cold spot in the middle of the city (low UII numbers in the surroundings) and a hot part in the eastern part (low UII number in an area with predominance of high values) as seen in the Figure 13.

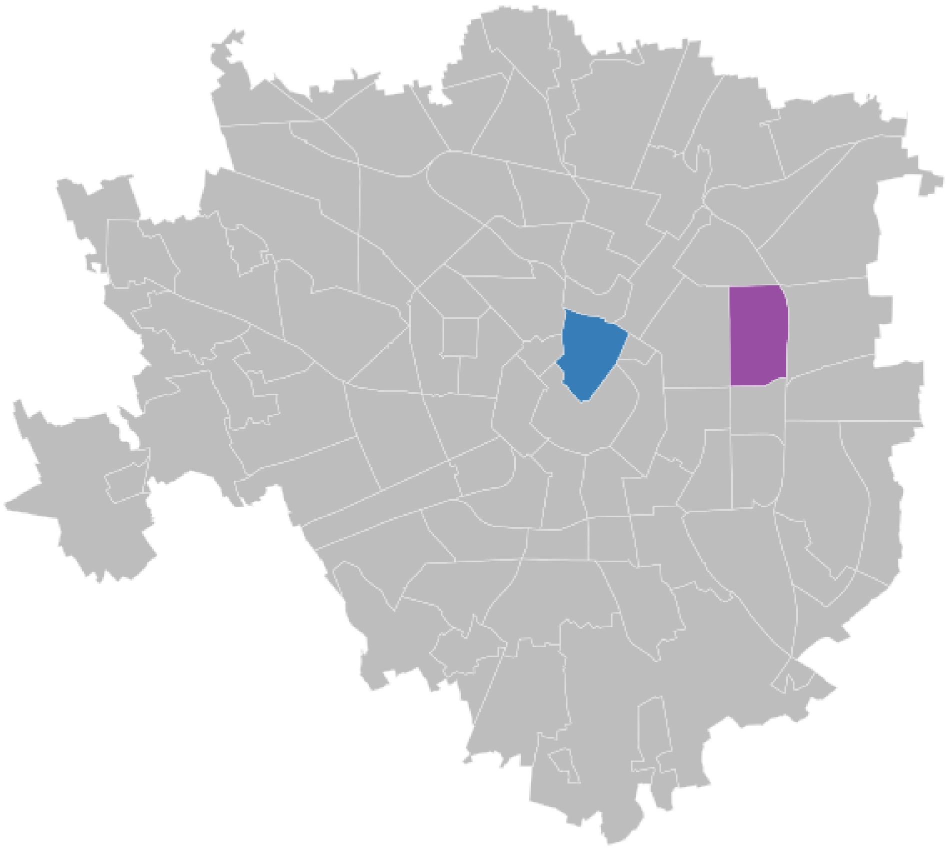


Figure 14: Local Moran's clustering identification

The reasoning behind these results suggests the following:

⇒ **The "Brera" cluster as a reference:** this values reinforce the point of having low values around it and situate the city center as a barrier for inequalities (with this distribution).

⇒ **Eastern pocket of high values:** the presence of a LH outlier is saying that the surrounding of it are hot spots. Consequently, this place is inside a non-identified hot spot. The others could extract practices from this zone to palliate the inequalities.

The tendency is latent to higher values; however, the local analysis shows a more complicated behavior, coherent to the low-medium value in the Moran's calculation. So, the results compared, indicate that the clusters of high values are not bigger enough to be considered as HH hotspot patterns (big areas with many high values all together).

In the sub-dimensions, the comments are the succeeding:

⇒ **Educational matrix:** a better separation of the clusters, indicating a big LL cold spot in the middle of the town, with five existing NILs. Global calculations corroborate the idea of equality within zones. More information at the Annex: *Image representation of the educational global and local calculations*

⇒ **Socio-demographic matrix:** here there is an interesting pattern. Our city center is another time the focus of the low values. Nonetheless in this particular time there are two high values surrounded by low values, indicating a disparity in this little zones, located in the upper part of the central layout. Another hot spot is present in the outskirts of the city center, elucidating a predisposition. More information available here: *Image representation of the socio-demographic global and local calculations.*

⇒ **Living environment matrix:** here there is a change in the tendency as the low spots were at the upper part of the city. Even not randomly distributed, the data shows a clear part of the surroundings similar to each other. This representation could be found at: *Image representation of the living environment global and local calculations.-*

5.2.2. Comparing the results with the bias study.

Having done the survey and the representation of the generalist, equally distributed graphic, now the results are going to be tested and compared with real data extracted from people. As calculated in the section *Phase 4: Integrating subjective data into the composite indicator.* the percentages will be applied. In this part the breakdown will have the same structure as the last section.

Before talking about the indicators, in the next figures it could be seen the representations referring to each age group and reflecting the final indicator calculation.

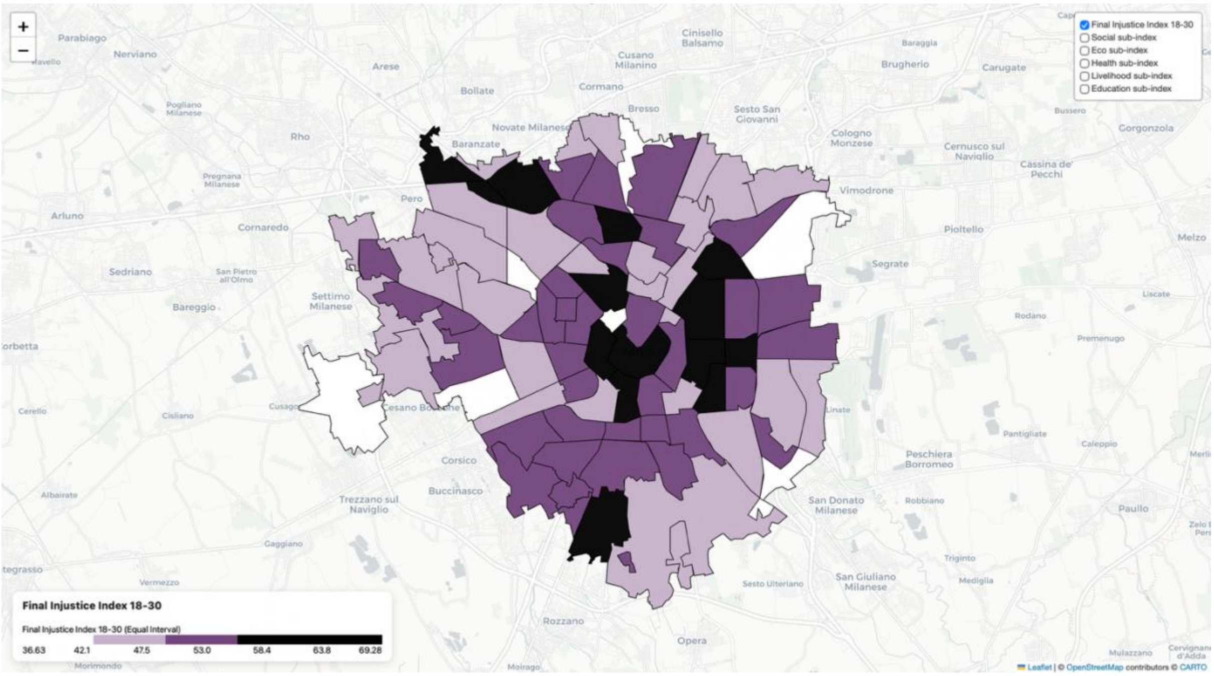


Figure 15: Representation of the Milan's urban reality by the 18-30 age gap

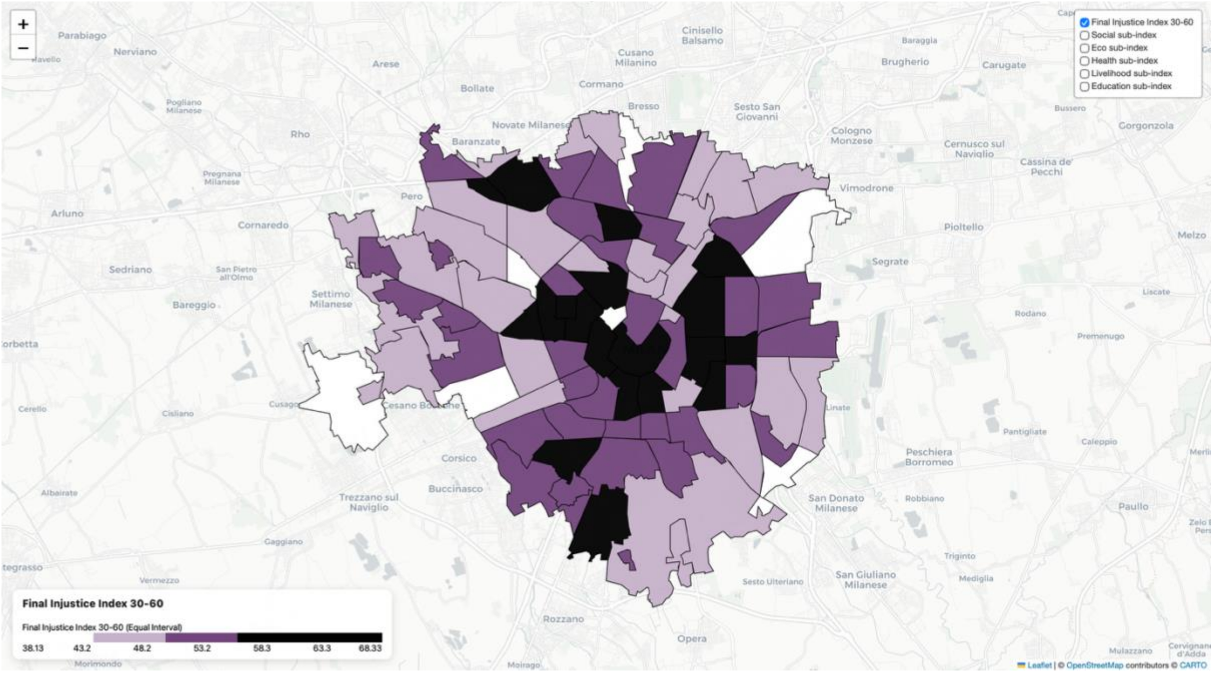


Figure 16: Representation of the Milan's urban reality by the 30-60 age gap

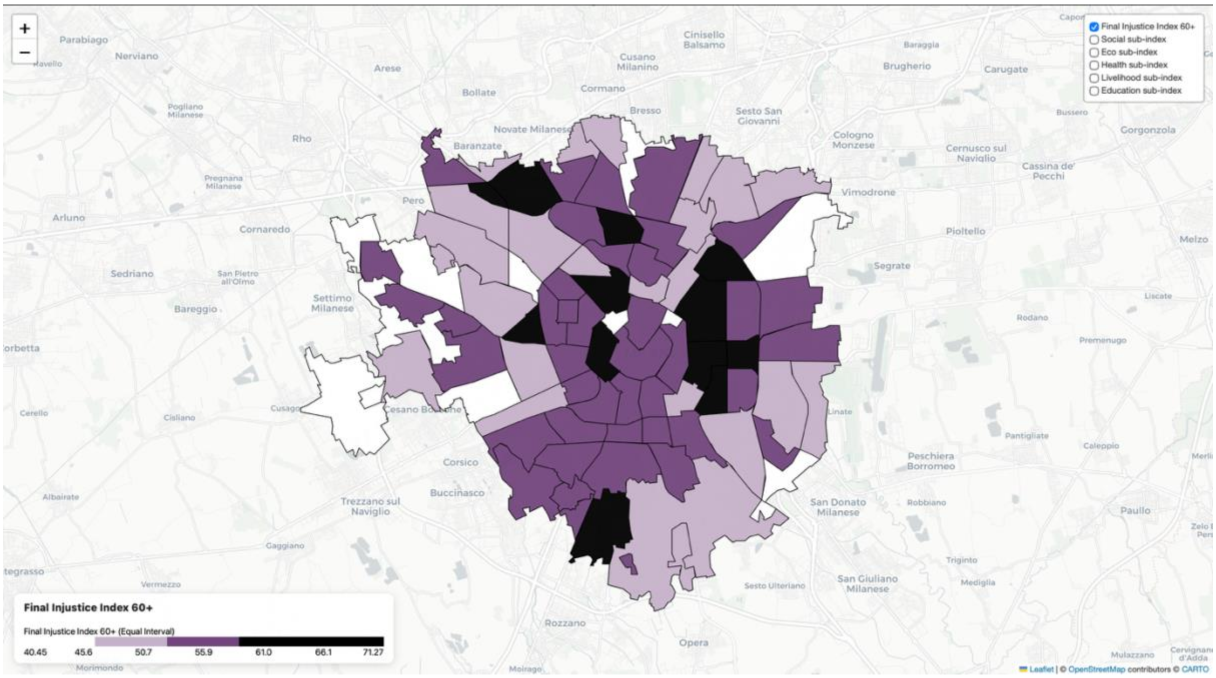


Figure 17: Representation of the Milan's urban reality by the 60+ age gap

In this case, as it is not an objective representation and because of people's bias toward particular segments of inequality, the global and local calculations were not relevant to our study. In other words, there was no evidence of a geographically based cluster of low or high values. This means that the people are valuing the categories as a personal view of the whole city and the problematic perception is not subjected to a single location.

5.2.3. How the representations help into sketching the reality

Looking at the previous images, it is clear that the reality of inequality varies by age; we can see some similarities from image to image.

The initial comment pertains to the city's central and central-eastern districts, where the highest values are observed. This fact is clearly different to the normal representation, where the injustice in the city center was lower. However, the analysis of the representations of the selected age groups indicates a clear tendency for the values of greatest social injustice to be found in the center of the city, except for the last age group.

In this last representation, the values are less concentrated in the center of the municipality, largely due to lower valuation of rental prices (sub-indicator ECO_3) for this age group compared to the other age segments. Therefore, the appreciation of social justice within these margins is different. Despite residing in areas with the highest rental prices, age is not a decisive factor in judging and valuing. These confirmed the literature review's findings, which stated that younger people were more preoccupied with rental prices.

By the other hand it should be noted that the presence of health headquarters does not constitute an issue for people under the age of 60. Consequently, this specific category is of lower importance for them.

There is a clear correlation between the proximity of educational sites and their state, and the high propensity of young people to use public transport or cycle (sub-indicators LIV_2 and LIV_4). They demonstrate a willingness to prioritize these living environment indicators in determining the injustice of a specific zone. This is sufficiently enough to determine that the connectivity is another main issue for the younger people.

Considering the middle age group, they present the highest concentration of upper values in the inequality scale. Up to twenty NILs are consider by them as top tier in inequality perception. This is explained by a consequence of being in the middle road between the two age groups. However here it should be said that the pattern is more like the first group rather than the senior group. Some sub-indicators, like the social environment one, are nearly the same between these two age cohorts. They both prioritize more the leisure time and the experiences rather than the density population. On the other way around happens in the +60 representations, saying that they prioritize more the density of population.

5.2.4. Implications of subjective bias in data-driven decision making.

The findings detailed in the last section provide a clear change of view on the form of urban governance.

The previous part demonstrated that the absence of global or local indicators indicates that human perception differs from what the data shows. Because a machine could say that a one zone is considered bad because of the lack of green spaces or leisure centers, but if people are considering more important to determine inequalities the cost of living and mobility access, it should be considered.

Raising a voice over these injustices ought to be natural. Now, people are considered in these representations, and the uniform landscape is diverse, encompassing multiple realities. For example, in the first non-biased representation of Figure 13 The city center of Milan was considered medium in inequality, and there was a LL spot around Brera. For municipalities and governments, seeing that representation would not have been clear enough to recognize a problem.

Nonetheless, when asking people, now the city center for people under sixty years of age, emerges as a epicenter of injustice, driven by the exacerbated cost of living. If policies were driven only by objective data representations, the efforts would not be targeting the right direction. It is also counterproductive to aggregate divergent needs into a single calculation; this would mask exposure to inequalities. The aggregation of needs should be divided into groups of interest (age, social status…).

Here, it is important to clarify that the representation of the population's bias is mandatory. The information must be accurate and reflect the realities of the age cohorts so as to facilitate municipalities to allocate resources and focus on a specific part of the demographic profile.

Lastly, this requires a shift in how decision-makers view citizens. It passes through a radical change in the conception of civic consideration, not being mere consumers or voters, but evolving into people with specific necessities. Rather than orchestrating political decisions, like building more infrastructure, neighbors should be listened. Political planners have the tools available, but the willingness is the key factor in changing reality.

6 Conclusions

The thesis described has the main objective of breaking with traditional paradigms of urban data representation and analysis that lack a social scope. The case of Milan exemplifies that spatial measurements are not static or just a geographical representation without implications. It is indeed influenced by demographic bias.

Having this new conversation is considered the core achievement of this work. Now it is proven that there is no such thing as a method that fits all the requirements faced by citizens.

Following the closing, these were the main results of the thesis.

- **The Novel UII Methodology**

  One of the main contributions is the creation of a new methodological approach to indicator construction. Regarding the technical part, aggregating the arithmetic mean in the sub-indicator calculation to avoid misalignments due to a single factor and using a geometric mean in the global index calculation, yields to a well-balanced mathematical index.

  Furthermore, the integration is not limited to this; it also covers the subjective demographic bias by applying a new weighting system. Just by classifying the dimensions by target audience, the personal perceptions could be added. Now, data analysis is moving into the sociological area.

- **The Interactive Visualization Platform**

Not only was the indicator constructed, but an innovative manner to represent the results was applied. Using tools like Python, GIS, and coding strategies, this allows for bridging the data to the final decision for policymakers.

With a medium interactive result, the choropleth maps were done by tailoring different age-groups into the weighting calculation. For the 88 NILs, the platform shows dedicated values for each. Ensuring, in all cases, an ethical treatment of the data and a careful design choice made specifically to enhance interpretability.

Considering the two main questions that nurture this project work, each of the two contribution are answering how people interpret the urban reality (RQ1) and how it could be represented to enhance the interpretability to stakeholders (RQ2).

6.1. Limitations of the study

Despite that the UII provides a strong framework, during the realization of the thesis some limitations were encountered:

- **Number of participants in the questionnaire**: one of the main complications was finding some relevant data, actually from people in Milan, according to the age-groups defined. Specially in the senior category was a tough task. Nevertheless, it needs to be said that online and on presence dynamics were done to gather all this information in a truthful way

- **Data available:** second biggest issue was to find updated data frames at a NIL level. The are not so many platforms putting together this information by free. From the local headquarters web pages, information was extracted, but some dimensionalities talked about in the literature review were not include it, since no data was found. One main example is the internet connection or the technological development of each city (key aspect considered by the under thirty years old).
- **Testing with real policy makers:** the platform is an strong outcome, nevertheless it was not proved in a controlled environment and experiment if the design choices were increasing the interpretability. It is based on theory and papers doing these type of experiments. Unfortunately, it was beyond the scope of this work testing that with an experiment.

6.2. Future research

Regarding the next steps of the project, some came as straightforward.

- **Applying this methodology to other cities:** with the same problems as Milan (Barcelona, Paris, Amsterdam…). The UII indicator is highly scalable, and future lines of investigation should apply this cross-demographic analysis of the spatial justice.
- **Integrate real-time data:** the current methodology is based on historical datasets. Further interactions need to go in the direction of integrating APIs from IoT devices in the city to track the dimensionalities and recurrent surveys could be done to readjust the weights within demographic groups.

- **Track more dimensions:** this refers to tracking more information about the people surveyed. Now, it was only the age; next steps should be seeing how these age groups see the reality, considering where they live. This could increase the likelihood that a person will feel a certain way about the urban ecosystem, depending on their age and location.

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8 Appendix A

A.1. Table specification of population, NILs and municipal numbers

ID	NIL	CAP	MUNICIPI	POPULATION
1	DUOMO	20123	1	16226
2	BRERA	20121	1	18361
3	GIARDINI P.TA VENEZIA	20121	1	40
4	GUASTALLA	20122	1	15470
5	PORTA VIGENTINA - PORTA LODOVICA	20122	1	13537
6	PORTA TICINESE - CONCA DEL NAVIGLIO	20122	1	20348
7	MAGENTA - S. VITTORE	20123	1	18026
8	PARCO SEMPIONE	20121	1	0
9	PORTA GARIBALDI - PORTA NUOVA	20159	1	5817
10	STAZIONE CENTRALE - PONTE SEVESO	20124	2	17543
11	ISOLA	20159	2	22458
12	MACIACHINI - MAGGIOLINA	20159	2	26490
13	GRECO - SEGNANO	20125	9	16380
14	NIGUARDA - CA' GRANDA - PRATO CENTENARO - Q.RE FULVIO TESTI	20162	9	36306
15	BICOCCA	20126	2	8711
16	GORLA - PRECOTTO	20127	2	30101
17	ADRIANO	20132	2	18169
18	CIMIANO - ROTTOLE - Q.RE FELTRE	20134	2	19636
19	PADOVA - TURRO - CRESCENZAGO	20128	2	38167
20	LORETO - CASORETTO - NOLO	20131	2	43513
21	BUENOS AIRES - PORTA VENEZIA - PORTA MONFORTE	20129	1	62520
22	CITTA' STUDI	20133	3	36144
23	LAMBRATE - ORTICA	20134	3	12592
24	PARCO FORLANINI - CAVRIANO	20134	3	2675

25	CORSICA	20136	3	19746
26	XXII MARZO	20135	3	31477
27	PTA ROMANA	20137	4	16367
28	UMBRIA - MOLISE - CALVAIRATE	20135	4	23166
29	ORTOMERCATO	20136	4	4170
30	TALIEDO - MORSENCHIO - Q.RE FORLANINI	20138	4	19666
31	MONLUE' - PONTE LAMBRO	20138	4	5893
32	TRIULZO SUPERIORE	20139	4	1724
33	ROGOREDO - SANTA GIULIA	20138	4	11776
34	CHIARAVALLE	20139	4	1074
35	LODI - CORVETTO	20138	4	37184
36	SCALO ROMANA	20141	4	12164
37	MORIVIONE	20141	5	7722
38	VIGENTINO - Q.RE FATIMA	20141	5	16135
39	QUINTOSOLE	20141	5	34900
40	RONCHETTO DELLE RANE	20142	5	66756
41	GRATOSOGLIO - Q.RE MISSAGLIA - Q.RE TERRAZZE	20142	2	18912
42	STADERA - CHIESA ROSSA - Q.RE TORRETTA - CONCA FALLATA	20142	5	29331
43	TIBALDI	20141	5	11407
44	PORTA TICINESE - CONCHETTA	20143	1	16593
45	MONCUCCO - SAN CRISTOFORO	20143	6	13831
46	BARONA	20142	6	16579
47	CANTALUPA	20142	5	72576
48	RONCHETTO SUL NAVIGLIO - Q.RE LODOVICO IL MORO	20142	6	14528
49	GIAMBELLINO	20146	6	30865
50	PORTA GENOVA	20144	1	15170
51	PORTA MAGENTA	20146	6	26819
52	BANDE NERE	20147	6	44137
53	LORENTEGGIO	20147	6	15152
54	MUGGIANO	20152	7	3045
55	BAGGIO - Q.RE DEGLI OLMI - Q.RE VALSESIA	20152	6	30860
56	FORZE ARMATE	20153	6	25315
57	SAN SIRO	20148	7	26072
58	DE ANGELI - MONTE ROSA	20149	7	21552
59	TRE TORRI	20145	8	2490
60	STADIO - IPPODROMI	20151	7	13180
61	QUARTO CAGNINO	20153	7	9940

62	QUINTO ROMANO	20153	7	4744
63	FIGINO	20153	7	2637
64	TRENNO	20151	8	3986
65	Q.RE GALLARATESE - Q.RE SAN LEONARDO - LAMPUGNANO	20151	7	33236
66	QT 8	20148	7	3973
67	PORTELLO	20149	8	8925
68	PAGANO	20145	1	17768
69	SARPI	20154	1	30942
70	GHISOLFA	20155	8	18641
71	VILLAPIZZONE - CAGNOLA - BOLDINASCO	20156	8	42031
72	MAGGIORE - MUSOCCO - CERTOSA	20156	8	9930
73	CASCINA MERLATA	20157	8	1130
74	ROSERIO	20157	8	267
75	STEPHENSON	20157	8	172
76	QUARTO OGGIARO - VIALBA - MUSOCCO	20157	8	32744
77	BOVISA	20158	8	13879
78	FARINI	20154	9	3861
79	DERGANO	20158	9	24179
80	AFFORI	20161	9	26395
81	BOVISASCA	20157	8	7584
82	COMASINA	20161	9	10087
83	BRUZZANO	20161	9	12758
84	PARCO NORD	20161	9	100
85	PARCO DELLE ABBAZIE	20141	4	329
86	PARCO DEI NAVIGLI	20142	5	352
87	ASSIANO	20152	7	224
88	PARCO BOSCO IN CITTA'	20151	7	666

A.2. Economic indicator data ECO_3 and ECO_4

ZONE	VENDITA(€/M²)	AFFITTO(€/M²)	PERCENTILE	PERCENTILE	CAP
CENTRO	11.028	30,73	100	100	23,22
ARCO DELLA PACE, ARENA,	9.316	27,43	90,3	93,5	45
GENOVA, TICINESE	8.029	25,66	87	87	44,36
QUADRONNO, PALESTRO,	8.963	27,55	93,5	90,3	35,29
GARIBALDI, MOSCOVA, PORTA	9.935	29,56	96,7	96,7	21

FIERA, SEMPIONE, CITY LIFE,	6.841	23,45	74,1	74,1	45,49
NAVIGLI	6.453	23,1	67,7	64,5	43
PORTA ROMANA, CADORE,	7.244	23,67	77,4	80,6	35
PORTA VENEZIA,	7.848	24,74	83,8	83,8	29
CENTRALE, REPUBBLICA	6.676	23,33	70,9	70,9	24
CENISIO, SARPI, ISOLA	6.532	22,97	64,5	67,7	59,58,54
VIALE CERTOSA, CASCINA	4.286	18,81	19,3	22,5	55,56,53
BANDE NERE, INGANNI	4.752	18,9	22,5	45,1	47
FAMAGOSTA, BARONA	4.457	19,32	32,2	35,4	42
ABBIATEGRASSO, CHIESA	4.339	19,92	45,1	25,8	41
PORTA VITTORIA, LODI	5.266	20,93	58	51,6	37
CIMIANO, CRESCENZAGO,	3.713	17,61	9,6	6,4	28
BICOCCA, NIGUARDA	3.922	17,85	12,9	16,1	26,62
SOLARI, WASHINGTON	7.174	23,71	80,6	77,4	44
AFFORI, BOVISA	3.885	19,25	29	12,9	58,57,61
SAN SIRO, TRENNO	4.182	17,86	16,1	19,3	51,48
BISCEGLIE, BAGGIO, OLMI	3.137	15,93	0	0	52
RIPAMONTI, VIGENTINO	4.624	20,42	51,6	41,9	39
FORLANINI	3.834	16,95	3,2	9,6	34
CITTÀ STUDI, SUSA	5.770	20,51	54,8	61,2	33,31
MAGGIOLINA, ISTRIA	5.344	20,12	48,3	54,8	59
PRECOTTO, TURRO	4.546	19,48	35,4	38,7	28
UDINE, LAMBRATE	4.365	19	25,8	29	32
PASTEUR, ROVERETO	4.808	21,04	61,2	48,3	25,27
PONTE LAMBRO, SANTA GIULIA	3.374	17,16	6,4	3,2	38
CORVETTO, ROGOREDO	4.397	19,6	38,7	32,2	38
NAPOLI, SODERINI	5.604	19,74	41,9	58	46

A.3. Universities count per neighborhood

NIL	COUN	CAP	CAP_TO	N_AVERAG	SMD_VALUE	P_RANK
BARONA	5	2014	5	0	3,333333333	58,8
CANTALUPA	0	2014	5	0,833333333	0,277777778	14,7
GRATOSOGLIO - Q.RE	0	2014	5	0,833333333	0,277777778	14,7
PARCO DEI NAVIGLI	0	2014	5	0,833333333	0,277777778	14,7
RONCHETTO DELLE RANE	0	2014	5	0,833333333	0,277777778	14,7

RONCHETTO SUL	0	2014	5	0,833333333	0,277777778	14,7
STADERA - CHIESA ROSSA	0	2014	5	0,833333333	0,277777778	14,7
BICOCCA	113	2012	113	0	75,33333333	95,5
BOVISA	19	2015	19	0	12,66666667	70,5
DERGANO	0	2015	19	19	6,333333333	64,7
BRERA	20	2012	20	0	13,33333333	73,5
GIARDINI P.TA VENEZIA	0	2012	20	10	3,333333333	58,8
PARCO SEMPIONE	0	2012	20	10	3,333333333	58,8
BUENOS AIRES - PORTA	19	2012	19	0	12,66666667	70,5
CIMIANO - ROTTOLE - Q.RE	18	2013	38	4	13,33333333	73,5
LAMBRATE - ORTICA	1	2013	38	7,4	3,133333333	55,8
PARCO FORLANINI -	0	2013	38	7,6	2,533333333	52,9
CITTA' STUDI	153	2013	153	0	102	97
LORETO - CASORETTO -	0	2013	153	153	51	94,1
CORSICA	1	2013	1	0	0,666666667	39,7
ORTOMERCATO	0	2013	1	1	0,333333333	23,5
DE ANGELI - MONTE ROSA	1	2014	1	0	0,666666667	39,7
PORTELLO	0	2014	1	1	0,333333333	23,5
DUOMO	187	2012	380	64,33333333	146,1111111	98,5
MAGENTA - S. VITTORE	3	2012	380	125,6666667	43,88888889	91,1
FIGINO	0	2015	1	0,333333333	0,111111111	0
FORZE ARMATE	1	2015	1	0	0,666666667	39,7
QUARTO CAGNINO	0	2015	1	0,333333333	0,111111111	0
QUINTO ROMANO	0	2015	1	0,333333333	0,111111111	0
GUASTALLA	51	2012	156	21	41	88,2
PORTA TICINESE - CONCA	0	2012	156	31,2	10,4	66,1
PORTA VIGENTINA -	27	2012	156	25,8	26,6	85,2
CIMIANO - ROTTOLE - Q.RE	18	2013	38	4	13,33333333	73,5
LAMBRATE - ORTICA	1	2013	38	7,4	3,133333333	55,8
PARCO FORLANINI -	0	2013	38	7,6	2,533333333	52,9
DUOMO	187	2012	380	64,33333333	146,1111111	98,5
MAGENTA - S. VITTORE	3	2012	380	125,6666667	43,88888889	91,1
MONCUCCO - SAN	27	2014	74	15,66666667	23,22222222	82,3
PORTA TICINESE -	10	2014	74	21,33333333	13,77777778	77,9
MONLUE' - PONTE	1	2013	1	0	0,666666667	39,7
TALIEDO - MORSENCHIO -	0	2013	1	0,333333333	0,111111111	0
LODI - CORVETTO	0	2013	1	0,333333333	0,111111111	0

ROGOREDO - SANTA	0	2013	1	0,333333333	0,111111111	0
NIGUARDA - CA' GRANDA	3	2016	3	0	2	48,5
PADOVA - TURRO -	1	2012	1	0	0,666666667	39,7
PAGANO	1	2014	1	0	0,666666667	39,7
TRE TORRI	0	2014	1	1	0,333333333	23,5
MONCUCCO - SAN	27	2014	74	15,66666667	23,22222222	82,3
PORTA TICINESE -	10	2014	74	21,33333333	13,77777778	77,9
GUASTALLA	51	2012	156	21	41	88,2
PORTA TICINESE - CONCA	0	2012	156	31,2	10,4	66,1
PORTA VIGENTINA -	27	2012	156	25,8	26,6	85,2
BOVISASCA	0	2015	3	0,75	0,25	8,8
CASCINA MERLATA	0	2015	3	0,75	0,25	8,8
QUARTO OGGIARO -	0	2015	3	0,75	0,25	8,8
ROSERIO	3	2015	3	0	2	48,5
STEPHENSON	0	2015	3	0,75	0,25	8,8
PARCO BOSCO IN CITTA'	0	2015	3	1	0,333333333	23,5
Q.RE GALLARATESE - Q.RE	0	2015	3	1	0,333333333	23,5
STADIO - IPPODROMI	3	2015	3	0	2	48,5
TRENNO	0	2015	3	1	0,333333333	23,5
MORIVIONE	0	2014	8	1,6	0,533333333	32,3
PARCO DELLE ABBAZIE	0	2014	8	1,6	0,533333333	32,3
QUINTOSOLE	0	2014	8	1,6	0,533333333	32,3
SCALO ROMANA	0	2014	8	1,6	0,533333333	32,3
TIBALDI	0	2014	8	1,6	0,533333333	32,3
VIGENTINO - Q.RE FATIMA	8	2014	8	0	5,333333333	63,2
UMBRIA - MOLISE -	0	2013	32	32	10,66666667	69,1
XXII MARZO	32	2013	32	0	21,33333333	80,8

A.4. Schools distribution across Milan

ID_NIL	NIL	COUNT_BABIES	COUNT_PRIMARIE	COUNT_SECONDARIE	COUNT_TOTALE	PERCENTILE
2	BRERA	5	5	3	13	80,4
3	GIARDINI P.TA VENEZIA	1	7	3	11	59,7
8	PARCO SEMPIONE	4	2	3	9	49,4

4	GUASTALLA	5	6	7	18	90,8
6	PORTA TICINESE - CONCA	6	3	3	12	71,2
5	PORTA VIGENTINA -	4	3	3	10	55,1
1	DUOMO	3	4	3	10	55,1
7	MAGENTA - S. VITTORE	4	6	4	14	82,7
10	STAZIONE CENTRALE -	5	5	4	14	82,7
13	GRECO - SEGNANO	2	2	2	6	25,2
15	BICOCCA	3	2	1	6	25,2
16	GORLA - PRECOTTO	10	7	3	20	96,5
19	PADOVA - TURRO -	7	4	4	15	89,6
21	BUENOS AIRES - PORTA	9	5	4	18	90,8
22	CITTA' STUDI	6	8	5	19	95,4
20	LORETO - CASORETTO -	4	4	3	11	59,7
17	ADRIANO	4	1	1	6	25,2
18	CIMIANO - ROTTOLE - Q.RE	6	3	2	11	59,7
23	LAMBRATE - ORTICA	5	4	2	11	59,7
24	PARCO FORLANINI -	1	1	1	3	0
25	CORSICA	7	4	3	14	82,7
29	ORTOMERCATO	1	1	1	3	0
28	UMBRIA - MOLISE -	3	1	1	5	17,2
26	XXII MARZO	5	3	2	10	55,1
27	PTA ROMANA	6	5	3	14	82,7
31	MONLUE' - PONTE	1	1	2	4	10,3
30	TALIEDO - MORSENCHIO -	5	4	2	11	59,7
34	CHIARAVALLE	6	3	2	11	59,7
35	LODI - CORVETTO	9	8	4	21	98,8
33	ROGOREDO - SANTA	2	1	1	4	10,3
32	TRIULZO SUPERIORE	3	1	1	5	17,2
37	MORIVIONE	2	2	2	6	25,2
85	PARCO DELLE ABBAZIE	1	1	1	3	0
39	QUINTOSOLE	2	1	1	4	10,3
36	SCALO ROMANA	1	1	1	3	0
43	TIBALDI	2	1	1	4	10,3
38	VIGENTINO - Q.RE FATIMA	4	2	1	7	42,5
46	BARONA	3	3	1	7	42,5
47	CANTALUPA	6	3	2	11	59,7
41	GRATOSOGLIO - Q.RE	2	3	1	6	25,2

86	PARCO DEI NAVIGLI	1	1	1	3	0
40	RONCHETTO DELLE RANE	4	4	4	12	71,2
48	RONCHETTO SUL	4	4	4	12	71,2
42	STADERA - CHIESA ROSSA -	7	8	3	18	90,8
45	MONCUCCO - SAN	4	2	2	8	47,1
44	PORTA TICINESE -	3	1	3	7	42,5
50	PORTA GENOVA	4	2	3	9	49,4
68	PAGANO	3	2	2	7	42,5
59	TRE TORRI	2	1	1	4	10,3
49	GIAMBELLINO	2	3	3	8	47,1
51	PORTA MAGENTA	4	3	3	10	55,1
52	BANDE NERE	13	6	6	25	100
53	LORENTEGGIO	6	4	2	12	71,2
66	QT 8	3	2	1	6	25,2
57	SAN SIRO	2	2	1	5	17,2
58	DE ANGELI - MONTE ROSA	2	1	3	6	25,2
67	PORTELLO	3	2	1	6	25,2
88	PARCO BOSCO IN CITTA'	1	1	1	3	0
65	Q.RE GALLARATESE - Q.RE	6	5	3	14	82,7
60	STADIO - IPPODROMI	7	8	3	18	90,8
64	TRENNO	2	1	1	4	10,3
87	ASSIANO	7	3	2	12	71,2
55	BAGGIO - Q.RE DEGLI OLMI	7	3	2	12	71,2
54	MUGGIANO	1	1	4	6	25,2
63	FIGINO	2	2	1	5	17,2
56	FORZE ARMATE	7	5	2	14	82,7
61	QUARTO CAGNINO	7	1	1	9	49,4
62	QUINTO ROMANO	1	1	1	3	0
78	FARINI	2	2	1	5	17,2
69	SARPI	5	4	3	12	71,2
70	GHISOLFA	2	3	1	6	25,2
72	MAGGIORE - MUSOCCO -	2	3	1	6	25,2
71	VILLAPIZZONE -	10	7	3	20	96,5
81	BOVISASCA	3	1	1	5	17,2
73	CASCINA MERLATA	6	3	2	11	59,7
76	QUARTO OGGIARO -	6	4	2	12	71,2
74	ROSERIO	2	2	1	5	17,2

75	STEPHENSON	5	4	2	11	59,7
77	BOVISA	3	2	1	6	25,2
79	DERGANO	3	3	3	9	49,4
11	ISOLA	3	2	1	6	25,2
12	MACIACHINI -	8	3	2	13	80,4
9	PORTA GARIBALDI -	4	2	3	9	49,4
80	AFFORI	6	3	2	11	59,7
83	BRUZZANO	3	2	1	6	25,2
82	COMASINA	2	2	2	6	25,2
84	PARCO NORD	1	1	1	3	0
14	NIGUARDA - CA' GRANDA	1	1	1	3	0

A.5. Level of studies in the city of Milan

ROW LABELS	DIPLOMA DI SCUOLA	LICENZA DI	MINORI DI 6 ANNI	NESSUN TITOLO O	TITOLI	GRAND
ADRIANO	4232	3426	977	2631	1755	13021
AFFORI	6737	5730	1404	4457	2895	21223
BAGGIO	7916	8666	1396	7479	2571	28028
BANDE NERE	13985	9121	1907	6575	9058	40646
BARONA	4726	5322	515	4478	1426	16467
BICOCCA	2008	1299	435	1156	1402	6300
BOVISA	3561	3018	666	2262	1721	11228
BOVISASCA	2153	1956	297	1558	723	6687
BRERA	4758	2298	1033	1841	6726	16656
BRUZZANO	3740	3164	667	2562	1278	11411
BUENOS AIRES -	17053	9413	3053	7718	19849	57086
CANTALUPA	157	105	36	46	81	425
CASCINA	70	125	3	40	7	245
CENTRALE	4857	3015	854	2177	4808	15711
CHIARAVALLE	353	299	36	203	140	1031
CITT_TUDI	10577	6861	1593	5066	10123	34220
COMASINA	2602	2896	601	2338	681	9118
CORSICA	5996	3497	924	2476	4922	17815
DE ANGELI -	5978	2943	939	2362	6897	19119

DERGANO	6074	5210	1219	3805	2851	19159
DUOMO	3980	2282	791	1845	6657	15555
EX OM -	1994	1478	412	1542	1582	7008
FARINI	1063	816	201	477	598	3155
FIGINO	523	462	80	381	154	1600
FORZE ARMATE	6362	6592	996	5498	2711	22159
GALLARATESE	9701	9575	1271	7933	3371	31851
GARIBALDI	1592	1002	208	724	1497	5023
GHISOLFA	5408	3315	980	2515	3728	15946
GIAMBELLINO	8983	7437	1654	5737	4892	28703
GIARDINI PORTA	32	21	2	16	19	90
GRATOSOGLIO -	4817	5447	741	5017	1577	17599
GRECO	4738	3239	851	2387	2771	13986
GUASTALLA	3850	2012	831	1641	5820	14154
ISOLA	6061	4393	1055	3670	5057	20236
LAMBRATE	3023	2250	578	1763	1747	9361
LODI -	10103	8930	1557	6901	4991	32482
LORENTEGGIO	3821	3356	577	2629	1988	12371
LORETO	11646	9067	2098	6475	7967	37253
MACIACHINI -	7745	5508	1238	3717	5719	23927
MAGENTA - S.	4479	2289	912	1746	6815	16241
MAGGIORE -	1672	1228	249	843	614	4606
MECENATE	5437	4886	939	4324	2289	17875
MUGGIANO	1005	712	275	515	327	2834
NAVIGLI	4446	3114	888	2702	4481	15631
NIGUARDA - CA	10656	10295	1628	7828	4138	34545
ORTOMERCATO	1019	1053	180	766	481	3499
PADOVA	9930	8479	1681	7069	4360	31519
PAGANO	4342	2097	938	1868	6715	15960
PARCO	55	58	20	114	20	267
PARCO BOSCO IN	128	170	51	158	51	558
PARCO DEI	86	73	24	60	56	299
PARCO DELLE	79	84	37	84	42	326
PARCO	259	162	50	166	138	775
PARCO LAMBRO -	6061	4451	843	3704	3629	18688
PARCO MONLU	1083	1332	249	1137	290	4091
PARCO NORD	37	19	5	31	12	104

PORTA ROMANA	4412	2753	856	2261	5244	15526
PORTELLO	2308	1259	330	873	2360	7130
QT 8	1309	655	144	592	1180	3880
QUARTO	3403	2459	461	1940	1342	9605
QUARTO	7455	9885	1495	8844	1722	29401
QUINTO	1513	1419	158	1086	447	4623
QUINTOSOLE	432	365	21	147	296	1261
RIPAMONTI	4472	2769	660	2103	2572	12576
ROGOREDO	2653	1840	615	1438	1731	8277
RONCHETTO	236	198	56	180	70	740
RONCHETTO SUL	4382	3707	671	3436	1774	13970
S. CRISTOFORO	3717	3081	669	2562	2029	12058
S. SIRO	3664	2321	628	1809	3288	11710
SACCO	93	44	3	46	21	207
SARPI	7981	5205	1646	4201	8056	27089
SCALO ROMANA	2823	2670	540	2125	1374	9532
SELINUNTE	6732	6197	1209	5243	3491	22872
STADERA	8289	7112	1528	5526	4322	26777
STEPHENSON	15	17	0	6	0	38
TIBALDI	3298	2583	506	1868	2426	10681
TICINESE	5310	3097	894	2691	6532	18524
TORTONA	4440	2257	710	2002	4776	14185
TRE TORRI	392	196	51	142	541	1322
TRENNO	1514	1032	125	907	567	4145
TRIULZO	428	375	101	243	165	1312
UMBRIA -	6405	4865	1097	3803	4503	20673
VIALE MONZA	8460	6545	1463	4922	4044	25434
VIGENTINA	3506	1820	655	1582	4921	12484
VILLAPIZZONE	11056	10076	2220	7632	4767	35751
WASHINGTON	7584	3726	1519	3211	9081	25121
XXII MARZO	8656	5318	1637	4529	9202	29342

A.6. Infrastructural state

NIL	NUMBERS_OF_DAM	PERCENTILE
NIGUARDA - CA'	22	81,2

QUINTO ROMANO	6	17,1
LODI - CORVETTO	45	95,3
PORTA VIGENTINA -	9	39
STADERA - CHIESA	8	34,3
GUASTALLA	14	54,6
MORIVIONE	11	46,8
BANDE NERE	23	82,8
CORSICA	17	65,6
BUENOS AIRES -	53	98,4
ORTOMERCATO	18	71,8
QUARTO CAGNINO	14	54,6
GORLA - PRECOTTO	17	65,6
SARPI	26	87,5
STAZIONE CENTRALE -	8	34,3
TALIEDO -	8	34,3
GRECO - SEGNANO	14	54,6
MUGGIANO	4	6,2
DE ANGELI - MONTE	11	46,8
LORETO - CASORETTO	80	100
XXII MARZO	12	50
BAGGIO - Q.RE DEGLI	21	79,6
DERGANO	6	17,1
PAGANO	16	62,5
VILLAPIZZONE -	28	89
BOVISASCA	6	17,1
MACIACHINI -	28	89
PTA ROMANA	4	6,2
Q.RE GALLARATESE -	24	85,9
BARONA	10	42,1
FORZE ARMATE	19	76,5
STADIO - IPPODROMI	17	65,6
DUOMO	23	82,8
BOVISA	5	14
BRUZZANO	4	6,2
MAGENTA - S.	52	96,8
GIAMBELLINO	4	6,2
PORTA MAGENTA	18	71,8

RONCHETTO SUL	18	71,8
PORTA TICINESE -	16	62,5
AFFORI	37	93,7
FARINI	0	0
CIMIANO - ROTTOLE -	7	28,1
LORENTEGGIO	10	42,1
PORTA TICINESE -	3	4,6
SCALO ROMANA	5	14
PORTELLO	9	39
QUARTO OGGIARO -	15	59,3
UMBRIA - MOLISE -	7	28,1
QT 8	13	53,1
GRATOSOGLIO - Q.RE	6	17,1
PORTA GENOVA	7	28,1
MONLUE' - PONTE	2	3,1
PADOVA - TURRO -	20	78,1
BRERA	12	50
SAN SIRO	15	59,3
ISOLA	17	65,6
MAGGIORE -	7	28,1
VIGENTINO - Q.RE	10	42,1
CITTA' STUDI	35	92,1
COMASINA	0	0
LAMBRATE - ORTICA	6	17,1
MONCUCCO - SAN	6	17,1
ROGOREDO - SANTA	4	6,2
ADRIANO	6	17,1

A.7. Population density in the city of Milan

NIL	POPULATION_TOTALE	AREA_M2	POPULATION DENSITY	PERCENTILE
1	16226,00	2341704,00	0,006929142	35,6
2	18361,00	1637395,00	0,011213543	64,3

3	40,00	249647,00	0,000160226	6,8
4	15470,00	1548021,00	0,009993404	57,4
5	13537,00	1135239,00	0,011924361	67,8
6	20348,00	1255065,00	0,016212706	78,1
7	18026,00	1390147,00	0,012966974	71,2
8	0,00	470434,00	0	0
9	5817,00	785668,00	0,007403891	39
10	17543,00	1556078,00	0,011273856	65,5
11	22458,00	1322966,00	0,016975493	83,9
12	26490,00	1674981,00	0,015815105	77
13	16380,00	1768669,00	0,009261202	52,8
14	36306,00	4251282,00	0,008540012	47,1
15	8711,00	1534521,00	0,00567669	29,8
16	30101,00	3005624,00	0,010014892	58,6
17	18169,00	2431560,00	0,007472158	40,2
18	19636,00	4971970,00	0,00394934	24,1
19	38167,00	2061946,00	0,018510184	89,6
20	43513,00	1747566,00	0,024899203	95,4
21	62520,00	2877542,00	0,021726877	94,2
22	36144,00	2207487,00	0,016373369	81,6
23	12592,00	3096862,00	0,004066051	25,2
24	2675,00	2925815,00	0,000914275	11,4
25	19746,00	1081330,00	0,018260845	88,5
26	31477,00	1637500,00	0,019222595	90,8
27	16367,00	1002794,00	0,016321398	80,4
28	23166,00	1192397,00	0,019428093	91,9
29	4170,00	1402520,00	0,00297322	17,2
30	19666,00	3821390,00	0,005146295	28,7
31	5893,00	2639289,00	0,002232798	14,9
32	1724,00	1395022,00	0,001235823	12,6
33	11776,00	1200162,00	0,009812009	56,3
34	1074,00	311640,00	0,003446284	19,5
35	37184,00	3639093,00	0,010217931	60,9
36	12164,00	1736728,00	0,007003975	36,7
37	7722,00	817977,00	0,009440363	54
38	16135,00	1853234,00	0,008706402	49,4
39	34900,00	1057529,00	0,033001459	97,7

40	66756,00	188871,00	0,353447591	100
41	18912,00	3312818,00	0,005708735	31
42	29331,00	3232237,00	0,00907452	51,7
43	11407,00	786214,00	0,014508772	73,5
44	16593,00	1483928,00	0,011181809	63,2
45	13831,00	1596174,00	0,008665095	48,2
46	16579,00	2006325,00	0,008263367	44,8
47	72576,00	926717,00	0,078315171	98,8
48	14528,00	2406775,00	0,006036293	33,3
49	30865,00	1965274,00	0,015705189	75,8
50	15170,00	996786,00	0,015218914	74,7
51	26819,00	1306451,00	0,020528133	93,1
52	44137,00	2663881,00	0,016568683	82,7
53	15152,00	2635327,00	0,005749571	32,1
54	3045,00	444218,00	0,006854742	34,4
55	30860,00	3478600,00	0,008871385	50,5
56	25315,00	3206902,00	0,007893911	42,5
57	26072,00	984926,00	0,026471024	96,5
58	21552,00	1323079,00	0,016289277	79,3
59	2490,00	513316,00	0,004850813	27,5
60	13180,00	3435307,00	0,003836629	21,8
61	9940,00	986392,00	0,01007713	59,7
62	4744,00	1645860,00	0,002882384	16
63	2637,00	1424714,00	0,001850898	13,7
64	3986,00	489711,00	0,008139495	43,6
65	33236,00	3894538,00	0,008534003	45,9
66	3973,00	1024437,00	0,003878228	22,9
67	8925,00	909637,00	0,009811606	55,1
68	17768,00	1289734,00	0,013776484	72,4
69	30942,00	1811915,00	0,01707696	85
70	18641,00	1051452,00	0,017728817	86,2
71	42031,00	3427071,00	0,012264409	68,9
72	9930,00	3030189,00	0,003277023	18,3
73	1130,00	1729127,00	0,000653509	10,3
74	267,00	708466,00	0,000376871	9,1
75	172,00	560098,00	0,000307089	8
76	32744,00	2778264,00	0,011785777	66,6

77	13879,00	1913133,00	0,007254592	37,9
78	3861,00	1010231,00	0,003821898	20,6
79	24179,00	1358615,00	0,0177968	87,3
80	26395,00	2070894,00	0,012745703	70,1
81	7584,00	1576826,00	0,004809662	26,4
82	10087,00	926735,00	0,010884449	62
83	12758,00	1667691,00	0,007650098	41,3
84	100,00	1533639,00	6,52044E-05	3,4
85	329,00	13722000,00	2,39761E-05	1,1
86	352,00	3617836,00	9,72957E-05	5,7
87	224,00	5844580,00	3,83261E-05	2,2
88	666,00	7837669,00	8,49742E-05	4,5

A.8. Immigration rate

ID	Size	Sites_attending_size	Percentile
17	**2431560**	**0,000173962**	**62,3**
80	**2070894**	**0,000431215**	**94,1**
87	**5844580**	**5,13296E-07**	**0**
55	**3478600**	**0,000167309**	**58,8**
52	**2663881**	**0,000265778**	**75,2**
46	**2006325**	**0,000113641**	**36,4**
15	**1534521**	**8,60203E-05**	**31,7**
77	**1913133**	**0,000252988**	**72,9**
81	**1576826**	**8,43467E-05**	**29,4**
2	**1637395**	**0,000289484**	**80**
83	**1667691**	**8,93451E-05**	**32,9**
21	**2877542**	**0,000401384**	**90,5**
47	**926717**	**9,7117E-06**	**7**
73	**1729127**	**7,28691E-05**	**23,5**
34	**311640**	**4,49236E-05**	**17,6**
18	**4971970**	**5,2092E-05**	**18,8**
22	**2207487**	**0,000267725**	**77,6**
82	**926735**	**0,000473706**	**95,2**
25	**1081330**	**0,000229347**	**70,5**
58	**1323079**	**0,000221453**	**69,4**

79	1358615	0,000683785	97,6
1	2341704	0,000147329	47
78	1010231	0,000173228	61,1
63	1424714	3,57967E-05	15,2
56	3206902	0,000160279	54,1
70	1051452	0,000257739	74,1
49	1965274	0,000301739	82,3
3	249647	4,00566E-06	4,7
16	3005624	0,000219921	68,2
41	3312818	8,54258E-05	30,5
13	1768669	0,000164531	57,6
4	1548021	0,000142763	45,8
11	1322966	0,000388521	89,4
23	3096862	4,32696E-05	16,4
35	3639093	0,000276168	78,8
53	2635327	5,91957E-05	21,1
20	1747566	0,000737597	100
12	1674981	0,000333735	87
72	3030189	0,000111874	35,2
72	3030189	5,80822E-05	20
45	1596174	0,000169154	60
31	2639289	0,000149662	48,2
37	817977	0,000161374	55,2
54	444218	3,15161E-05	11,7
14	4251282	0,000119023	40
29	1402520	0,000119071	41,1
19	2061946	0,0005747	96,4
68	1289734	0,000202367	63,5
88	7837669	4,97597E-06	5,8
86	3617836	1,93486E-06	1,1
85	13722000	2,18627E-06	3,5
24	2925815	0,000232414	71,7
84	1533639	1,95613E-06	2,3
9	785668	0,000156555	51,7
50	996786	0,00015249	49,4
51	1306451	0,000210494	67
6	1255065	0,000322692	85,8

44	1483928	0,000153646	50,5
5	1135239	0,000142701	44,7
67	909637	0,000118729	38,8
27	1002794	0,000210412	65,8
65	3894538	0,000162279	56,4
66	1024437	2,92844E-05	10,5
61	986392	0,000118614	37,6
76	2778264	0,000309906	83,5
62	1645860	3,46324E-05	14,1
39	1057529	2,8368E-05	9,4
33	1200162	0,000141648	43,5
40	188871	3,17677E-05	12,9
48	2406775	9,09931E-05	34,1
74	708466	1,83495E-05	8,2
57	984926	0,000702591	98,8
69	1811915	0,000411167	91,7
36	1736728	0,000209014	64,7
42	3232237	0,000158404	52,9
60	3435307	7,83045E-05	27
10	1556078	0,000311681	84,7
30	3821390	8,08606E-05	28,2
43	786214	0,000295085	81,1
59	513316	7,79247E-05	25,8
64	489711	7,75968E-05	24,7
32	1395022	6,66656E-05	22,3
28	1192397	0,000424355	92,9
38	1853234	0,000123568	42,3
71	3427071	0,000342275	88,2
26	1637500	0,00026687	76,4

A.9. Thrid sector services per ID_NIL

ID_NIL	COUNT_NIL(1)	COUNT_NIL(2)	TOTAL_SERVICES	AREA_NIL	NUMBER_COMPARED_AREA	PERCENTILE
0	0	0	0	0	1E-27	0
69	205	76	281	1811915	0,000155085	100
75	6	0	6	560098	1,07124E-05	40,9
5	64	18	82	1135239	7,22315E-05	83,1
50	59	24	83	996786	8,32676E-05	85,5
1	234	47	281	2341704	0,000119998	91,5
44	149	47	196	1483928	0,000132082	95,1
4	90	29	119	1548021	7,68723E-05	84,3
15	44	17	61	1534521	3,97518E-05	69,8
21	262	88	350	2877542	0,000121632	92,7
23	24	11	35	3096862	1,13018E-05	43,3
52	50	39	89	2663881	3,34099E-05	63,8
9	80	18	98	785668	0,000124735	93,9
10	120	25	145	1556078	9,3183E-05	86,7
38	17	9	26	1853234	1,40295E-05	49,3
30	14	13	27	3821390	7,06549E-06	30,1
2	148	26	174	1637395	0,000106266	89,1
14	29	12	41	4251282	9,64415E-06	38,5
71	68	36	104	3427071	3,03466E-05	61,4
51	56	29	85	1306451	6,50618E-05	81,9
58	34	13	47	1323079	3,55232E-05	68,6
77	27	31	58	1913133	3,03168E-05	60,2
35	60	41	101	3639093	2,77542E-05	59
26	128	44	172	1637500	0,000105038	87,9
27	98	35	133	1002794	0,000132629	97,5
68	38	6	44	1289734	3,41156E-05	66,2
22	68	38	106	2207487	4,80184E-05	75,9
20	130	58	188	1747566	0,000107578	90,3
36	15	5	20	1736728	1,15159E-05	44,5
17	12	8	20	2431560	8,22517E-06	33,7
19	66	29	95	2061946	4,6073E-05	73,4
25	27	11	38	1081330	3,51419E-05	67,4
43	26	7	33	786214	4,19733E-05	72,2

79	45	21	66	1358615	4,85789E-05	77,1
37	7	0	7	817977	8,5577E-06	36,1
7	57	15	72	1390147	5,17931E-05	78,3
76	16	10	26	2778264	9,35836E-06	37,3
57	33	23	56	984926	5,68571E-05	79,5
13	18	9	27	1768669	1,52657E-05	50,6
6	111	55	166	1255065	0,000132264	96,3
54	1	2	3	444218	6,75344E-06	28,9
49	49	32	81	1965274	4,12156E-05	71
41	7	5	12	3312818	3,62229E-06	20,4
80	30	12	42	2070894	2,02811E-05	51,8
16	40	24	64	3005624	2,12934E-05	54,2
29	6	8	14	1402520	9,98203E-06	39,7
11	141	38	179	1322966	0,000135302	98,7
31	4	2	6	2639289	2,27334E-06	10,8
61	6	1	7	986392	7,09657E-06	31,3
56	18	9	27	3206902	8,41934E-06	34,9
67	22	9	31	909637	3,40795E-05	65
46	4	2	6	2006325	2,99054E-06	16,8
42	20	18	38	3232237	1,17566E-05	45,7
70	39	21	60	1051452	5,70639E-05	80,7
28	40	17	57	1192397	4,78029E-05	74,6
55	22	20	42	3478600	1,20738E-05	46,9
33	14	13	27	1200162	2,2497E-05	55,4
87	4	0	4	5844580	6,84395E-07	7,2
45	23	20	43	1596174	2,69394E-05	57,8
18	17	9	26	4971970	5,22932E-06	24
12	22	21	43	1674981	2,56719E-05	56,6
81	3	4	7	1576826	4,4393E-06	22,8
88	2	1	3	7837669	3,82767E-07	4,8
60	5	5	10	3435307	2,91095E-06	14,4
78	19	2	21	1010231	2,07873E-05	53
24	7	1	8	2925815	2,73428E-06	12
32	4	1	5	1395022	3,58417E-06	18
82	4	8	12	926735	1,29487E-05	48,1
72	7	5	12	3030189	3,96015E-06	21,6
83	7	2	9	1667691	5,39668E-06	25,3

86	1	0	1	3617836	2,76408E-07	3,6
53	12	8	20	2635327	7,58919E-06	32,5
48	16	10	26	2406775	1,08028E-05	42,1
66	1	2	3	1024437	2,92844E-06	15,6
65	4	10	14	3894538	3,59478E-06	19,2
63	2	2	4	1424714	2,80758E-06	13,2
73	1	0	1	1729127	5,78327E-07	6
59	16	0	16	513316	3,11699E-05	62,6
64	2	1	3	489711	6,12606E-06	26,5
62	2	0	2	1645860	1,21517E-06	9,6
34	1	1	2	311640	6,41766E-06	27,7
39	1	0	1	1057529	9,45601E-07	8,4

A.10. State of living buildings

ID_NIL	NUMBER_BUILDINGS	AREA(M2)	BUILDINGS_PER_AREA	PERCENTILE
80	3	2070894	1,44865E-06	58,1
71	12	3427071	3,50153E-06	89
28	4	1192397	3,35459E-06	85,4
33	7	1200162	5,83255E-06	100
36	7	1736728	4,03057E-06	94,5
19	7	2061946	3,39485E-06	87,2
27	1	1002794	9,97214E-07	43,6
35	9	3639093	2,47314E-06	80
30	6	3821390	1,57011E-06	65,4
37	2	817977	2,44506E-06	78,1
79	5	1358615	3,68022E-06	92,7
26	3	1637500	1,83206E-06	67,2
83	5	1667691	2,99816E-06	83,6
25	2	1081330	1,84957E-06	69
23	18	3096862	5,81234E-06	98,1
38	2	1853234	1,07919E-06	49
16	14	3005624	4,65793E-06	96,3
50	1	996786	1,00322E-06	45,4

78	2	1010231	1,97975E-06	74,5
52	1	2663881	3,75392E-07	9
42	2	3232237	6,18767E-07	18,1
55	1	3478600	2,87472E-07	3,6
46	1	2006325	4,98424E-07	12,7
43	1	786214	1,27192E-06	54,5
72	2	3030189	6,60025E-07	23,6
10	1	1556078	6,42641E-07	20
29	1	1402520	7,13002E-07	29
85	2	13722000	1,45751E-07	0
12	2	1674981	1,19404E-06	52,7
5	1	1135239	8,80872E-07	41,8
75	2	560098	3,5708E-06	90,9
77	3	1913133	1,56811E-06	63,6
58	2	1323079	1,51163E-06	60
14	2	4251282	4,70446E-07	10,9
76	2	2778264	7,19874E-07	30,9
45	3	1596174	1,87949E-06	70,9
20	2	1747566	1,14445E-06	50,9
84	1	1533639	6,52044E-07	21,8
4	3	1548021	1,93796E-06	72,7
69	1	1811915	5,51902E-07	14,5
1	2	2341704	8,54079E-07	40
7	3	1390147	2,15805E-06	76,3
21	1	2877542	3,47519E-07	7,2
48	2	2406775	8,30988E-07	38,1
51	1	1306451	7,65432E-07	32,7
13	5	1768669	2,82698E-06	81,8
24	1	2925815	3,41785E-07	5,4
49	3	1965274	1,5265E-06	61,8
17	2	2431560	8,22517E-07	36,3
57	1	984926	1,0153E-06	47,2
41	2	3312818	6,03716E-07	16,3
74	1	708466	1,4115E-06	56,3
65	1	3894538	2,5677E-07	1,8
6	1	1255065	7,96771E-07	34,5
44	1	1483928	6,73887E-07	25,4

63	1	1424714	7,01895E-07	27,2

A.11. Number of hospital beds per CAP

CAP	N_beds	Population	Percentage	Percentile
20133	486	36144	13,4462151	60
20121	342	18401	18,5859464	80
20122	1370	49355	27,7580792	90
20123	327	34252	9,54688777	30
20126	126	8711	14,4644702	70
20129	99	62520	1,58349328	0
20142	473	219034	2,15948209	10
20153	470	42636	11,0235482	50
20154	191	34803	5,48803264	20
20157	457	41897	10,9077022	40
20162	1184	36306	32,6116895	100

A.12. Number of pharmacies

NIL	HEA_1	POPULATION_OF_NIL	FARMACIES_PER_1000_HABITANTS	PERCENTILE
BRERA	16	18361	0,871412232	95,4
GIARDINI P.TA VENEZIA	0	40	0	0
PARCO SEMPIONE	0	0	0	0
GUASTALLA	9	15470	0,58177117	94,2
PORTA TICINESE - CONCA DEL	10	20348	0,491448791	90,8
PORTA VIGENTINA - PORTA	6	13537	0,443229667	85
DUOMO	22	16226	1,355848638	97,7
MAGENTA - S. VITTORE	6	18026	0,332852546	72,4
STAZIONE CENTRALE - PONTE SEVESO	8	17543	0,456022345	88,5
GRECO - SEGNANO	3	16380	0,183150183	34,4
BICOCCA	1	8711	0,114797383	24,1

GORLA - PRECOTTO	4	30101	0,132885951	26,4
PADOVA - TURRO - CRESCENZAGO	8	38167	0,209605156	41,3
BUENOS AIRES - PORTA VENEZIA -	26	62520	0,415866923	81,6
CITTA' STUDI	14	36144	0,387339531	79,3
LORETO - CASORETTO - NOLO	12	43513	0,275779652	66,6
ADRIANO	4	18169	0,220155209	47,1
CIMIANO - ROTTOLE - Q.RE FELTRE	5	19636	0,254634345	54
LAMBRATE - ORTICA	2	12592	0,158831004	29,8
PARCO FORLANINI - CAVRIANO	0	2675	0	0
CORSICA	4	19746	0,202572673	37,9
ORTOMERCATO	2	4170	0,479616307	89,6
UMBRIA - MOLISE - CALVAIRATE	5	23166	0,215833549	44,8
XXII MARZO	14	31477	0,444769197	86,2
PTA ROMANA	6	16367	0,366591312	75,8
MONLUE' - PONTE LAMBRO	2	5893	0,339385712	74,7
TALIEDO - MORSENCHIO - Q.RE	5	19666	0,254245907	52,8
CHIARAVALLE	0	1074	0	0
LODI - CORVETTO	6	37184	0,161359725	32,1
ROGOREDO - SANTA GIULIA	2	11776	0,169836957	33,3
TRIULZO SUPERIORE	0	1724	0	0
MORIVIONE	3	7722	0,388500389	80,4
PARCO DELLE ABBAZIE	0	329	0	0
QUINTOSOLE	0	34900	0	0
SCALO ROMANA	1	12164	0,082209799	19,5
TIBALDI	3	11407	0,262996406	56,3
VIGENTINO - Q.RE FATIMA	4	16135	0,247908274	50,5
BARONA	2	16579	0,120634538	25,2
CANTALUPA	0	72576	0	0
GRATOSOGLIO - Q.RE MISSAGLIA -	2	18912	0,105752961	22,9
PARCO DEI NAVIGLI	2	352	5,681818182	100
RONCHETTO DELLE RANE	0	66756	0	0
RONCHETTO SUL NAVIGLIO - Q.RE	3	14528	0,206497797	39
STADERA - CHIESA ROSSA - Q.RE	8	29331	0,272748969	64,3
MONCUCCO - SAN CRISTOFORO	6	13831	0,433808112	83,9
PORTA TICINESE - CONCHETTA	9	16593	0,542397396	93,1
PORTA GENOVA	4	15170	0,263678312	57,4
PAGANO	5	17768	0,281404773	67,8

TRE TORRI	0	2490	0	0
GIAMBELLINO	8	30865	0,259193261	55,1
PORTA MAGENTA	9	26819	0,335582982	73,5
BANDE NERE	12	44137	0,271880735	63,2
LORENTEGGIO	4	15152	0,263991552	59,7
QT 8	2	3973	0,503397936	91,9
SAN SIRO	6	26072	0,230131942	48,2
DE ANGELI - MONTE ROSA	8	21552	0,371195249	77
PORTELLO	4	8925	0,448179272	87,3
PARCO BOSCO IN CITTA'	2	666	3,003003003	98,8
Q.RE GALLARATESE - Q.RE SAN	10	33236	0,300878565	70,1
STADIO - IPPODROMI	4	13180	0,303490137	71,2
TRENNO	1	3986	0,250878073	51,7
ASSIANO	0	224	0	0
BAGGIO - Q.RE DEGLI OLMI - Q.RE	6	30860	0,194426442	35,6
MUGGIANO	0	3045	0	0
FIGINO	1	2637	0,379218809	78,1
FORZE ARMATE	5	25315	0,197511357	36,7
QUARTO CAGNINO	1	9940	0,100603622	20,6
QUINTO ROMANO	1	4744	0,21079258	42,5
FARINI	0	3861	0	0
SARPI	13	30942	0,420140909	82,7
GHISOLFA	3	18641	0,160935572	31
MAGGIORE - MUSOCCO - CERTOSA	1	9930	0,100704935	21,8
VILLAPIZZONE - CAGNOLA -	9	42031	0,214127668	43,6
BOVISASCA	2	7584	0,26371308	58,6
CASCINA MERLATA	0	1130	0	0
QUARTO OGGIARO - VIALBA -	9	32744	0,274859516	65,5
ROSERIO	0	267	0	0
STEPHENSON	0	172	0	0
BOVISA	3	13879	0,216153902	45,9
DERGANO	5	24179	0,206791017	40,2
ISOLA	6	22458	0,267165375	62
MACIACHINI - MAGGIOLINA	7	26490	0,264250661	60,9
PORTA GARIBALDI - PORTA NUOVA	6	5817	1,031459515	96,5
AFFORI	4	26395	0,151543853	27,5
BRUZZANO	2	12758	0,156764383	28,7

COMASINA	3	10087	0,297412511	68,9
PARCO NORD	0	100	0	0
NIGUARDA - CA' GRANDA - PRATO	9	36306	0,24789291	49,4

A.13. Heat wave index

ID_NIL	NIL	VALUE	PERCENTILE
48	RONCHETTO SUL NAVIGLIO - Q.RE LODOVICO IL MORO	0,1049	39
64	TRENNO	0,1283	50,5
67	PORTELLO	0,1495	60,9
81	BOVISASCA	0,0763	31
84	PARCO NORD	0,0124	10,3
63	FIGINO	0,0178	13,7
20	LORETO - CASORETTO - NOLO	0,4129	98,8
76	QUARTO OGGIARO - VIALBA - MUSOCCO	0,1823	66,6
11	ISOLA	0,2918	90,8
61	QUARTO CAGNINO	0,1377	54
60	STADIO - IPPODROMI	0,0590	24,1
62	QUINTO ROMANO	0,0395	20,6
1	DUOMO	0,1457	58,6
4	GUASTALLA	0,1792	65,5
57	SAN SIRO	0,4308	100
82	COMASINA	0,1492	59,7
43	TIBALDI	0,2535	78,1
13	GRECO - SEGNANO	0,1412	55,1
58	DE ANGELI - MONTE ROSA	0,2554	79,3
78	FARINI	0,0808	36,7
83	BRUZZANO	0,1075	41,3
66	QT 8	0,0603	25,2
75	STEPHENSON	0,0105	6,8
47	CANTALUPA	0,0111	8
39	QUINTOSOLE	0,0158	11,4
8	PARCO SEMPIONE	0,0119	9,1

46	BARONA	0,1218	47,1
71	VILLAPIZZONE - CAGNOLA - BOLDINASCO	0,1950	68,9
88	PARCO BOSCO IN CITTA'	0,0036	4,5
16	GORLA - PRECOTTO	0,1744	64,3
14	NIGUARDA - CA' GRANDA - PRATO CENTENARO - Q.RE FULVIO	0,1431	57,4
32	TRIULZO SUPERIORE	0,0170	12,6
27	PTA ROMANA	0,3090	93,1
30	TALIEDO - MORSENCHIO - Q.RE FORLANINI	0,0688	27,5
6	PORTA TICINESE - CONCA DEL NAVIGLIO	0,3006	91,9
59	TRE TORRI	0,0707	29,8
87	ASSIANO	0,0016	0
37	MORIVIONE	0,1676	63,2
38	VIGENTINO - Q.RE FATIMA	0,1083	43,6
15	BICOCCA	0,0780	33,3
29	ORTOMERCATO	0,0690	28,7
35	LODI - CORVETTO	0,1575	62
54	MUGGIANO	0,0806	35,6
44	PORTA TICINESE - CONCHETTA	0,2150	73,5
28	UMBRIA - MOLISE - CALVAIRATE	0,2846	88,5
74	ROSERIO	0,0214	14,9
40	RONCHETTO DELLE RANE	0,0439	21,8
65	Q.RE GALLARATESE - Q.RE SAN LEONARDO - LAMPUGNANO	0,1231	48,2
31	MONLUE' - PONTE LAMBRO	0,0307	17,2
19	PADOVA - TURRO - CRESCENZAGO	0,2776	85
41	GRATOSOGLIO - Q.RE MISSAGLIA - Q.RE TERRAZZE	0,0777	32,1
51	PORTA MAGENTA	0,3436	95,4
56	FORZE ARMATE	0,1131	44,8
70	GHISOLFA	0,2807	86,2
34	CHIARAVALLE	0,0322	18,3
85	PARCO DELLE ABBAZIE	0,0016	1,1
12	MACIACHINI - MAGGIOLINA	0,2511	77
52	BANDE NERE	0,2615	82,7
23	LAMBRATE - ORTICA	0,0562	22,9
42	STADERA - CHIESA ROSSA - Q.RE TORRETTA - CONCA FALLATA	0,1374	52,8
5	PORTA VIGENTINA - PORTA LODOVICA	0,2067	71,2
36	SCALO ROMANA	0,1074	40,2
26	XXII MARZO	0,3659	96,5

18	CIMIANO - ROTTOLE - Q.RE FELTRE	0,0650	26,4
79	DERGANO	0,2809	87,3
55	BAGGIO - Q.RE DEGLI OLMI - Q.RE VALSESIA	0,1252	49,4
24	PARCO FORLANINI - CAVRIANO	0,0078	5,7
3	GIARDINI P.TA VENEZIA	0,0264	16
9	PORTA GARIBALDI - PORTA NUOVA	0,1361	51,7
80	AFFORI	0,1905	67,8
21	BUENOS AIRES - PORTA VENEZIA - PORTA MONFORTE	0,3985	97,7
45	MONCUCCO - SAN CRISTOFORO	0,1418	56,3
10	STAZIONE CENTRALE - PONTE SEVESO	0,2110	72,4
77	BOVISA	0,1081	42,5
72	MAGGIORE - MUSOCCO - CERTOSA	0,0344	19,5
49	GIAMBELLINO	0,2602	81,6
22	CITTA' STUDI	0,2737	83,9
50	PORTA GENOVA	0,2556	80,4
25	CORSICA	0,3183	94,2
7	MAGENTA - S. VITTORE	0,2272	74,7
73	CASCINA MERLATA	0,0030	2,2
69	SARPI	0,2891	89,6
86	PARCO DEI NAVIGLI	0,0032	3,4
68	PAGANO	0,2288	75,8
2	BRERA	0,2047	70,1
33	ROGOREDO - SANTA GIULIA	0,1215	45,9
17	ADRIANO	0,1047	37,9
53	LORENTEGGIO	0,0792	34,4

A.14. Pollution AQI measurement

Stazioni	AQI*	Municipi	Valore (>100 e maligno)
ROMOLO	160	6	100
NOVERASCO DI OPERA	152	5	100
VETRA	132	1	100
VIA VARESE	124	9	100
BIANCA MARIA	129	3	100

VIA TRIULZIANA, SAN DONATO	154	4	100
AFFORI	149	8	100
VIA SAULI/VENINI	152	2	100
VIA PLUTARCO	149	7	100

A.15. Green space index

ID_NIL	NIL	count	fid	max	min	value	Percentile
48	RONCHETTO SUL	196600	0	90,13982391	0	14,00865844	88,5
64	TRENNO	40043	1	69,66846466	0	6,249660521	48,2
67	PORTELLO	74380	2	87,66056061	0	4,426296131	25,2
81	BOVISASCA	128878	3	100	0	15,859528	93,1
84	PARCO NORD	124129	4	100	0	27,08547157	100
63	FIGINO	116511	5	100	0	10,02020839	73,5
20	LORETO -	142936	6	89,29480743	0	3,645480757	14,9
76	QUARTO	227188	7	100	0	8,347250955	63,2
11	ISOLA	108181	8	96,86988831	0	3,93428808	18,3
61	QUARTO	80643	9	100	0	12,22126068	83,9
60	STADIO -	280838	10	100	0	11,37565696	80,4
62	QUINTO ROMANO	134555	11	94,89581299	0	10,11933039	74,7
1	DUOMO	191400	12	85,02353668	0	2,48700578	1,1
4	GUASTALLA	126532	13	89,52576447	0	3,979806986	19,5
57	SAN SIRO	80509	14	82,57017517	0	3,642016343	13,7
82	COMASINA	75782	15	100	0	12,47179739	85
43	TIBALDI	64235	16	69,16339111	0	4,66076224	31
13	GRECO -	144668	17	99,62254333	0	4,762413336	33,3
58	DE ANGELI -	108167	18	88,55144501	0	4,813477655	34,4
78	FARINI	82625	19	64,89232635	0	3,454287443	11,4
83	BRUZZANO	135471	20	100	0	14,18538746	90,8
66	QT 8	83770	21	100	0	25,73134177	98,8
75	STEPHENSON	45808	22	90,33686829	0	4,37103167	22,9
47	CANTALUPA	75703	23	100	0	10,5065288	75,8
39	QUINTOSOLE	86304	24	67,32642365	0	9,269458107	68,9
8	PARCO SEMPIONE	38456	25	100	0	24,76657739	97,7
46	BARONA	163896	26	92,15479279	0	10,94114789	79,3
71	VILLAPIZZONE -	280287	27	100	0	5,411091132	40,2

88	PARCO BOSCO IN	639965	28	100	0	16,74331878	94,2
16	GORLA -	245335	29	96,03608704	0	5,637336703	41,3
14	NIGUARDA - CA'	347127	30	100	0	11,66736166	82,7
32	TRIULZO	113500	31	81,04356384	0	6,684063877	50,5
27	PTA ROMANA	81951	32	84,51416779	0	2,83593607	5,7
30	TALIEDO -	312255	33	99,15981293	0	7,795385983	58,6
6	PORTA TICINESE -	102565	34	82,38141632	0	3,489758629	12,6
59	TRE TORRI	41970	35	89,42207336	0	6,06367234	47,1
87	ASSIANO	475608	36	100	0	10,80136057	78,1
37	MORIVIONE	66837	37	78,15911102	0	5,728867899	43,6
38	VIGENTINO - Q.RE	151403	38	88,84733582	0	8,420145242	64,3
15	BICOCCA	124055	39	99,43667603	0	5,403628431	39
29	ORTOMERCATO	114612	40	76,90609741	0	4,662948142	32,1
35	LODI - CORVETTO	297294	41	95,66203308	0	6,751110433	51,7
54	MUGGIANO	36302	42	100	0	14,11260829	89,6
44	PORTA TICINESE -	121260	43	75,33084869	0	3,806945561	17,2
28	UMBRIA - MOLISE -	97427	44	82,54080963	0	4,116615517	21,8
74	ROSERIO	57531	45	100	0	13,74336445	87,3
40	RONCHETTO	15426	46	60,60121918	0	7,126781185	55,1
65	Q.RE	318607	47	100	0	11,49550622	81,6
31	MONLUE' - PONTE	214784	48	90,13395691	0	7,759154546	57,4
19	PADOVA - TURRO -	168656	49	92,63061523	0	6,33230733	49,4
41	GRATOSOGLIO -	270771	50	100	0	9,529758541	70,1
51	PORTA MAGENTA	106770	51	92,89733887	0	4,482612157	28,7
56	FORZE ARMATE	262114	52	97,0618515	0	12,5504933	86,2
70	GHISOLFA	86009	53	93,52214813	0	5,929062656	44,8
34	CHIARAVALLE	25277	54	94,4106369	0	19,91424145	95,4
85	PARCO DELLE	1136952	55	100	0	8,073774443	60,9
12	MACIACHINI -	137005	56	89,82318878	0	7,554185979	56,3
52	BANDE NERE	217763	57	87,43800354	0	6,914148639	52,8
23	LAMBRATE -	252808	58	90,61789703	0	4,845055833	35,6
42	STADERA - CHIESA	263995	59	100	0	9,014925472	67,8
5	PORTA	92773	60	93,3791275	0	5,704233047	42,5
36	SCALO ROMANA	141896	61	83,92937469	0	4,460338029	27,5
26	XXII MARZO	133870	62	68,10205078	0	3,100541337	6,8
18	CIMIANO -	406544	63	100	0	15,40970719	91,9
79	DERGANO	111102	64	88,32548523	0	4,402457595	24,1

55	BAGGIO - Q.RE	283494	65	94,87727356	0	9,802388234	71,2
24	PARCO	239003	66	98,23355865	0	10,7628398	77
3	GIARDINI P.TA	20409	67	100	0	24,17619065	96,5
9	PORTA GARIBALDI	64247	68	87,0515213	0	2,541638861	3,4
80	AFFORI	169421	69	100	0	10,01257592	72,4
21	BUENOS AIRES -	235241	70	94,15089417	0	2,51615896	2,2
45	MONCUCCO - SAN	130426	71	73,54216003	0	4,590713316	29,8
10	STAZIONE	127241	72	100	0	2,202142244	0
77	BOVISA	156491	73	100	0	8,254145606	62
72	MAGGIORE -	247889	74	91,3756485	0	6,058675456	45,9
49	GIAMBELLINO	160833	75	93,53005981	0	4,43861723	26,4
22	CITTA' STUDI	180491	76	70,35005188	0	2,72210595	4,5
50	PORTA GENOVA	81476	77	84,67491913	0	3,405830398	10,3
25	CORSICA	88375	78	71,52536011	0	3,200969943	9,1
7	MAGENTA - S.	113622	79	83,35237885	0	3,690292428	16
73	CASCINA	140634	80	100	0	5,39405878	37,9
69	SARPI	148122	81	88,61634827	0	5,262500675	36,7
86	PARCO DEI	295915	82	100	0	8,530365983	65,5
68	PAGANO	105441	83	100	0	8,840420828	66,6
2	BRERA	133873	84	87,18388367	0	3,110967811	8
33	ROGOREDO -	98045	85	73,13789368	0	4,080800908	20,6
17	ADRIANO	198971	86	94,17411041	0	7,870840474	59,7
53	LORENTEGGIO	216000	87	93,57532501	0	7,036208333	54

A.16. Public transport usage

ROW	A PIEDI O	ALTRI	AUTO	MEZZI	GRAND	SUM OF	PERCENTAGE	PERCENTILE
1	3705	808	1651	1808	7972	1808	0,226793778	3,4
2	3468	948	1895	2006	8317	2006	0,241192738	8
3	19	8	11	13	51	13	0,254901961	12,6
4	3228	738	1736	1733	7435	1733	0,233086752	5,7
5	2615	758	1408	1672	6453	1672	0,259104293	13,7
6	3620	1022	2187	3157	9986	3157	0,3161426	33,3
7	3582	994	1883	2309	8768	2309	0,263343978	16

9	991	254	636	780	2661	780	0,293122886	22,9
10	2691	592	2087	3100	8470	3100	0,365997639	50,5
11	2973	725	2538	4249	10485	4249	0,405245589	75,8
12	3222	944	3839	4722	12727	4722	0,371022236	58,6
13	1847	560	2505	2833	7745	2833	0,365784377	49,4
14	3895	948	6211	6123	17177	6123	0,35646504	47,1
15	765	238	1471	1324	3798	1324	0,348604529	43,6
16	3124	701	3814	6079	13718	6079	0,443140399	91,9
17	1239	587	3162	2966	7954	2966	0,372894141	60,9
18	1966	536	3012	3722	9236	3722	0,402988307	73,5
19	3432	839	4326	7904	16501	7904	0,479001273	97,7
20	5386	1100	4643	9499	20628	9499	0,460490595	96,5
21	10824	2596	7549	10119	31088	10119	0,325495368	35,6
22	4986	1269	4916	6591	17762	6591	0,371073077	59,7
23	1026	397	2036	2022	5481	2022	0,368910783	54
24	84	31	180	128	423	128	0,302600473	28,7
25	2579	831	2664	3362	9436	3362	0,35629504	45,9
26	5629	1269	3889	4835	15622	4835	0,309499424	29,8
27	2752	886	2161	3044	8843	3044	0,344227072	40,2
28	2795	796	3090	4222	10903	4222	0,387232872	66,6
29	356	88	552	802	1798	802	0,446051168	94,2
30	1837	571	2960	3164	8532	3164	0,370839194	57,4
31	423	131	663	976	2193	976	0,44505244	93,1
32	113	62	211	425	811	425	0,52404439	100
33	815	231	2002	2183	5231	2183	0,417319824	80,4
34	42	38	253	219	552	219	0,39673913	70,1
35	3827	754	4059	7142	15782	7142	0,452540869	95,4
36	1054	253	1569	2086	4962	2086	0,420395002	83,9
37	908	395	1366	1142	3811	1142	0,299658882	27,5
38	1428	608	2727	2003	6766	2003	0,296039019	25,2
39	34	14	67	44	159	44	0,27672956	17,2
40	26	33	257	168	484	168	0,347107438	41,3
41	1381	530	3010	3149	8070	3149	0,390210657	67,8
42	2901	900	4522	5856	14179	5856	0,413005148	79,3
43	1279	458	1508	2179	5424	2179	0,401733038	72,4
44	2375	838	2024	3410	8647	3410	0,394356424	68,9
45	1297	444	2084	2538	6363	2538	0,398868458	71,2

46	1219	433	2599	3228	7479	3228	0,431608504	86,2
47	19	25	154	63	261	63	0,24137931	9,1
48	1271	518	2694	2667	7150	2667	0,373006993	62
49	3426	866	4256	6458	15006	6458	0,430361189	85
50	2596	899	1924	2278	7697	2278	0,295959465	24,1
51	4066	1565	3958	3913	13502	3913	0,289808917	20,6
52	4778	1388	6496	7746	20408	7746	0,379557036	64,3
53	1285	344	1907	2394	5930	2394	0,403709949	74,7
54	162	115	1103	564	1944	564	0,290123457	21,8
55	2383	639	5829	5196	14047	5196	0,369901046	55,1
56	2002	493	3724	4741	10960	4741	0,432572993	87,3
57	2795	551	2766	4695	10807	4695	0,43444064	89,6
58	2530	1082	3328	3141	10081	3141	0,311576233	31
59	210	73	260	133	676	133	0,196745562	1,1
60	1150	644	2898	1658	6350	1658	0,261102362	14,9
61	907	311	2199	1827	5244	1827	0,348398169	42,5
62	253	133	1322	947	2655	947	0,356685499	48,2
63	104	39	426	335	904	335	0,370575221	56,3
64	359	165	969	728	2221	728	0,327780279	36,7
65	2394	721	5244	6001	14360	6001	0,417896936	82,7
66	522	175	666	630	1993	630	0,316106372	32,1
67	940	343	1234	1015	3532	1015	0,287372593	19,5
68	3023	1053	2546	1966	8588	1966	0,22892408	4,5
69	5380	1370	3566	4386	14702	4386	0,298326758	26,4
70	2124	690	3048	2770	8632	2770	0,320898981	34,4
71	4263	1177	5905	7100	18445	7100	0,384928165	65,5
72	416	134	1041	816	2407	816	0,339011217	37,9
73	14	1	18	11	44	11	0,25	11,4
74	7	6	39	56	108	56	0,518518519	98,8
75	9	3	12	0	24	0	0	0
76	2707	627	5853	5355	14542	5355	0,368243708	52,8
77	1416	331	1665	2637	6049	2637	0,435939825	90,8
78	344	93	532	744	1713	744	0,434325744	88,5
79	2570	584	3034	4440	10628	4440	0,417764396	81,6
80	2654	629	3700	4852	11835	4852	0,409970427	78,1
81	676	149	1435	1178	3438	1178	0,34264107	39
82	1085	208	1581	1975	4849	1975	0,407300474	77

83	1355	289	2086	2229	5959	2229	0,37405605	63,2
84	12	4	30	25	71	25	0,352112676	44,8
85	23	31	91	40	185	40	0,216216216	2,2
86	32	29	93	48	202	48	0,237623762	6,8
87	9	15	64	34	122	34	0,278688525	18,3
88	42	20	95	52	209	52	0,248803828	10,3

A.17. Walkability and bike usage

ROW	A PIEDI O IN	ALTRI	AUTO	MEZZI	GRAND	PERCENTAGE	PERCENTILE
1	3705	808	1651	1808	7972	0,464751631	100
2	3468	948	1895	2006	8317	0,416977275	97,7
3	19	8	11	13	51	0,37254902	93,1
4	3228	738	1736	1733	7435	0,434162744	98,8
5	2615	758	1408	1672	6453	0,405237874	95,4
6	3620	1022	2187	3157	9986	0,362507511	89,6
7	3582	994	1883	2309	8768	0,408531022	96,5
9	991	254	636	780	2661	0,372416385	91,9
10	2691	592	2087	3100	8470	0,317709563	82,7
11	2973	725	2538	4249	10485	0,283547926	78,1
12	3222	944	3839	4722	12727	0,253162568	66,6
13	1847	560	2505	2833	7745	0,238476436	60,9
14	3895	948	6211	6123	17177	0,22675671	50,5
15	765	238	1471	1324	3798	0,201421801	36,7
16	3124	701	3814	6079	13718	0,22772999	52,8
17	1239	587	3162	2966	7954	0,155770681	11,4
18	1966	536	3012	3722	9236	0,212862711	43,6
19	3432	839	4326	7904	16501	0,207987395	40,2
20	5386	1100	4643	9499	20628	0,261101416	71,2
21	10824	2596	7549	10119	31088	0,348172928	86,2
22	4986	1269	4916	6591	17762	0,280711632	77
23	1026	397	2036	2022	5481	0,187192118	28,7
24	84	31	180	128	423	0,19858156	33,3
25	2579	831	2664	3362	9436	0,273314964	74,7

26	5629	1269	3889	4835	15622	0,360325182	88,5
27	2752	886	2161	3044	8843	0,311206604	81,6
28	2795	796	3090	4222	10903	0,256351463	68,9
29	356	88	552	802	1798	0,197997775	32,1
30	1837	571	2960	3164	8532	0,215307079	45,9
31	423	131	663	976	2193	0,192886457	29,8
32	113	62	211	425	811	0,139334155	10,3
33	815	231	2002	2183	5231	0,15580195	12,6
34	42	38	253	219	552	0,076086957	4,5
35	3827	754	4059	7142	15782	0,242491446	63,2
36	1054	253	1569	2086	4962	0,212414349	42,5
37	908	395	1366	1142	3811	0,238257675	59,7
38	1428	608	2727	2003	6766	0,211055276	41,3
39	34	14	67	44	159	0,213836478	44,8
40	26	33	257	168	484	0,053719008	0
41	1381	530	3010	3149	8070	0,171127633	20,6
42	2901	900	4522	5856	14179	0,20459835	39
43	1279	458	1508	2179	5424	0,235803835	58,6
44	2375	838	2024	3410	8647	0,274661732	75,8
45	1297	444	2084	2538	6363	0,203834669	37,9
46	1219	433	2599	3228	7479	0,162989705	16
47	19	25	154	63	261	0,072796935	2,2
48	1271	518	2694	2667	7150	0,177762238	24,1
49	3426	866	4256	6458	15006	0,228308677	54
50	2596	899	1924	2278	7697	0,337274263	85
51	4066	1565	3958	3913	13502	0,301140572	79,3
52	4778	1388	6496	7746	20408	0,234123873	57,4
53	1285	344	1907	2394	5930	0,216694772	47,1
54	162	115	1103	564	1944	0,083333333	5,7
55	2383	639	5829	5196	14047	0,169644764	19,5
56	2002	493	3724	4741	10960	0,182664234	26,4
57	2795	551	2766	4695	10807	0,258628667	70,1
58	2530	1082	3328	3141	10081	0,250967166	65,5
59	210	73	260	133	676	0,310650888	80,4
60	1150	644	2898	1658	6350	0,181102362	25,2
61	907	311	2199	1827	5244	0,172959573	22,9
62	253	133	1322	947	2655	0,095291902	6,8

63	104	39	426	335	904	0,115044248	8
64	359	165	969	728	2221	0,161638901	14,9
65	2394	721	5244	6001	14360	0,166713092	17,2
66	522	175	666	630	1993	0,261916708	72,4
67	940	343	1234	1015	3532	0,266138165	73,5
68	3023	1053	2546	1966	8588	0,352002795	87,3
69	5380	1370	3566	4386	14702	0,365936607	90,8
70	2124	690	3048	2770	8632	0,246061168	64,3
71	4263	1177	5905	7100	18445	0,231119545	55,1
72	416	134	1041	816	2407	0,172829248	21,8
73	14	1	18	11	44	0,318181818	83,9
74	7	6	39	56	108	0,064814815	1,1
75	9	3	12	0	24	0,375	94,2
76	2707	627	5853	5355	14542	0,186150461	27,5
77	1416	331	1665	2637	6049	0,234088279	56,3
78	344	93	532	744	1713	0,20081728	34,4
79	2570	584	3034	4440	10628	0,241814076	62
80	2654	629	3700	4852	11835	0,224250106	49,4
81	676	149	1435	1178	3438	0,196625945	31
82	1085	208	1581	1975	4849	0,223757476	48,2
83	1355	289	2086	2229	5959	0,227387145	51,7
84	12	4	30	25	71	0,169014085	18,3
85	23	31	91	40	185	0,124324324	9,1
86	32	29	93	48	202	0,158415842	13,7
87	9	15	64	34	122	0,073770492	3,4
88	42	20	95	52	209	0,200956938	35,6

A.18. Hottest NILs

ID_NIL	NIL	COUNT	FID	MAX	MIN	VALUE	PERCENTILE
48	RONCHETTO SUL NAVIGLIO -	196493	0	0,81155831	0,11279793	0,3976031	21,8
64	TRENNO	40061	1	0,6230523	0,1732491	0,39514252	20,6
67	PORTELLO	74401	2	0,82658732	0,26489115	0,56729454	74,7
81	BOVISASCA	128603	3	0,74643999	0,1760755	0,44049292	32,1

84	PARCO NORD	123504	4	0,65257627	0,12676644	0,32013519	8
63	FIGINO	116527	5	0,71352988	0,06884469	0,33208049	10,3
20	LORETO - CASORETTO - NOLO	142876	6	0,82229841	0,18932842	0,61926322	100
76	QUARTO OGGIARO - VIALBA -	227140	7	0,8182224	0,19438721	0,48806205	41,3
11	ISOLA	108209	8	0,76305491	0,30036798	0,5883778	87,3
61	QUARTO CAGNINO	80656	9	0,73900032	0,16725267	0,40224614	24,1
60	STADIO - IPPODROMI	280907	10	0,73271459	0,14631431	0,39483972	18,3
62	QUINTO ROMANO	134581	11	0,63007003	0,15582411	0,33104262	9,1
1	DUOMO	191446	12	0,82463574	0,27216408	0,61390839	98,8
4	GUASTALLA	126535	13	0,85522354	0,24616086	0,59571259	93,1
57	SAN SIRO	80522	14	0,73782426	0,23499483	0,51885694	49,4
82	COMASINA	75392	15	0,77353853	0,18619744	0,46690812	39
43	TIBALDI	64227	16	0,85564345	0,26250875	0,54590773	59,7
13	GRECO - SEGNANO	144689	17	0,80520356	0,24434859	0,57814455	80,4
58	DE ANGELI - MONTE ROSA	108171	18	0,77227509	0,19853517	0,52624158	51,7
78	FARINI	82628	19	0,81717229	0,26910526	0,5529716	63,2
83	BRUZZANO	134859	20	0,68341893	0,15445602	0,39445611	17,2
66	QT 8	83776	21	0,73619348	0,17572759	0,39834578	22,9
75	STEPHENSON	45828	22	0,87619478	0,26176921	0,60223796	95,4
47	CANTALUPA	75722	23	0,77115327	0,05570898	0,30633544	4,5
39	QUINTOSOLE	86071	24	0,7524364	0,02594459	0,30903688	6,8
8	PARCO SEMPIONE	38465	25	0,73473412	0,25987288	0,42877367	27,5
46	BARONA	163924	26	0,84843791	0,10370822	0,40973794	25,2
71	VILLAPIZZONE - CAGNOLA -	280328	27	0,86011255	0,20533258	0,55950992	68,9
88	PARCO BOSCO IN CITTA'	638895	28	0,82303512	0,02910705	0,29555399	2,2
16	GORLA - PRECOTTO	245075	29	0,84162104	0,20761451	0,58666499	86,2
14	NIGUARDA - CA' GRANDA -	346938	30	0,80703193	0,11509644	0,44147036	33,3
32	TRIULZO SUPERIORE	113105	31	0,83832365	0,11209438	0,44250714	35,6
27	PTA ROMANA	81941	32	0,91743124	0,32661143	0,60352199	96,5
30	TALIEDO - MORSENCHIO - Q.RE	312258	33	1	0,17292812	0,52628881	52,8
6	PORTA TICINESE - CONCA DEL	102589	34	0,81482422	0,2908853	0,5785317	82,7
59	TRE TORRI	41977	35	0,80429876	0,25293449	0,5120605	47,1
87	ASSIANO	473409	36	0,7597515	0,07445249	0,30116225	3,4
37	MORIVIONE	66862	37	0,93747723	0,27890453	0,54028517	57,4
38	VIGENTINO - Q.RE FATIMA	151399	38	0,84300739	0,15159494	0,43865909	31
15	BICOCCA	123944	39	0,86081946	0,20112467	0,54850244	60,9
29	ORTOMERCATO	114662	40	0,89860517	0,30155927	0,59319204	88,5

35	LODI - CORVETTO	297334	41	0,96306318	0,12392948	0,51591066	48,2
54	MUGGIANO	36312	42	0,617957	0,1825414	0,36480884	13,7
44	PORTA TICINESE - CONCHETTA	121278	43	0,86152905	0,25145674	0,56776129	75,8
28	UMBRIA - MOLISE -	97430	44	0,8691231	0,29090941	0,56687562	73,5
74	ROSERIO	56774	45	0,89290148	0,24116521	0,49276941	43,6
40	RONCHETTO DELLE RANE	15428	46	0,59872442	0,04139388	0,34121608	12,6
65	Q.RE GALLARATESE - Q.RE SAN	318414	47	0,81817418	0,11762717	0,4415713	34,4
31	MONLUE' - PONTE LAMBRO	214408	48	0,99133337	0,17794622	0,52326497	50,5
19	PADOVA - TURRO -	168673	49	0,83117497	0,19488665	0,55475193	65,5
41	GRATOSOGLIO - Q.RE	270307	50	0,79812086	0,0145341	0,33277353	11,4
51	PORTA MAGENTA	106798	51	0,82953382	0,28444335	0,57480843	78,1
56	FORZE ARMATE	262156	52	0,71607554	0,16255252	0,39508737	19,5
70	GHISOLFA	85987	53	0,84381741	0,23694959	0,55381923	64,3
34	CHIARAVALLE	25262	54	0,62425649	0,06408761	0,30873643	5,7
85	PARCO DELLE ABBAZIE	1135834	55	0,71541417	0	0,28249611	1,1
12	MACIACHINI - MAGGIOLINA	137004	56	0,82337397	0,27512559	0,55565867	66,6
52	BANDE NERE	217774	57	0,77487493	0,25013202	0,50902968	45,9
23	LAMBRATE - ORTICA	252376	58	0,8589412	0,15236764	0,48840052	42,5
42	STADERA - CHIESA ROSSA -	264083	59	0,76367176	0,14158551	0,4351398	28,7
5	PORTA VIGENTINA - PORTA	92802	60	0,87813628	0,27382499	0,56998717	77
36	SCALO ROMANA	141929	61	0,99395704	0,18857381	0,55841956	67,8
26	XXII MARZO	133886	62	0,86731952	0,29517725	0,59379201	90,8
18	CIMIANO - ROTTOLE - Q.RE	405954	63	0,81588942	0,10546039	0,38289552	14,9
79	DERGANO	111157	64	0,91718984	0,24140379	0,57612305	79,3
55	BAGGIO - Q.RE DEGLI OLMI -	282660	65	0,79105628	0,1548669	0,38883528	16
24	PARCO FORLANINI -	238581	66	0,90015793	0,07815357	0,41962115	26,4
3	GIARDINI P.TA VENEZIA	20418	67	0,7143175	0,25697297	0,4460031	37,9
9	PORTA GARIBALDI - PORTA	64242	68	0,80090827	0,28545448	0,578457	81,6
80	AFFORI	169441	69	0,7474556	0,1749862	0,46866373	40,2
21	BUENOS AIRES - PORTA	235302	70	0,84587717	0,29374319	0,59555566	91,9
45	MONCUCCO - SAN	130439	71	0,87153816	0,25719664	0,55956328	70,1
10	STAZIONE CENTRALE - PONTE	127281	72	0,78798223	0,26926714	0,6041825	97,7
77	BOVISA	156509	73	0,90170169	0,1768631	0,53755036	56,3
72	MAGGIORE - MUSOCCO -	247873	74	0,87266529	0,18899088	0,54226118	58,6
49	GIAMBELLINO	160762	75	0,79779106	0,16201256	0,49997881	44,8
22	CITTA' STUDI	180499	76	0,80708754	0,27533421	0,56293296	71,2
50	PORTA GENOVA	81477	77	0,84667987	0,3224228	0,58179278	83,9

25	CORSICA	88442	78	0,86863554	0,31943145	0,56306044	72,4
7	MAGENTA - S. VITTORE	113641	79	0,82963592	0,27575716	0,58494197	85
73	CASCINA MERLATA	139643	80	0,83323771	0,20877716	0,55172543	62
69	SARPI	148184	81	0,84427351	0,30906942	0,5934595	89,6
86	PARCO DEI NAVIGLI	295147	82	0,67490834	0,00659649	0,2371506	0
68	PAGANO	105452	83	0,76117063	0,23634367	0,52668257	54
2	BRERA	133884	84	0,89050078	0,25542772	0,60121046	94,2
33	ROGOREDO - SANTA GIULIA	98064	85	0,91908282	0,18520123	0,52963032	55,1
17	ADRIANO	198305	86	0,82494181	0,13098657	0,43808338	29,8
53	LORENTEGGIO	215462	87	0,73247749	0,14435802	0,44263319	36,7

9 Appendix B

B.7. Final index calculation with the weight of each of the sub indicators

ID	NIL	FINAL_INJUSTICE_INDICATOR	CONTRIBUTION_EC	CONTRIBUTION_ED	CONTRIBUTION_HE	CONTRIBUTION_SO	CONTRIBUTION_LI
1	DUOM	37,66	0,226	0,158	0,234	0,168	0,214
2	BRERA	37,26	0,227	0,211	0,234	0,153	0,176
3	GIARDI	19,91	0,286	0,208	0,263	0,015	0,228
4	GUAST	44,20	0,216	0,193	0,208	0,187	0,196
5	PORTA	46,12	0,214	0,197	0,208	0,177	0,205
6	PORTA	45,64	0,214	0,205	0,213	0,174	0,194
7	MAGE	41,75	0,22	0,219	0,236	0,158	0,168
8	PARCO	11,71	0,362	0,198	0,318	0	0,122
9	PORTA	23,83	0,253	0,132	0,201	0,152	0,262
10	STAZIO	29,77	0,233	0,152	0,195	0,202	0,218

11	ISOLA	28,95	0,237	0,173	0,202	0,162	0,226
12	MACIA	36,13	0,221	0,162	0,186	0,216	0,215
13	GRECO	33,36	0,22	0,164	0,183	0,218	0,216
14	NIGUA	36,44	0,196	0,231	0,178	0,179	0,215
15	BICOC	31,01	0,203	0,185	0,239	0,147	0,226
16	GORLA	31,82	0,223	0,151	0,189	0,233	0,205
17	ADRIA	30,15	0,222	0,161	0,184	0,203	0,23
18	CIMIA	25,06	0,203	0,234	0,188	0,148	0,226
19	PADOV	32,81	0,144	0,229	0,194	0,246	0,188
20	LORET	44,10	0,202	0,226	0,183	0,207	0,183
21	BUENO	53,43	0,198	0,203	0,231	0,165	0,202
22	CITTA'	43,44	0,207	0,192	0,233	0,16	0,208
23	LAMBR	32,82	0,187	0,218	0,171	0,2	0,224
24	PARCO	25,12	0,203	0,217	0,159	0,174	0,246
25	CORSIC	47,89	0,216	0,202	0,176	0,202	0,205
26	XXII	45,86	0,216	0,201	0,179	0,195	0,209
27	PTA	30,09	0,233	0,142	0,2	0,194	0,232
28	UMBRI	46,44	0,215	0,201	0,176	0,219	0,19
29	ORTOM	36,91	0,232	0,23	0,167	0,172	0,199
30	TALIED	34,09	0,201	0,217	0,172	0,19	0,22
31	MONL	25,01	0,221	0,232	0,177	0,156	0,214
32	TRIULZ	14,58	0,294	0,167	0,207	0,166	0,166
33	ROGOR	37,87	0,195	0,211	0,174	0,218	0,203
34	CHIAR	19,17	0,264	0,139	0,196	0,159	0,242
35	LODI -	35,95	0,198	0,22	0,18	0,218	0,184
36	SCALO	38,93	0,204	0,211	0,171	0,213	0,201
37	MORIVI	43,24	0,198	0,211	0,172	0,201	0,219
38	VIGEN	38,86	0,204	0,216	0,171	0,19	0,22
39	QUINT	20,34	0,251	0,156	0,182	0,129	0,282
40	RONC	26,68	0,236	0,198	0,253	0,069	0,244
41	GRATO	43,66	0,202	0,204	0,223	0,166	0,206
42	STADE	42,88	0,203	0,194	0,231	0,18	0,192
43	TIBALD	36,24	0,208	0,183	0,186	0,212	0,211
44	PORTA	35,55	0,227	0,203	0,184	0,169	0,217
45	MONC	40,32	0,219	0,204	0,173	0,198	0,206
46	BARON	43,32	0,202	0,208	0,229	0,171	0,189
47	CANTA	24,17	0,246	0,21	0,244	0,033	0,266

48	RONC	44,99	0,2	0,209	0,225	0,17	0,196
49	GIAMB	31,00	0,225	0,149	0,196	0,226	0,204
50	PORTA	34,33	0,226	0,148	0,19	0,197	0,239
51	PORTA	34,60	0,218	0,159	0,193	0,204	0,226
52	BANDE	26,43	0,232	0,113	0,206	0,213	0,235
53	LOREN	24,05	0,239	0,172	0,194	0,158	0,237
54	MUGGI	18,38	0,159	0,18	0,214	0,167	0,28
55	BAGGI	22,39	0,148	0,188	0,206	0,204	0,254
56	FORZE	38,31	0,205	0,219	0,232	0,154	0,191
57	SAN	34,23	0,198	0,165	0,197	0,23	0,209
58	DE	45,21	0,205	0,206	0,175	0,2	0,214
59	TRE	27,10	0,199	0,207	0,185	0,15	0,258
60	STADIO	29,81	0,21	0,225	0,177	0,146	0,243
61	QUART	40,84	0,201	0,213	0,23	0,15	0,205
62	QUINT	33,08	0,214	0,221	0,227	0,127	0,211
63	FIGINO	33,28	0,213	0,194	0,216	0,156	0,221
64	TRENN	28,35	0,213	0,196	0,191	0,158	0,242
65	Q.RE	32,21	0,204	0,232	0,183	0,179	0,202
66	QT 8	20,72	0,233	0,186	0,199	0,15	0,232
67	PORTE	35,59	0,219	0,22	0,18	0,153	0,228
68	PAGAN	34,86	0,184	0,226	0,187	0,166	0,237
69	SARPI	37,02	0,22	0,162	0,25	0,144	0,224
70	GHISO	25,81	0,224	0,132	0,209	0,187	0,248
71	VILLAP	33,22	0,211	0,156	0,188	0,234	0,212
72	MAGGI	27,34	0,224	0,171	0,174	0,188	0,243
73	CASCI	29,01	0,233	0,202	0,207	0,124	0,234
74	ROSERI	20,39	0,264	0,226	0,259	0,09	0,162
75	STEPHE	35,83	0,218	0,189	0,206	0,133	0,253
76	QUART	51,56	0,197	0,202	0,219	0,185	0,196
77	BOVISA	37,46	0,218	0,21	0,173	0,203	0,196
78	FARINI	31,97	0,23	0,125	0,244	0,203	0,198
79	DERGA	45,97	0,206	0,199	0,176	0,225	0,193
80	AFFORI	34,28	0,207	0,173	0,186	0,223	0,211
81	BOVISA	39,24	0,213	0,21	0,225	0,138	0,214
82	COMAS	24,45	0,23	0,136	0,202	0,198	0,234
83	BRUZZ	29,46	0,217	0,154	0,186	0,216	0,227
84	PARCO	12,52	0,303	0,179	0,219	0,056	0,243

85	PARCO	18,00	0,272	0,244	0,17	0,006	0,309
86	PARCO	21,50	0,253	0,223	0,16	0,085	0,279
87	ASSIAN	12,22	0,19	0,172	0,194	0,1	0,345
88	PARCO	19,21	0,245	0,234	0,155	0,093	0,273

B.8. Importing instances for the code

```
import geopandas as gpd
import pandas as pd
import folium
import branca
import mapclassify as mc

# ── 1) Load your data
# Load your Milan shapefile
gdf_shp = gpd.read_file("/Users/adriancantera/Library/CloudStorage/OneDrive-
PolitecnicodiMilano/Thesis/Thesis_Code/Data_Milano/REAL_NIL/NIL_WM.shp")
# Sort by NIL alphabetically
gdf_shp.sort_values(by="NIL", inplace=True)
# Load Excel with indicators
df_excel = pd.read_excel("Milan_indicator_index.xlsx", sheet_name="Reference_table_2", engine="openpyxl")
# Sort by NIL alphabetically
df_excel.sort_values(by="NIL", inplace=True)

# ── 2) Clean join keys to avoid mismatches
df_excel['NIL'] = df_excel['NIL'].astype(str).str.strip()
gdf_shp['NIL'] = gdf_shp['NIL'].astype(str).str.strip()

# ── 3) Merge
gdf_merged_2 = gdf_shp.merge(
    df_excel[['NIL',
'FINAL_INDICATOR_INJUSTICE','ECO_iNDEX','EDU_iNDEX','HEA_iNDEX','SOC_iNDEX','LIV_iNDEX']].rena
me(
        columns={'FINAL_INDICATOR_INJUSTICE': 'indicator',
            'ECO_iNDEX': 'eco_index',
```

```
            'EDU_iNDEX': 'edu_index',
            'HEA_iNDEX': 'hea_index',
            'SOC_iNDEX': 'soc_index',
            'LIV_iNDEX': 'liv_index'}
  ),
  on='NIL', how='left'
)

# ── 4) Ensure WGS84 (lat/lon) for web maps
if gdf_merged_2.crs is None:
  # set your source CRS if you know it, then convert
  # gdf_merged_2 = gdf_merged_2.set_crs("EPSG:32632")  # example for UTM32N
  pass
gdf_merged_2 = gdf_merged_2.to_crs(epsg=4326)

# Optional: simplify geometry to reduce file size (tune tolerance)
gdf_for_web = gdf_merged_2.copy()
gdf_for_web['geometry'] = gdf_for_web.geometry.simplify(0.00003, preserve_topology=True)
```

B.9. Building the representation

```
import folium, branca, mapclassify as mc
import geopandas as gpd
import pandas as pd
import numpy as np

# Base Map
center = gdf_for_web.geometry.unary_union.centroid
m = folium.Map(location=[center.y, center.x], zoom_start=12, tiles=None)
folium.TileLayer('cartodbpositron', name='Base (fixed)', control=False).add_to(m)

#  Shape of the NILS
outline_style = {
```

```
    'fillColor': 'white',
    'fillOpacity': 0.0,
    'color': '#333333',
    'weight': 1,
}
folium.GeoJson(
    gdf_for_web.geometry,
    style_function=lambda x: outline_style,
    name='Milan Outline (Fixed)',
    control=False,
    interactive=False,
    tooltip=False
).add_to(m)


# Creation of a function to add layers and legends
def add_layer_and_legend(map_obj, gdf, field, layer_name, colors, n_classes=4, show=False):

    gdf_local = gdf.copy()
    gdf_local[field] = pd.to_numeric(gdf_local[field], errors='coerce')
    vals = gdf_local[field].dropna()
    vals = vals[np.isfinite(vals)]

    vmin = float(vals.min()) if vals.notna().any() else 0.0
    vmax = float(vals.max()) if vals.notna().any() else 1.0
    if vmin == vmax and vals.notna().any():
        vmin = vmin - 0.5
        vmax = vmax + 0.5
        if vmin < 0 and vals.min() >= 0: vmin = 0

    classifier = None # Force equal interval by default

    # Create the Colormap
    if vals.empty:
        cmap = branca.colormap.LinearColormap(colors=['#d3d3d3', '#d3d3d3'], vmin=0, vmax=1).to_step(n=2)
        cmap.caption = "Sin datos"
```

```
    cmap.index = [0, 1]

elif classifier:
    bins = [vmin] + list(classifier.bins)
    cmap = branca.colormap.LinearColormap(colors=colors, vmin=vmin, vmax=vmax).to_step(index=bins)
    cmap.caption = f"{layer_name} (Quantiles)"
    cmap.index = [round(x, 2) for x in cmap.index]

else:

    cmap = branca.colormap.LinearColormap(colors=colors, vmin=vmin, vmax=vmax).to_step(n=n_classes)
    cmap.caption = f"{layer_name} (Equal Interval)"
    cmap.index = [round(x, 2) for x in cmap.index] #

# Define the style function
def style_fn(feature):
    val = feature['properties'].get(field)
    if val is None or not np.isfinite(val):
        return {'fillColor': '#d3d3d3', 'color': 'black', 'weight': 0.8, 'fillOpacity': 0.7, 'fill': True}
    # Compara float vs float (¡correcto!)
    return {'fillColor': cmap(val), 'color': 'black', 'weight': 0.8, 'fillOpacity': 0.95, 'fill': True}

tooltip = folium.GeoJsonTooltip(
    fields=['NIL', field], aliases=['NIL:', f'{layer_name}:'],
    localize=True, sticky=True, labels=True
)

# Adding the style_fn to the folium GeoJson layer
layer = folium.GeoJson(
    data=gdf_local[['NIL', field, 'geometry']].to_json(),
    style_function=style_fn,
    tooltip=tooltip,
    name=layer_name, show=show
).add_to(map_obj)

# Create the HTML
```

```
    legend_html = f"""
    <div style="font-weight:800; margin-bottom:12px;">{layer_name}</div>
    {cmap._repr_html_()}
    """

    return layer, legend_html

# Adding each of the layers and legends

# FINAL_INDEX_LAYER
final_colors = ['#FEFDE7','#FCFABB','#FAF68F','#F8F363','#F5EE27','#F4EC0B',
                '#C8C109','#9C9707','#706C05','#444203']
final_layer, final_legend_html = add_layer_and_legend(
    m, gdf_for_web, field='indicator', layer_name='Final Injustice Index',
    colors=final_colors, n_classes=3, show=True
)

# SOCIAL sub-index
social_colors = ['#f7fbff','#deebf7','#c6dbef','#9ecae1','#6baed6',
                 '#4292c6','#2171b5','#08519c','#08306b']
social_layer, social_legend_html = add_layer_and_legend(
    m, gdf_for_web, field='soc_index', layer_name='Social sub-index',
    colors=social_colors, n_classes=3, show=False
)

# ECO sub-index
eco_colors = ['#fff7ec','#fee8c8','#fdd49e','#fdbb84','#fc8d59','#ef6548','#d7301f','#990000']
eco_layer, eco_legend_html = add_layer_and_legend(
    m, gdf_for_web, field='eco_index', layer_name='Eco sub-index',
    colors=eco_colors, n_classes=3, show=False
)

# HEALTH sub-index
health_colors = ['#f7fcf5','#e5f5e0','#c7e9c0','#a1d99b','#74c476','#41ab5d','#238b45','#005a32']
health_layer, health_legend_html = add_layer_and_legend(
    m, gdf_for_web, field='hea_index', layer_name='Health sub-index',
```

```
    colors=health_colors, n_classes=3, show=False
)

# Livelihood (si existe)
liv_colors = ['#f7fbff','#deebf7','#c6dbef','#9ecae1','#6baed6','#4292c6','#2171b5','#084594']
livelihood_layer, livelihood_legend_html = add_layer_and_legend(
    m, gdf_for_web, field='liv_index', layer_name='Livelihood sub-index',
    colors=liv_colors, n_classes=3, show=False
)

# EDUCATION sub-index
edu_colors = ['#fff5f0','#fee0d2','#fcbba1','#fc9272','#fb6a4a','#ef3b2c','#cb181d','#99000d']
education_layer, education_legend_html = add_layer_and_legend(
    m, gdf_for_web, field='edu_index', layer_name='Education sub-index',
    colors=edu_colors, n_classes=3, show=False
)

# Control from layers
folium.LayerControl(collapsed=False).add_to(m)


# ===== 3) CSS and JS for legends =====
legend_css = """
<style>
#legend-container{
  position:absolute; bottom:14px; left:14px; z-index:9999;
  background:rgba(255,255,255,.95); color:#222;
  padding:8px 12px; border-radius:8px; box-shadow:0 2px 10px rgba(0,0,0,.15);
  max-width: 500px;
  min-width: 440px;
  font-family: system-ui,-apple-system,Segoe UI,Roboto,Ubuntu,Helvetica,Arial,sans-serif;
  font-size: 13px;
}
#legend-container .branca-colormap {
  width: 100%;
  margin: 0;
```

```
}
#legend-container .branca-colormap span {
    height: 12px !important;
}
#legend-container .branca-colormap ul {
  list-style-type: none;
  padding: 0;
  margin: 2px 0 0 0;
  width: 100%;
  display: flex;
  justify-content: space-between;
}
#legend-container .branca-colormap li {
  font-size: 10px !important;
  text-align: center;
  white-space: nowrap;
  flex-basis: 0;
  flex-grow: 1;
}
#legend-container .branca-colormap li:first-child {
  text-align: left;
}
#legend-container .branca-colormap li:last-child {
  text-align: right;
}
#legend-container .branca-colormap-caption {
  font-size: 11px;
  margin-top: 4px;
}
</style>
"""
m.get_root().html.add_child(folium.Element(legend_css))

# Exporting layer names for JS
map_name         = m.get_name()
final_jsname      = final_layer.get_name()
```

```
social_jsname     = social_layer.get_name()
eco_jsname        = eco_layer.get_name()
health_jsname     = health_layer.get_name()
livelihood_jsname = livelihood_layer.get_name()
education_jsname  = education_layer.get_name()

# Dictionary of legends in JS
legend_js = f"""
<script>
  setTimeout(function() {{
    var map = {map_name};

    function ensureLegendContainer(){{
      var c = document.getElementById('legend-container');
      if(!c){{
        c = document.createElement('div');
        c.id = 'legend-container';
        c.style.display = 'none';
        map.getContainer().appendChild(c);
      }}
      return c;
    }}

    var layers = [
      {{ layer: {final_jsname},      legend: `{final_legend_html}` }},
      {{ layer: {social_jsname},     legend: `{social_legend_html}` }},
      {{ layer: {eco_jsname},        legend: `{eco_legend_html}` }},
      {{ layer: {health_jsname},     legend: `{health_legend_html}` }},
      {{ layer: {livelihood_jsname}, legend: `{livelihood_legend_html}` }},
      {{ layer: {education_jsname},  legend: `{education_legend_html}` }}
    ];

    function keepOnly(activeLayer){{
      layers.forEach(function(o){{
        if(o.layer !== activeLayer && map.hasLayer(o.layer)) {{
          map.removeLayer(o.layer);
```

```
      }}
    }});
  }}

  function updateLegendFor(activeLayer){{
    var c = ensureLegendContainer();
    var entry = null;
    if (activeLayer) {{
      entry = layers.find(function(o){{ return o.layer === activeLayer; }});
    }}
    if (!entry) {{
      entry = layers.find(function(o){{ return map.hasLayer(o.layer); }});
    }}
    if(entry){{
      c.innerHTML = entry.legend;
      c.style.display = 'block';
    }} else {{
      c.innerHTML = '';
      c.style.display = 'none';
    }}
  }}

  map.on('overlayadd', function(e) {{
    keepOnly(e.layer);
    updateLegendFor(e.layer);
  }});
  map.on('overlayremove', function(e) {{
    updateLegendFor(null);
  }});
  updateLegendFor(null);

 }}, 100);
</script>
"""
m.get_root().html.add_child(folium.Element(legend_js))
```

```
# Save and show
m.save('milan_injustice_map_def.html')
print("Saved: milan_injustice_map_def.html")
m
```

B.10. Spatial analysis code

```
# ---- Imports
import geopandas as gpd
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

from libpysal.weights import Queen, KNN, lag_spatial
from esda.moran import Moran, Moran_Local
from esda.geary import Geary
from esda.getisord import G, G_Local

# Optional: FDR multiple-testing correction
try:
    from statsmodels.stats.multitest import multipletests
    HAS_SM = True
except Exception:
    HAS_SM = False

# ---- 0) (OPTIONAL) Start from your merge result
# gdf_merged_2 = ...  # your object after merging indicator by NIL

# Keep only rows with a valid indicator and geometry
gdf = gdf_merged_2.dropna(subset=['indicator', gdf_merged_2.geometry.name]).copy()
gdf = gdf.reset_index(drop=True)

# Ensure projected CRS for contiguity (or distance) operations
```

```python
# If your layer is EPSG:4326, pick a projected CRS for Milan (e.g., EPSG:32632 or 25832)
if gdf.crs is None or gdf.crs.to_epsg() in (4326,):
    gdf = gdf.to_crs(epsg=32632)

# Target variable as a numpy array
y = gdf['indicator'].values.astype(float)

# ── 1) Build spatial weights (Queen contiguity, row-standardized)
w = Queen.from_dataframe(gdf)
w.transform = 'R'

# Handle islands (areas with no neighbors): attach 1-NN links so every NIL has at least one neighbor
if w.islands:
    print(f"Found {len(w.islands)} island NIL(s). Adding 1-NN links to ensure connectivity.")
    w_knn = KNN.from_dataframe(gdf, k=1)
    w = w.union(w_knn)    # combine contiguity and kNN
    w.transform = 'R'

# ── 2) GLOBAL INDICATORS
# Moran's I
mi = Moran(y, w, permutations=9999)
# Geary's C
gc = Geary(y, w, permutations=9999)
# Getis–Ord G
g_global = G(y, w, permutations=9999)

print("\n=== GLOBAL SPATIAL AUTOCORRELATION ===")
print(f"Moran's I: {mi.I:.4f}  p-value (perm.): {mi.p_sim:.4f}")
print(f"Geary's C: {gc.C:.4f}  p-value (perm.): {gc.p_sim:.4f}")
print(f"Getis–Ord G: {g_global.G:.4f}  p-value (perm.): {g_global.p_sim:.4f}")

# Store global results for reporting
global_results = {
    "moran_I": mi.I, "moran_p": mi.p_sim,
    "geary_C": gc.C, "geary_p": gc.p_sim,
    "getis_G": g_global.G, "getis_p": g_global.p_sim
```

```
}

# ── 3) LOCAL INDICATORS
# Local Moran's I (LISA)
lisa = Moran_Local(y, w, permutations=9999)
# Local Getis–Ord Gi*
gi = G_Local(y, w, permutations=9999)  # Z-scores and p-values

# Benjamini–Hochberg FDR correction for multiple testing (recommended)
if HAS_SM:
    reject_lisa, p_lisa_fdr, _, _ = multipletests(lisa.p_sim, alpha=0.05, method='fdr_bh')
    reject_gi,   p_gi_fdr,   _, _ = multipletests(gi.p_sim,   alpha=0.05, method='fdr_bh')
else:
    reject_lisa = lisa.p_sim < 0.05
    p_lisa_fdr = lisa.p_sim
    reject_gi   = gi.p_sim   < 0.05
    p_gi_fdr    = gi.p_sim

# Quadrant mapping for LISA:
# 1 HH, 2 LH, 3 LL, 4 HL  (Anselin, 1995)
labels = np.array(['NS','HH','LH','LL','HL'])
lisa_sig = np.where(reject_lisa, lisa.q, 0)  # 0 => NS
lisa_labels = labels[lisa_sig]

# Attach results to GeoDataFrame
gdf['moran_I']     = mi.I
gdf['moran_p']     = mi.p_sim
gdf['geary_C']     = gc.C
gdf['geary_p']     = gc.p_sim
gdf['getis_G']     = g_global.G
gdf['getis_p']     = g_global.p_sim

gdf['lisa_li']     = lisa.Is
gdf['lisa_p']      = lisa.p_sim
gdf['lisa_p_fdr']  = p_lisa_fdr
gdf['lisa_cluster']= lisa_labels  # 'HH','LL','HL','LH','NS'
```

```
gdf['gi_z']       = gi.Zs
gdf['gi_p']       = gi.p_sim
gdf['gi_p_fdr']   = p_gi_fdr
gdf['gi_sig']     = reject_gi

# ── 4) QUICK DIAGNOSTIC PLOTS (optional)
try:
   import mapclassify as mc

   # Choropleth of the indicator
   ax = gdf.plot(column='indicator', cmap='viridis', scheme='Quantiles', k=5, edgecolor='white', linewidth=0.2,
legend=True, figsize=(8,8))
   ax.set_title('Indicator by NIL (Quantiles)')
   ax.axis('off')
   plt.show()

   # LISA cluster map
   cluster_colors = {
      'HH':'#e41a1c','LL':'#377eb8','HL':'#4daf4a','LH':'#984ea3','NS':'#bdbdbd'
   }
   gdf['_color'] = gdf['lisa_cluster'].map(cluster_colors)
   ax = gdf.plot(color=gdf['_color'], edgecolor='white', linewidth=0.2, figsize=(8,8))
   ax.set_title('Local Moran's I clusters (FDR 5%)')
   ax.axis('off')
   plt.show()

   # Gi* hotspots/coldspots (z-scores)
   # Significant only
   gdf['gi_class'] = np.select(
      [ (gdf['gi_sig']) & (gdf['gi_z']>0),
        (gdf['gi_sig']) & (gdf['gi_z']<0) ],
      ['Hotspot (+)','Coldspot (–)'],
      default='NS'
   )
   gi_colors = {'Hotspot (+)':'#d73027', 'Coldspot (–)':'#4575b4', 'NS':'#bdbdbd'}
```

```
    ax = gdf.plot(color=gdf['gi_class'].map(gi_colors), edgecolor='white', linewidth=0.2, figsize=(8,8))
    ax.set_title('Local Getis–Ord Gi* (FDR 5%)')
    ax.axis('off')
    plt.show()

except Exception as e:
    print("Plotting skipped:", e)
# LISA counts
lisa_counts = gdf['lisa_cluster'].value_counts().rename_axis('LISA').reset_index(name='n')

# Gi* classes (after you created gi_class)
gi_counts = gdf['gi_class'].value_counts().rename_axis('Gi_class').reset_index(name='n')

print(lisa_counts)
print(gi_counts)

# Top HH by local Moran's statistic
top_HH = (gdf[gdf['lisa_cluster']=='HH']
         .sort_values('lisa_li', ascending=False)[['NIL','indicator','lisa_li','lisa_p_fdr']].head(10))

# Top hotspots by Gi* z-score
top_hot = (gdf[gdf['gi_class']=='Hotspot (+)']
          .sort_values('gi_z', ascending=False)[['NIL','indicator','gi_z','gi_p_fdr']].head(10))

# Export for the thesis appendix
with pd.ExcelWriter('milan_local_clusters.xlsx') as xl:
    lisa_counts.to_excel(xl, sheet_name='LISA_counts', index=False)
    gi_counts.to_excel(xl, sheet_name='Gi_counts', index=False)
    top_HH.to_excel(xl, sheet_name='Top_HH', index=False)
    top_hot.to_excel(xl, sheet_name='Top_hotspots', index=False)

print("Saved: milan_local_clusters.xlsx")

summary = pd.DataFrame({
    'Moran_I':[gdf['moran_I'].iat[0]], 'Moran_p':[gdf['moran_p'].iat[0]],
    'Geary_C':[gdf['geary_C'].iat[0]], 'Geary_p':[gdf['geary_p'].iat[0]],
```

```
    'Getis_G':[gdf['getis_G'].iat[0]], 'Getis_p':[gdf['getis_p'].iat[0]],
    'LISA_HH':[int((gdf['lisa_cluster']=='HH').sum())],
    'LISA_LL':[int((gdf['lisa_cluster']=='LL').sum())],
    'LISA_HL':[int((gdf['lisa_cluster']=='HL').sum())],
    'LISA_LH':[int((gdf['lisa_cluster']=='LH').sum())],
    'Gi_hotspots':[int((gdf['gi_class']=='Hotspot (+)').sum())],
    'Gi_coldspots':[int((gdf['gi_class']=='Coldspot (–)').sum())]
})
summary.to_csv('milan_spatial_summary.csv', index=False)
summary

# ── 5) SAVE RESULTS
out_cols = ['NIL','indicator',
            'moran_I','moran_p','geary_C','geary_p','getis_G','getis_p',
            'lisa_Ii','lisa_p','lisa_p_fdr','lisa_cluster',
            'gi_z','gi_p','gi_p_fdr','gi_sig','geometry']

out_path = "milan_nil_spatial_stats.gpkg"
gdf[out_cols].to_file(out_path, layer='nil_stats', driver='GPKG')
print(f"\nResults written to {out_path}")

# LISA Low–Low clusters (FDR-significant)
ll = (gdf[gdf['lisa_cluster']=='LL']
      .sort_values('lisa_Ii', ascending=False)[['NIL','indicator','lisa_Ii','lisa_p_fdr']])

# Gi* coldspots (FDR-significant)
cold = (gdf[gdf['gi_class']=='Coldspot (–)']
        .sort_values('gi_z')[['NIL','indicator','gi_z','gi_p_fdr']])

print("LISA LL clusters:\n", ll)
print("\nGi* coldspots:\n", cold)

with pd.ExcelWriter('milan_LL_coldspots.xlsx') as xl:
    ll.to_excel(xl, sheet_name='LISA_LL', index=False)
    cold.to_excel(xl, sheet_name='Gi_coldspots', index=False)
```

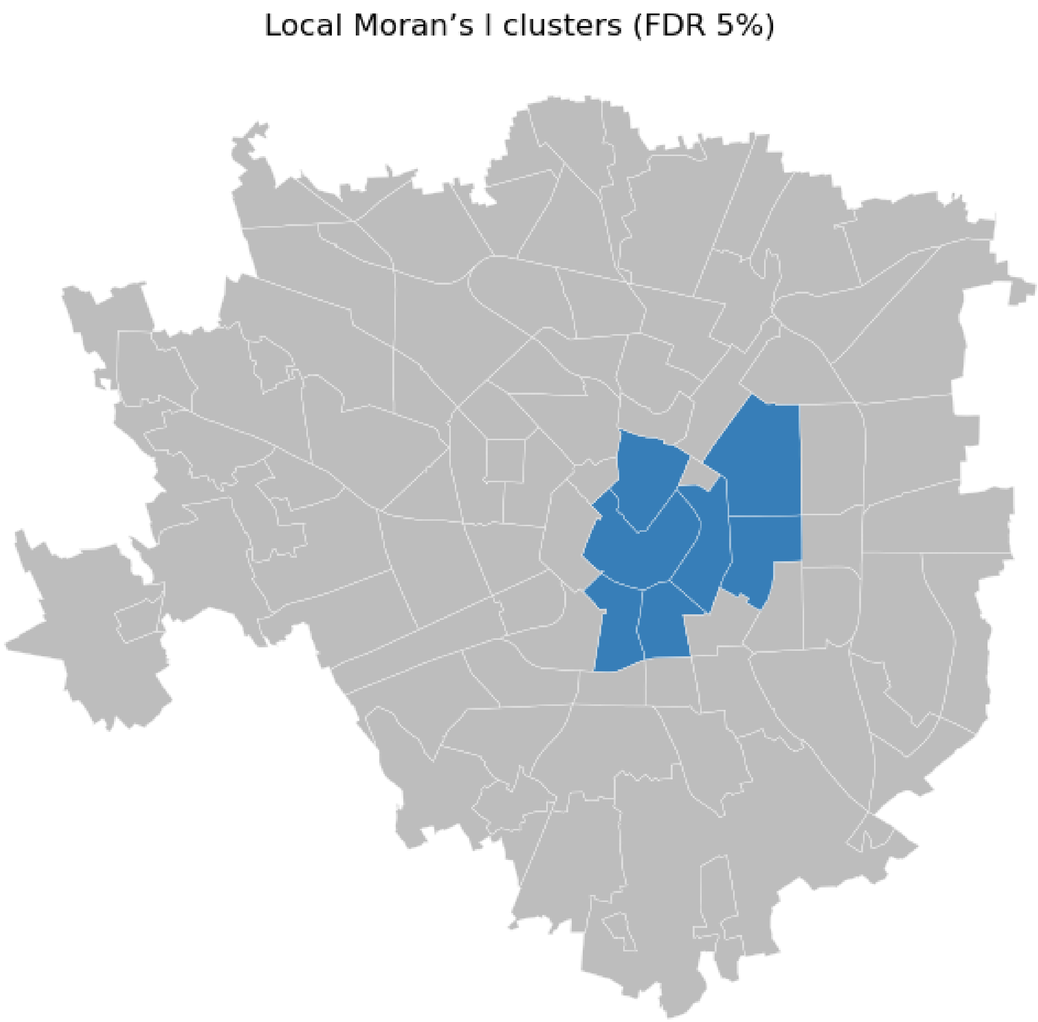
B.11. Final UII calculation

NIL	ECO_INDEX_AR	EDU_INDEX	HEA_INDEX	SOC_INDEX	LIV_INDEX	UII	UII_ARITMETIC
1	73,35	34,33	71,01	20,29	53,08	**54,65**	**50,41**
2	64,12	51,32	69,30	28,26	53,98	**55,33**	**53,40**
3	64,12	45,53	62,75	25,27	34,21	**48,58**	**46,38**
4	66,50	41,42	61,70	34,75	52,84	**52,89**	**51,44**
5	66,50	51,37	63,91	32,67	50,38	**54,40**	**52,97**
6	66,50	54,60	69,16	32,78	49,76	**56,31**	**54,56**
7	73,35	57,38	80,26	37,74	51,80	**63,13**	**60,11**
8	64,12	67,63	61,90	25,00	52,33	**56,32**	**54,20**
9	52,76	55,52	78,30	17,18	52,31	**55,12**	**51,21**
10	52,77	51,87	85,19	33,36	49,02	**58,93**	**54,44**
11	52,76	64,55	90,73	32,38	45,62	**64,08**	**57,21**
12	52,76	59,41	88,37	51,71	47,09	**64,22**	**59,87**
13	50,67	64,44	82,33	48,64	51,29	**62,07**	**59,47**
14	49,29	69,19	57,15	36,96	45,95	**53,02**	**51,71**
15	45,19	49,98	68,57	26,85	54,54	**50,82**	**49,03**
16	50,30	50,03	84,48	58,30	43,68	**60,84**	**57,36**
17	55,42	65,28	80,04	39,59	52,52	**61,06**	**58,57**
18	39,59	52,76	77,57	29,64	38,60	**51,11**	**47,63**
19	27,77	57,43	90,16	68,81	40,77	**64,25**	**56,99**
20	45,79	70,60	97,75	60,56	42,00	**74,52**	**63,34**
21	55,42	58,80	96,29	40,40	50,72	**70,23**	**60,33**
22	51,39	36,22	79,59	41,79	50,27	**54,97**	**51,85**
23	39,59	58,12	77,48	53,38	54,03	**58,51**	**56,52**
24	39,59	73,86	75,37	34,15	53,72	**58,73**	**55,34**
25	63,90	54,41	92,55	51,83	51,65	**68,65**	**62,87**
26	62,89	53,70	94,26	42,67	50,92	**68,64**	**60,89**
27	56,46	49,76	91,29	29,90	50,86	**63,02**	**55,65**
28	62,89	60,99	90,53	64,12	48,81	**69,56**	**65,47**
29	63,90	70,12	76,82	32,71	46,19	**60,90**	**57,95**
30	47,58	57,24	77,80	37,71	49,17	**56,33**	**53,90**
31	47,58	67,63	75,21	31,80	43,49	**56,08**	**53,14**
32	52,85	63,49	75,90	27,83	40,29	**55,21**	**52,07**
33	47,58	66,67	81,24	60,43	52,09	**63,73**	**61,60**
34	52,85	52,42	76,79	28,73	42,99	**53,67**	**50,76**
35	47,58	57,33	83,37	49,76	40,77	**59,24**	**55,76**
36	48,69	67,18	80,80	53,91	47,97	**62,09**	**59,71**

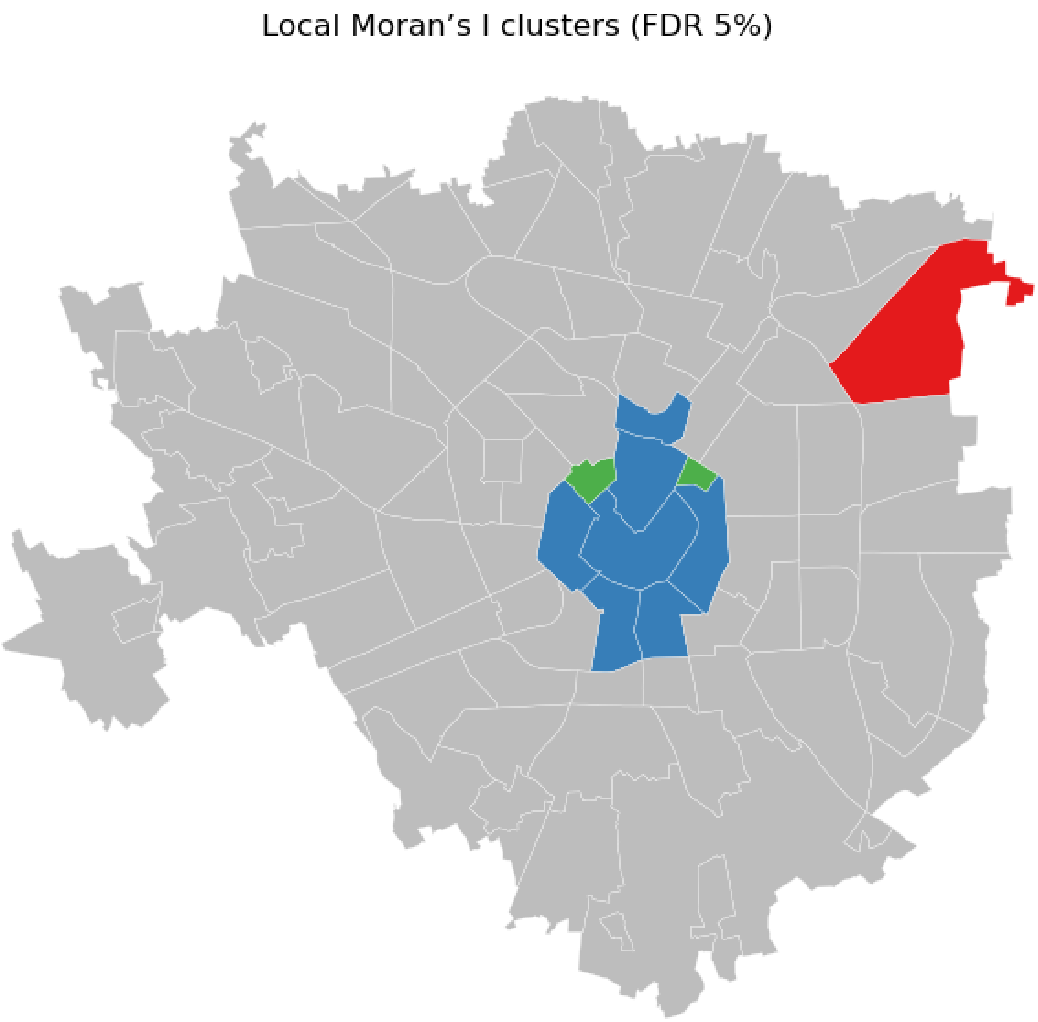
37	48,69	63,47	82,96	48,10	56,64	**62,64**	**59,97**
38	48,69	62,32	80,12	39,24	55,94	**59,88**	**57,26**
39	48,69	48,79	75,83	26,60	56,76	**54,13**	**51,33**
40	56,43	52,97	77,00	29,84	61,93	**58,25**	**55,63**
41	56,43	62,64	78,50	34,70	48,27	**58,76**	**56,11**
42	56,43	48,51	81,25	39,11	44,57	**57,19**	**53,97**
43	48,69	60,53	88,52	46,88	48,12	**63,35**	**58,55**
44	55,92	55,85	85,05	21,78	47,32	**58,54**	**53,18**
45	55,92	56,15	81,26	42,18	50,41	**59,80**	**57,18**
46	56,43	60,64	81,01	37,71	43,39	**58,97**	**55,84**
47	56,43	55,82	75,09	25,90	67,47	**58,96**	**56,14**
48	56,43	58,30	79,64	35,04	45,00	**57,82**	**54,88**
49	50,48	58,22	88,92	49,48	46,07	**63,53**	**58,63**
50	56,19	56,43	88,64	34,87	53,31	**63,13**	**57,89**
51	50,48	58,63	93,44	43,75	55,01	**67,43**	**60,26**
52	51,52	43,91	88,94	45,27	48,08	**61,15**	**55,54**
53	51,52	57,61	78,36	31,20	46,71	**56,02**	**53,08**
54	45,53	60,95	79,60	31,44	58,55	**58,39**	**55,21**
55	45,53	60,67	81,34	37,71	50,02	**58,30**	**55,05**
56	53,88	57,72	73,02	36,52	40,49	**54,28**	**52,33**
57	42,95	66,53	98,99	68,47	44,64	**77,37**	**64,32**
58	51,47	61,53	88,15	48,16	55,65	**65,03**	**60,99**
59	56,70	67,20	79,03	27,18	61,72	**61,56**	**58,37**
60	46,11	50,28	77,01	30,79	58,12	**55,22**	**52,46**
61	53,88	59,38	74,88	37,38	49,44	**56,84**	**54,99**
62	53,88	64,00	68,68	28,68	55,49	**55,95**	**54,15**
63	53,88	66,62	66,67	29,94	53,06	**55,76**	**54,03**
64	46,11	59,29	81,28	34,31	58,10	**59,10**	**55,82**
65	46,11	57,83	80,75	38,45	43,92	**56,66**	**53,41**
66	42,95	60,87	76,20	29,17	33,54	**52,09**	**48,55**
67	51,47	62,65	81,64	32,78	57,43	**60,47**	**57,19**
68	56,70	61,80	87,00	39,36	53,35	**63,78**	**59,64**
69	52,14	60,64	86,75	31,84	49,47	**61,18**	**56,17**
70	44,68	59,78	90,55	41,27	53,94	**64,12**	**58,04**
71	49,91	53,87	85,32	58,04	49,26	**62,56**	**59,28**
72	49,91	69,55	76,47	33,49	56,54	**59,83**	**57,19**
73	59,63	65,89	67,57	27,98	56,85	**57,46**	**55,58**
74	59,63	62,43	68,65	31,53	38,26	**54,18**	**52,10**
75	59,63	65,71	68,01	38,62	78,28	**64,12**	**62,05**
76	59,63	59,70	76,80	47,64	50,64	**60,34**	**58,88**
77	55,81	60,88	80,25	41,78	41,36	**58,86**	**56,02**
78	52,14	61,56	76,47	39,18	48,36	**57,61**	**55,54**
79	55,81	59,20	90,36	72,69	46,49	**69,50**	**64,91**
80	52,28	67,74	85,34	54,10	42,66	**63,99**	**60,42**

81	59,63	63,51	70,68	31,67	44,89	**56,08**	**54,08**
82	52,28	61,12	82,29	49,24	40,48	**60,14**	**57,08**
83	52,28	61,68	80,48	46,91	41,71	**59,30**	**56,61**
84	52,28	62,90	75,63	27,34	34,39	**53,93**	**50,51**
85	48,69	64,20	75,00	25,08	69,18	**59,65**	**56,43**
86	56,43	64,54	49,63	25,10	64,60	**53,95**	**52,06**
87	45,53	54,76	75,00	24,93	63,55	**55,74**	**52,75**
88	46,11	66,63	61,91	25,17	52,70	**52,44**	**50,50**

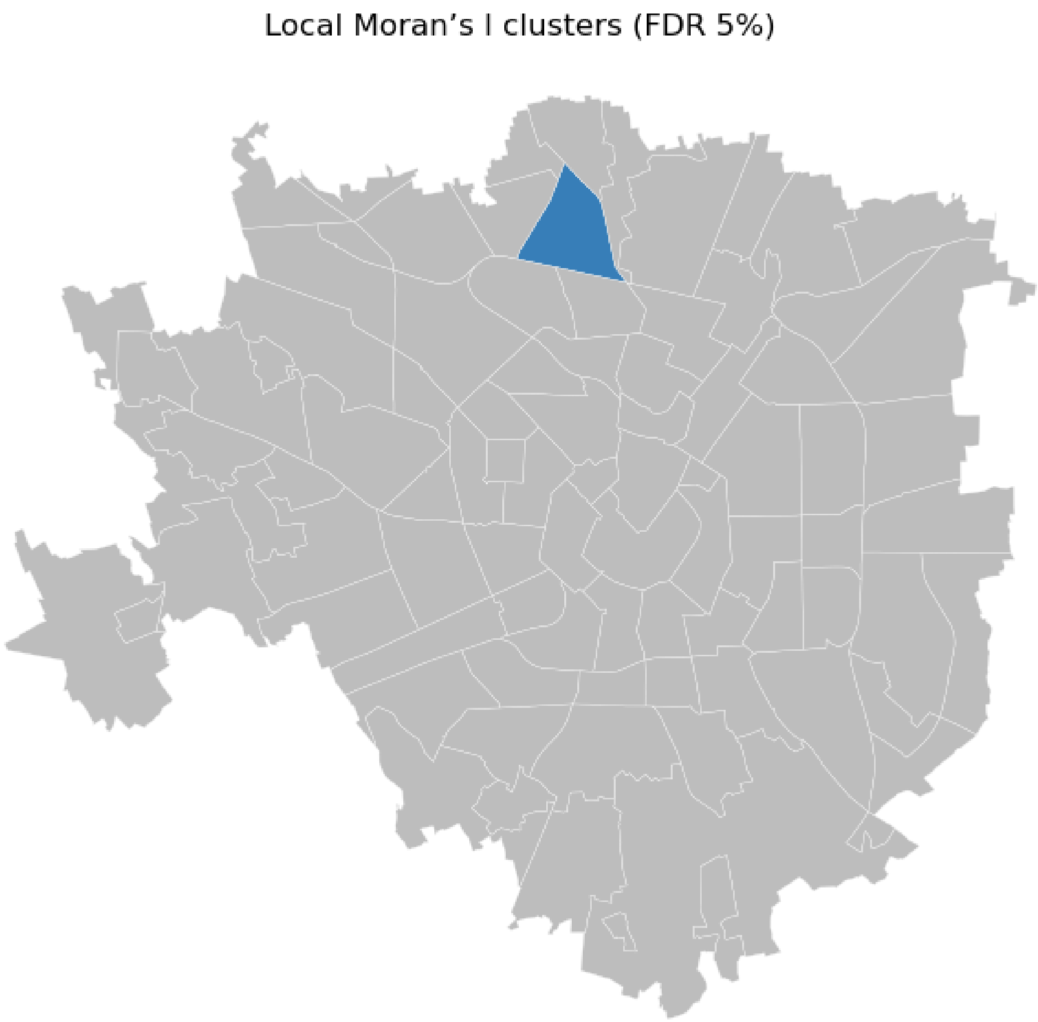
B.12. Image representation of the educational global and local calculations



B.13. Image representation of the socio-demographic global and local calculations



B.14. Image representation of the living environment global and local calculations



B.15. GitHub repository

https://github.com/AdrianCantera73/Milan_Urban_Viz

10 List of Figures

11 List if Tables