Urban Fragmentation & Spatial Segregation Patterns in Europe

A similarity analysis and the importance of local context

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by

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Cover: Highways and railway lines fragmenting the urban space (Lisbon, Portugal) (Vrublevskaia, 2022).

TU Delft

Preface

This thesis marks the culmination of an academic journey that has taken me far away from one side of the world to the other. I can say with certainty that I am satisfied with this experience, and I believe the work presented in this report is a fitting conclusion to my Master's programme. I would like to express my gratitude to everyone who has been part of this journey and contributed to this moment. My deepest appreciation goes to the members of my graduation committee. Special thanks to my both supervisors, Trivik Verma and Sander van Cranenburgh, for accepting my project and for welcoming me into their research groups. I am particularly indebted to my advisor, Lucas Spierenburg, my first contact in the project and the individual who has provided the most support throughout my thesis. The quality of this work reflects the considerable time and effort he dedicated to guiding me. I am also grateful to TU Delft for its generous sponsorship through the Justus & Louise van Effen Excellence Scholarship. Without this financial support, my studies in the Netherlands would not have been possible, and my life would be another. I want to acknowledge those who may not be physically near, but who are always close to my heart. To my mother, Lourdes, and my father, Sergio, who always encouraged me to dream big and pursue my aspirations. Their support and care have allowed to thrive, and their life lessons have showed me the value of perseverance and determination. I am also grateful to thank my partner, Airin, whose support and kind words have never been missing during challenging times. To my friends, both in the Netherlands and around the world, for making this journey an enjoyable and memorable experience. I hope this research advances our understanding of urban spaces and the complexities of their spatial processes. While my contribution may be modest, I hope it serves as a stepping stone for future researchers and students in this field.

Esteban David Ralon Santizo
Delft, July 2024

Summary

This thesis investigates the connections between urban fragmentation and the spatial segregation of non-EU immigrant communities in Europe. Previous research indicates that urban fragmentation can be connected to the degree of segregation. Particularly, in the American case, infrastructural barriers can be linked to the boundaries of ethnic groups. However, these connections cannot be generalized to other contexts since these correspond to unique historical causes. Therefore, merely identifying the existence of a connection between urban fragmentation and segregation is insufficient; these results need to be recontextualized in terms of the local dynamics of each city. Our study aims not only to determine the link between the spatial patterns of urban fragmentation and segregation, but also to examine how these connections are interpreted when analyzed in greater detail across various cases.

The research utilizes a mixed-methods approach that provides a generalizable methodology while still allowing for the detailed examination of specific cases. The quantitative component involves constructing spatial patterns of urban fragmentation and segregation. Urban fragmentation patterns are identified using OpenStreetMap data to identify areas 'enclosed' by large infrastructures that act as physical barriers. The patterns of segregation are constructed using data from the Data for Integration (D4I) initiative from the European Commission and following a regionalization approach to identify areas of high immigrant concentration. These patterns are compared using mutual information, a metric for the assessing the similarity of data partitions. To ensure that any observed similarities are not merely due to random chance, we also generate a set of synthetic urban fragmentation patterns. These synthetic patterns are designed to mimic the original urban fragmentation in terms of the number and distribution of fragments. The qualitative component of the study consist on selecting a set of cities from the different countries included in the study and observing their local context in relation to their regions of concentration and infrastructure.

From the 106 cities included in the study, only 33 obtained statistically significant relations between both patterns; 26 showed a positive correlation and 7 a negative correlation. These results suggest that a relation between urban fragmentation and spatial segregation of immigrant communities does not exist as a generalizable phenomenon in the European context. Our qualitative exploration focused on nine cities across seven countries. This city-level analysis suggests that even in instances where there is a similarity between both patterns, the infrastructure does not appear to be the element actively driving segregation. Instead, other aspects of the built environment, such as urban decay and the quality of housing stock, seem to be more closely associated with the high concentrations of immigrants. Future research could explore the segregation patterns of other social groups, such as the urban poor, or investigate other potential impacts of infrastructure on vulnerable groups that go beyond urban fragmentation.

Contents

1

Introduction

Our cities are *divided*, both physically and socially. The urban space contains gaps and barriers that lead to the '*concentration of disadvantages*' and the emergence of inequality (Monica et al., 2018). These urban inequalities, in turn, negatively impact social relations and can foment societal discontent (Lenzi & Perucca, 2023; Wilkinson, 2006), illustrating a clear divide between social groups within cities. However, in the urban context, inequalities assume an additional connotation. Urban inequalities correspond to a larger socio-spatial context, meaning that these must be understood through its geographies (Nelson, Warnier, & Verma, 2024). Inequalities are thus interpreted not only through demographic characteristics but also through their spatial distribution and their corresponding patterns of segregation. In simple terms, spatial segregation refers to the uneven distribution of elements across space (Rasse, 2019). 'Elements' meaning individuals or groups of people with certain common characteristics, who are overrepresented, concentrated, in certain areas. Spatial segregation, commonly associated with residential segregation, can be connected to religion, ethnicity or socio-economic status aspects depending on the context (Greenstein, Sabatini, & Smolka, 2020). As framed by Scarpa (2015), '*residential segregation is the spatial representation of inequality*'. It often coincides with social exclusion and a range of related social issues, including limited access to the labour market, fewer educational opportunities, or restricted participation in broader society (Kesteloot, 2005; Musterd, 2005; van Kempen & Şule Özüekren, 1998). Moreover, spatial segregation can lead to stigmatization, with neighbourhoods potentially becoming self-fulfilling regions of misery based solely on their perceived identity (van Kempen & Şule Özüekren, 1998).

Even though issues of spatial segregation are as old as human settlements, with known records of segregation patterns dating back to ancient Babylon (van Kempen & Şule Özüekren, 1998), recent decades have seen increased interest and concerns on spatial segregation by both academics and politicians in the European context (Arbaci, 2007; Musterd, 2005; Musterd & de Winter, 1998; Deborah Phillips, 2013; Semyonov & Glikman, 2009). Musterd and de Winter (1998) argued that the increased attention to areas with large ethnic minority population was the result of growing tensions between groups with different backgrounds. Tensions that have manifested in the form of riots or right-wing voting; a concern that 26 years since the original publication only seems more relevant than ever (Carroll & O'Carroll, 2023; Lauer & Durkin, 2023). Thus, spatial segregation continues to be a persistent issue affecting the European city; a complex issue characterized by its multidimensionality. Spatial segregation needs to be treated as an issue of ethnic and social spatial inequality, one that is influenced by various factors that may mutually relate to one another and that cannot be understood on a *'one-dimensional way'* (Musterd, 2005).

Among the various factors that influence spatial segregation, one dimension deserving particular attention is the role of urban form and infrastructure. The reason being that the built environment, and its different configurations, influence social interactions (Miranda, 2020). As argued by Hillier and Hanson (1989) (as cited in Vaughan and Arbaci (2011)):

> *'...that through its ordering of space the man-made physical world is already a social behaviour. It constitutes (not merely represents) a form of order in itself: one which is created for social purposes, whether by design or accumulatively, and through which society is both constrained and recognisable.'*

Vaughan and Arbaci (2011) emphasize that a proper understanding of urban form is essential for comprehending cities, migration, and settlement patterns. Such understanding necessitates the consideration of infrastructure, particularly transportation infrastructures, which have, throughout history and into the present day, shaped cities (Glaeser, 2020). Even though transportation infrastructures can be defined as *'the physical and organisational network which allows movements between different locations'* (Schroten et al., 2019), these play a paradoxical role in the urban space. In the process of connecting 'premium' locations, infrastructures not only facilitate mobility but also produce division, reinforcing local boundaries as highlighted in *Splintering Urbanism* (Stephen Graham, 2000; Steve Graham & Marvin, 2002). A process that has been exacerbated by globalisation and the process of competition between cities, which led to the emergence of spatial rearrangements and new infrastructures (Kesteloot, 2005). The nature of infrastructures as barriers leads to urban fragmentation, a partition of the urban space into distinct, and potentially isolated, patches.

Urban fragmentation and segregation are not unknown to each other. Previous research has shown that the degree of urban fragmentation can be associated to the level of segregation between black and white population in American cities (Ananat, 2011). This evidence has motivated other researchers to adopt urban fragmentation as a means of assessing inequality in the European context (Tóth et al., 2021). In both instances, urban fragmentation proved to be a robust predictor, suggesting that the separation of social groups in cities can be connected to its physical separation. However, these findings should be interpreted cautiously. Identifying a potential relation, or none, between urban fragmentation and segregation is only a partial answer. Properly understanding the connection between both requires addressing the local context involved in each case. The observation that the barriers created by infrastructure in America coincide with boundaries of spatial segregation of ethic groups (van Eldijk, Gil, & Marcus, 2022), may raise questions of whether similar relations might be observable in Europe. However, this relation corresponds to a unique historical context, since urban fragmentation in America has partially resulted from purposed policies aimed at segregation. For instance, in Atlanta, highway construction was intentionally intended to represent a barrier to separate white and black populations (Bayor, 1988). Therefore, these relations cannot simply be extrapolated to the European context. Rather, understanding issues of urban fragmentation and spatial segregation necessitates not only identifying the relation, but also considering its underlying motives.

Europe makes a compelling case to showcase the importance of accounting for local context in the analysis of urban fragmentation and spatial segregation. The continent exhibits high levels of urbanization alongside a dense network of roads and railways (Dyvik, 2023; Meijer, Huijbregts, Schotten, & Schipper, 2018; Statista Research Department, 2023), meaning that its urban context is in constant and close contact with infrastructure. Additionally, there is evidence that vulnerable groups, such as immigrants and the urban poor, are subject to spatial segregation in various cities across the continent (Kesteloot, 2005; Natale, Scipioni, Alessandrini, et al., 2018; Van Ham, Marcińczak, Tammaru, & Musterd, 2015). Since Europe is composed of a mixture of different national and historical contexts, it is unlikely for a single generalizable explanation to apply across all cities. Therefore, understanding these phenomena in Europe necessitates a detailed investigation that considers the unique local contexts.

It is in consideration of this need to further examine the relation between urban fragmentation and spatial segregation while accounting for the local context that we pose the following question:

> 'What is the connection between the spatial segregation patterns of non-EU immigrant groups and urban fragmentation patterns resulting from transportation infrastructures across European cities?'

For this study, we have chosen to focus on immigrant communities, recognizing them as a vulnerable demographic, particularly in terms of housing (Harrison, Law, & Phillips, 2006). Furthermore, the spatial segregation of immigrant communities in Europe has already been subject to quantitative studies (Lichter, Parisi, & Ambinakudige, 2020; Marcińczak, Mooses, Strömgren, & Tammaru, 2023). While insightful, these studies follow quantitative approaches that do not allow for more detailed exploration of context involved in each city, nor do they consider aspects of urban fragmentation. The purpose of this study is twofold: firstly, to determine whether the spatial segregation patterns of ethnic groups in Europe can be connected to infrastructure as a barrier in a manner similar to those documented in the American context; and secondly, to explore how the specific local contexts of the cities can enhance our understanding of these connections.

The rest of the chapter presents our theoretical background and the connection to the master program. The following chapter details the demographic and spatial data used in the study. Chapter 3 explains our mixed-methods approach. It described the techniques and processes used to identify the urban fragmentation and segregation patterns, along with an explanation of the similarity analysis and the individual qualitative city analysis. The results of the quantitative analysis are presented in Chapter 4 followed by a qualitative exploration of nine cities to account for their local contexts. The report concludes with Chapter 5, discussion and conclusion.

1.1. Theoretical Background

In this section, we explore the existing literature to provide a theoretical background that will help define the structure of the study and the stages necessary to address the main research question. In relation to spatial segregation, efforts across the literature have been varied, with some focusing on the root causes (Musterd, 2005), others on measurement metrics (Reardon & O'Sullivan, 2004; Yao, Wong, Bailey, & Minton, 2019), and some on the resulting patterns of segregation (Caldeira, 1996; de Córdova, Fernández-Maldonado, & del Pozo, 2016). However, this research is specifically centred around the interconnection between transportation infrastructure, urban fragmentation and spatial segregation. A literature overview was undertaken to examine state-of-the-art academic research on these topics. In order to ensure consistency during the review process, the search was limited exclusively to the Scopus research database. Furthermore, it represented a systematic review process to determine the studies of more relevance. The original search query used the string: (transport* AND infrastructure) AND segregation AND city*. The search resulted in 73 publications, which were first filtered based on title and abstract. The resulting 35 publications were further filtered based on the content of their introduction and conclusion. In addition to the original search, two extra search queries were performed to provide more literature on the themes of *barrier effect* and *urban fragmentation*. After following a similar filtering process to the original query, these searches provided 4 additional papers. In the total, the literature overview included 12 publications.

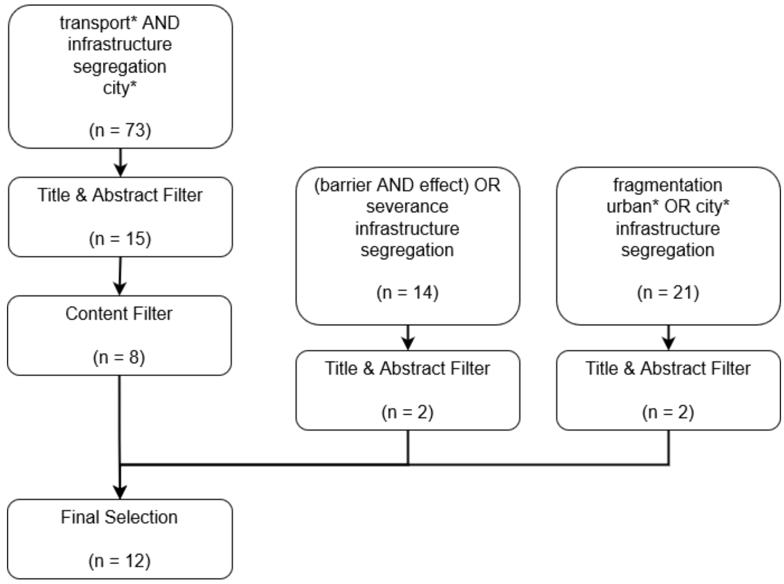


Figure 1.1: Selection flow for the literature review

One of the first points worth highlighting from the literature is the concept of the *'barrier effect'*. Matos and Lobo (2023) defined the barrier effect as *'a discontinuity in the urban structure caused by transport networks'*. This definition is echoed across the literature, with each publication adding additional context to the impacts of the barrier effect, such as decreased local mobility (Anciaes, 2013) and local accessibility (van Eldijk, 2019), and reduced opportunity for social contacts (van Eldijk et al., 2022). The concept of barrier effect is not monolithic, since different infrastructures can produce different type of barriers. For example, Anciaes (2013) categorized the barrier effect into three levels. The first level covers infrastructures with limited crossings, 'static barrier'; the second level includes road links with high volumes of traffic, 'dynamic barrier'; the third level even extends to non-transport infrastructures and certain land-uses, such as ports and industrial sites. For a more extensive review of the barrier effect, including its different dimensions, types and research directions, the reader is directed to van Eldijk et al. (2022).

One concept that is frequently mentioned with barrier effect is *'severance'*, particularly *'community severance'*. Even though there is no consensus on its definition, severance refers to the break of community cohesion product of the separations caused by the infrastructure (van Eldijk et al., 2022). Anciaes (2013) argues that community severance is the largest impact of the urban transportation system at the local scale. Furthermore, it has been mentioned that vulnerable groups are the ones mainly affected by severance (Rodriguez Lara & Rodrigues da Silva, 2019). Severance is considered a transport policy issue since transportation infrastructures represent the most common barrier that separate neighbourhoods in the urban space (Anciaes, Boniface, Dhanani, Mindell, & Groce, 2016, 3). Due to the complexity of its nature, research into the barrier effect and severance require a multidisciplinary approach (Anciaes et al., 2016, 3; van Eldijk et al., 2022).

A similar subject that appears in the literature is the concept *'socio-spatial fragmentation'*. As the names implies, socio-spatial fragmentation refers to the separation of the urban space by social characteristics (Adugbila, Martinez, & Pfeffer, 2023). In some contexts, such as Rio de Janeiro, the spatial fragmentation of the city can be closely related to social segregation (Cruz & de Almeida Medeiros, 2019). The relevance of the concept arises from the potential of infrastructure to be a driver of socio-spatial fragmentation. As the work of Adugbila et al.

(2023) has shown, road expansion in the Global South can be linked to socio-spatial fragmentation. Even though not mentioned explicitly, other publications make allusion to issues of socio-spatial fragmentation in different contexts, such as Stockholm and Jerusalem (Rokem & Vaughan, 2018, 2019, 12).

Table 1.1: Publications obtained from the exploration of the literature.

Title	Authors	Year	Key Concepts
Urban transport and community severance: Linking research and policy to link people and places	Anciaes et al.	2016	Community severance, barrier effect, framework
Measuring community severance for transport policy and project appraisal	Anciaes	2013	Barrier effect, spatial data analysis
Equity issues associated with transport barriers in a Brazilian medium-sized city	Lara & Rodrigues da Silva	2019	Community severance, spatial data analysis, census data
The Barrier Effect and Pedestrian Mobility/Accessibility on Urban Highways: An Analysis Based on the Belo Horizonte/Minas Gerais/Brazil Ring Road	Matos & Lobo	2023	Barrier effect, severance, urban fragmentation
The Spatial Syntax of Urban Segregation	Vaughan	2007	Spatial syntax, fragmentation
Geographies of ethnic segregation in Stockholm: The role of mobility and co-presence in shaping the 'diverse' city	Rokem & Vaughan	2019	Spatial syntax, immigrant, accessibility
Segregation, mobility and encounters in Jerusalem: The role of public transport infrastructure in connecting the 'divided city'	Rokem & Vaughan	2018	Spatial syntax, public transportation infrastructure
Disentangling barrier effects of transport infrastructure: synthesising research for the practice of impact assessment	van Eldijk et al.	2022	Barrier effect, review
The wrong side of the tracks: Quantifying barrier effects of transport infrastructure on local accessibility	van Eldijk	2019	Barrier effect, severance, accessibility
Rio de Janeiro: Urban Tissue and Society	Porto Cruz & de Almeida Medeiros	2019	Space syntax, socio-spatial fragmentation

Continued on next page

Table 1.1 – continued from previous page

Title	Authors	Year	Key Concepts
Road infrastructure expansion and socio-spatial fragmentation in the peri-urban zone in Accra, Ghana	Adugbila et al.	2023	Socio-spatial fragmentation, road expansion, case study
Making sense of segregation in a well-connected city: The case of Berlin	Blokland & Vief	2021	social and residential segregation, accessibility, activity dispersion

1.2. Sub-questions

Based on the theoretical background, our study can be understood as investigating whether the *socio-spatial fragmentation* of European cities correlate to the *urban discontinuities and barriers* resulting from *severance-inducing* transportation infrastructures and the extent to which these relations can be understood through local contexts. The complexity of our main research question necessitates that the research process be divided into distinct stages. Since the intention of the study is to contextualize these relations to local dynamics, a traditional regression would not suffice. Rather, we need to observe the patterns of urban fragmentation and segregation for each city individually. Therefore, the first stage would involve construction of both sets of spatial patterns. The literature on the barrier effect will help guide the selection of relevant infrastructures and the definition of the urban fragmentation patterns. Once the patterns have been identified, both instances need to be compared to determine any potential correlation. For such purpose, it is necessary to select an appropriate set of metrics and perform an adequate statistical analysis. This similarity analysis needs to be generalizable and applicable for all cities in the study. Lastly, these quantitative results should be recontextualized through a more detailed examination of specific cases of interest. Conducting a qualitative analysis of the observed patterns of spatial segregation and their underlying mechanisms will help understand the role that infrastructures play in these contexts, providing deeper insights into the urban dynamics shaping segregation.

In order to structure the research, we have delineated a series of sub-questions that facilitate a sequential approach to addressing our main issue:

- SQ1. What are the urban fragmentation patterns resulting from severance-inducing transportation infrastructure? (Chapter 3.1)
- SQ2. What are the spatial segregation patterns for immigrant groups? (Chapter 3.2)
- SQ3. What metrics can be used to evaluate the similarity between both patterns? (Chapter 3.3.1)
- SQ4. Does a statistical significant relation exist between both patterns? (Chapter 4.2)
- SQ5. How does the local context of the city influence our interpretation of the similarity analysis results? (Chapter 4.3)

1.3. Relation to CoSEM

Complex Systems Engineering and Management (CoSEM) as a programme centred around sociotechnical systems is an appropriate study to investigate the challenges presented by urban fragmentation and spatial segregation. Cities represent the most intricate and largest kind of sociotechnical systems. The complexity of cities results from the various interaction within the multiple (sub)systems that compose them. Transport infrastructure *per se* correspond to a technical system that fulfil specific engineering requirements. Nevertheless, these infrastructures also have an influence on the population of cities, its social component. Transport infrastructures are purposed system interventions resulting from public policy decisions that inevitably impact individuals. Therefore, there is a need to balance the interest and values of different stakeholders. These considerations fall within the scope of the CoSEM Transport and Logistic (T&L) track, which addressed topics related to transport policy decision-making. The relation between segregation and transport infrastructure carries crucial insights for the way infrastructure projects are evaluated and for the overall design of transport policy and urban planning. CoSEM T&L with its holistic approach to transport policy and its various considerations is well suited for addressing the connection between transport infrastructure and spatial segregation.

2

Data

The format and limitations of the data conditioned to a large extent the type of analysis that could be conducted. Therefore, prior to a description of the methodology, it is necessary to provide additional details of the data, its processing and its sources. The data in this research can be divided into two categories: demographic and spatial. Naturally, the demographic data also contains a spatial component. However, its processing and format vary substantially from the spatial data. The subsequent sections of the chapter discuss each data class in detail.

2.1. Demographic Data

The lack of comparative studies between segregation patterns across cities was defined as one of the motivations behind the European Commission's Data for Integration (D4I) project (Alessandrini, Natale, Sermi, & Vespe, 2017; European Commission, 2020). The D4I initiative produced a *high-resolution and standardised* dataset for the concentration of immigrant groups across eight European countries (France, Germany, Ireland, Italy, Netherlands, Portugal, Spain, and the United Kingdom). The dataset compiled demographic census data from each country and harmonized labels and spatial units. The high resolution is attributed to the fact that the data is arranged in a standard grid composed of 100m×100m cells. Based on the ETRS89-LAEA Europe (EPSG:3035) coordinate reference system (CRS), each cell is given a unique identifier based on the coordinates of its centroid.

The D4I dataset covers three levels of aggregation. The lowest level has information of the country of origin. The second level has data aggregated by continent and lastly EU vs not EU. As mentioned in the dataset documentation, the highest level of aggregation has the least number of empty cells[1] and it covers all eight countries, unlike the lower levels (Alessandrini et al., 2017). This research uses the highest level of aggregation due to its completeness and the lack of focus on immigrants of a particular subgroup.

The dataset is quite extensive, as it includes demographic data not just for large urban areas but also small villages and rural towns. In order to ensure comparability, it is necessary to limit the scope to urban areas of similar magnitudes. For applicable cases, cells in the dataset were mapped to their respective Functional Urban Area (FUA). FUAs are spatially continuous regions meant to represent the functional and economic extent of cities, a terminology used both by the OECD and the EU (Dijkstra, Poelman, & Veneri, 2019). FUAs are classified into 4 classes: small, medium-sized, metropolitan and large metropolitan (OECD, 2022). Previous studies have shown that the concentration of immigrants in OECD countries tends to be higher

[1] Some cells were made empty due to confidentially reasons. For more information, refer to the original documentation (Alessandrini et al., 2017).

in large metropolitan areas (Liebig & Spielvogel, 2021). Therefore, we limited the research to the metropolitan and large metropolitan classes, with populations above 250,000 and 1.5 million, respectively. We used the latest FUA definitions as provided by the OECD (2022), which resulted in a selection of 106 cities. Figure 2.1 shows the location of the cities across the eight countries included in the study. Appendix A contains the full list of FUA.

The original dataset has demographic data arranged at the country level, as presented in Table 2.1. We used centroid coordinates to match cells to their corresponding FUA by verifying if the point is within its boundaries. Once the cells for each city have been defined, we reorganized the data to ensure that each cell is represented by a single row that contains all corresponding demographic information. In addition, two news columns were included to represent the total population and the percentage of people with non-EU background, as shown in Table 2.2. The restructured format facilitates further analysis, and serves as the backbone for the regionalization process to identify segregated regions.

Table 2.1: Demographic data aggregated by country

GRID_ID	origin	pop
3080450N4040550E	DEU	X_1
3080450N4040550E	EU27	Y_1
3080450N4040550E	NOTEU	Z_1
⋮	⋮	⋮

Table 2.2: Demographic data aggregated at the city level

GRID_ID	DEU	EU27	NOTEU	tot_pop	NOTEU_perc
3080450N4040550E	X_1	Y_1	Z_1	W_1	p_1
3080550N4040550E	X_2	Y_2	Z_2	W_2	p_2
3080450N4040650E	X_3	Y_3	Z_3	W_3	p_3
⋮	⋮	⋮	⋮	⋮	⋮

2.2. Spatial Data

Spatial data refers to those elements that have specific coordinates and geometric properties that can be represented in the 2D-space of a map. In the case of this research, there are two sets of spatial elements that are required: city boundaries and infrastructure lines.

2.2.1. City Boundaries

City boundaries are a collection of polygon geometries that demarcate the spacial extent of a city and serve to restrict the area of study. As previously mentioned, the scope of the research is restricted to FUAs with populations larger than 250,000. A FUA is an ensemble composed of two regions, the ‘urban core’ and its ‘commuting zone’ (Figure 2.2). The commuting zone represents a portion of the FUA that is spatially large but not densely populated. We decided to limit the area of study to urban cores, since these are the locations where the interaction between infrastructure, as a barrier, and people would be more noticeable. Despite the convenience of simply adopting the original boundaries, further adjustments to the boundaries were needed, as the ones defined by the OECD had limitations as analytical units.

One of the issue is that while a FUA is spatially continuous, its urban core is not necessarily. The size of urban cores can also be problematic, with some significant disparities in the size and extent of urban cores across countries. This issue is partially the result of urban cores

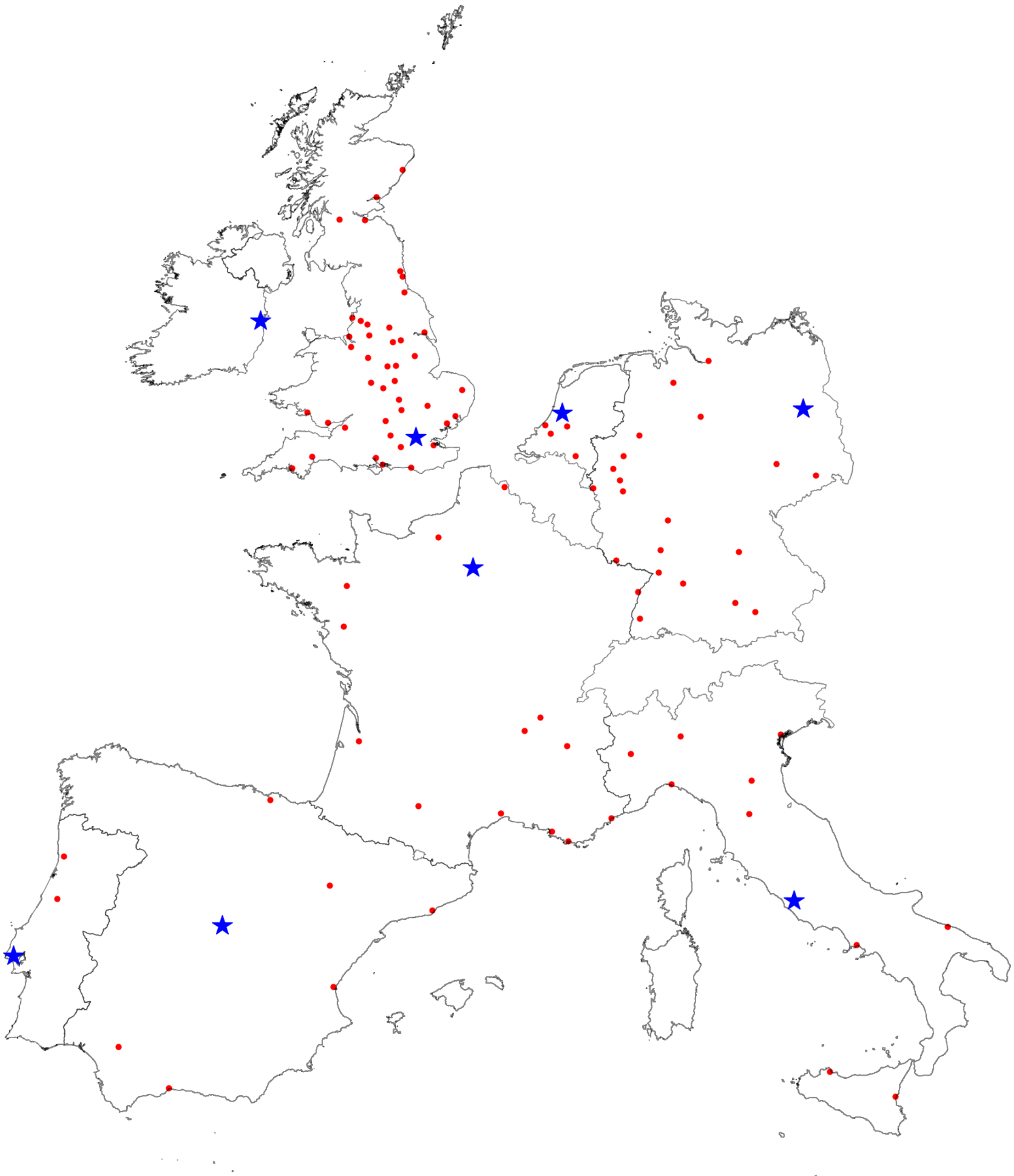


Figure 2.1: Location of cities included in the study

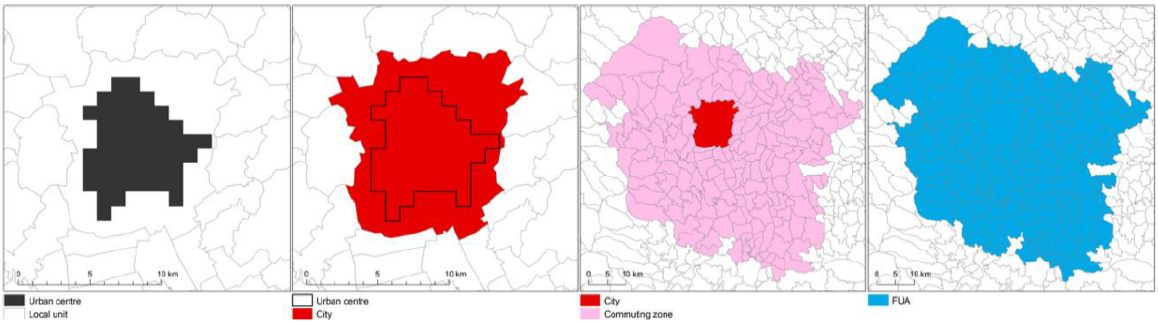
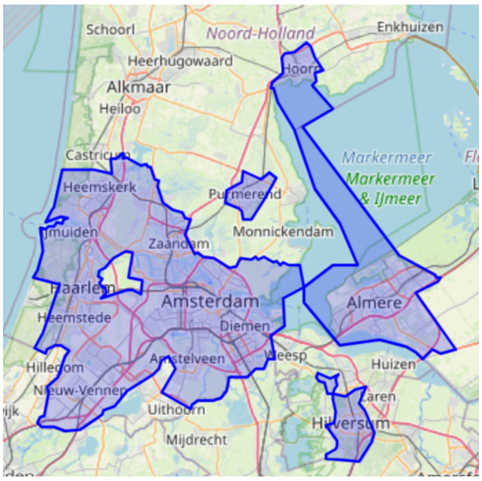


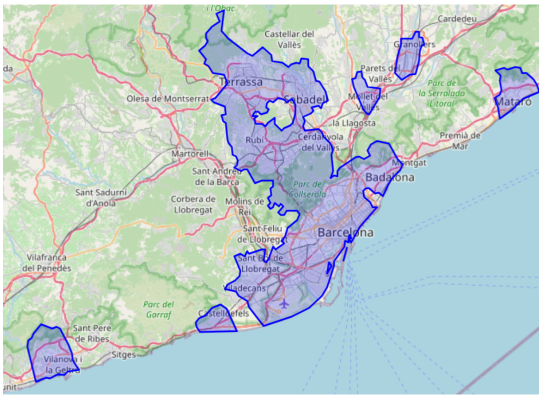
Figure 2.2: Process of defining a FUA (Dijkstra, Poelman, & Veneri, 2019)

being conditioned by traditional administrative boundaries (Dijkstra et al., 2019). The use of administrative units to construct the boundaries also results in the inclusion of non-relevant areas (e.g. non-populated areas) in the urban core. Furthermore, the level of aggregation of urban cores may be quite large, which could impact the results of the analysis for the segregation patterns. The reason is that the original urban cores are constructed based on the population density of a grid of 1 km^2 cells. However, the D41 demographic data is on a resolution of 0.01 km^2. The mismatch in resolution means that the urban cores, as per OECD resolution, may aggregate regions that could, or should, be analysed separately. Observing Figure 2.3 these issues becomes apparent.

These issues were tackle by adjusting the boundaries of the urban core to obtain a single continuous spatial unit based on the spatial distribution of the population using the 0.01 km^2 resolution of the demographic data. The resulting adjusted urban cores (AUC) also have the property that only populated areas that are sufficiently close will be aggregated to the same urban core. Figure 2.4 presents a comparison between the original urban core and the AUC for the case of Amsterdam. As can be noted, the AUC fall within the boundaries of the original urban core, but its extension is more conservative. Appendix B provides a detailed description of the construction of the new urban core boundaries. In addition, it contains a visual comparison between the original OECD urban core and the adjusted versions for all cities in the study. These AUCs represent the spatial unit of analysis that will be used to define the segregation and fragmentation patterns.



(a) Amsterdam. Notice the inclusion of smaller cities such as Hoorn and Purmerend in the urban core. In addition, a section of the Markermeer is included in the urban core.



(b) Barcelona. Notice that the city of Barcelona and the norther portions of the urban core are separated by un-habitated green space.

Figure 2.3: Discontinues urban cores.

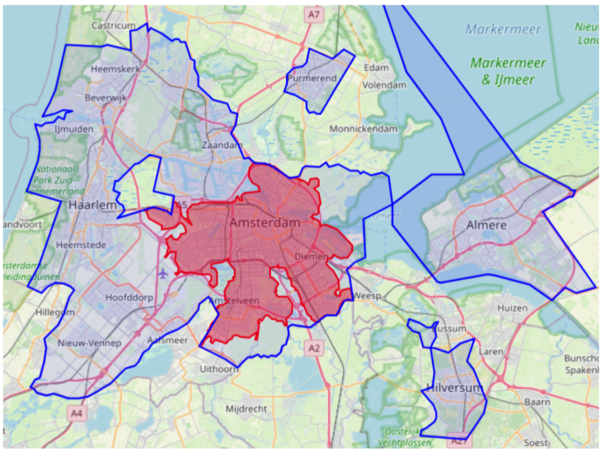


Figure 2.4: Original urban core as defined by the OECD (blue) and adjusted urban core (red) for Amsterdam FUA

2.2.2. Infrastructure Lines

Infrastructures are represented as line geometries that transverse the AUC and fall within its boundaries. The infrastructural data was extracted from OpenStreetMap (OSM) (OpenStreetMap contributors, 2024), a well-known 'citizen-driven' spatial data source, considered one of the most successful example of Volunteered Geographic Information (VGI) (Mooney, Minghini, et al., 2017). For most data, rather than extracting the data directly from OSM using its API, we opted for OSM snapshots[2] from 2014, available at the repository of Geofabrik (Geofabrik, 2014). This decision was made to align more closely with the demographic data from the 2011 census uses in the D41 dataset (Alessandrini et al., 2017), thereby minimizing the temporal mismatch between the two data types by utilizing the oldest available country-level snapshot from Geofabrik.

Selecting relevant infrastructures involved a harmonization between the terminology used in the literature and the labelling definitions used by OSM. In the literature, van Eldijk et al. (2022) argued that a barrier can be defined as any transportation infrastructure that limit opportunities for movement. This definition extends beyond road to includes railways and waterways. In OSM, map elements are labelled using tags, each containing a key and a value (OpenStreetMap contributors, n.a.). The aforementioned infrastructure types can easily be mapped to its corresponding keys: highway, railway and waterway. However, each key encompasses a variety of values that identify the different categories for each infrastructure type. For instance, the highway key covers any type of road, from major 4-lane motorways to small residential streets. Naturally, not all values are relevant, as only some may be classified as 'barrier-effect inducing' infrastructures.

The selected infrastructures adhere to the definition of a 'static barrier' as presented by Anciaes (2013) and van Eldijk et al. (2022): an objective physical barrier with limited number of crossings. Table 2.3 presents the selected tags and its description as provided by the OSM wiki (OpenStreetMap contributors, n.a.). As can be noted, each value represents an infrastructure type that restricts local mobility by nature of its physical composition. During the data filtering process, a conscious effort was made to exclude 'underground' elements. Both railways and highways can have long portions of their trajectories redirected underground, commonly near or inside urban areas, which prevents the emergence of the barrier effect. It is worth noting that we considered including secondary roads (highway:secondary) as infrastructures with a dynamic barrier. The argument was that its classification served as a proxy for the presence of a significant traffic volume on the road. However, due to the absence of adequate traffic volume data to substantiate this claim and in the interest of maintaining a more conservative and objective selection, we decided to exclude them from the analysis.

Figure 2.5 shows the line geometries extracted for the case Rotterdam AUC. One point that most be mentioned is the processing of rivers. In OSM, rivers can be represented as either a line or polygon geometries, or both. Narrow rivers tend to only be presented as line geometries, but larger rivers also have a polygon representation. In the case of large rivers, the line geometry obtained from the waterway tag does not fully capture its spatial dimensions. Therefore, we decided to also extract the polygon geometries of large rivers. Since working with polygons may difficult later stages of the research, these are represented as line based on its boundaries, the 'borders' of the river [3].

[2]files in the .pbf format

[3]Polygon geometries for rivers were extracted using the API rather than the osm.pbf files due to large size of files containing polygon geometries. These were extracted based on the tag natural=water.

Table 2.3: Relevant OSM features. Description provided by OpenStreetMap contributors (n.a.).

Key	Value	Description
highway		
	motorway	A restricted access major divided highway, normally with 2 or more running lanes plus emergency hard shoulder. Equivalent to the Freeway, Autobahn, etc.
	trunk	The most important roads in a country's system that aren't motorways. (Need not necessarily be a divided highway.)
	primary	The next most important roads in a country's system. (Often link larger towns.)
	*_link	The link roads (sliproads/ramps) leading to/from a motorway, trunk or primary road
railway		
	rail	Full sized passenger or freight train tracks in the standard gauge for the country or state.
	light_rail[1]	A higher-standard tram system, normally in its own right-of-way. Often it connects towns and thus reaches a considerable length (tens of kilometres).
waterway		
	river	Wide, natural watercourse that flows from a source to an ocean, sea, lake or another river.
	canal	An artificial open flow waterway used to carry useful water for transportation, waterpower, or irrigation

[1] Not to be confused with a standard tram. An example of a light rail line would be the Hoekse Lijn (Line B from Schiedam Centrum to Hoek van Holland) from the Rotterdam Metro. It has dedicated tracks and limited interactions with road traffic.

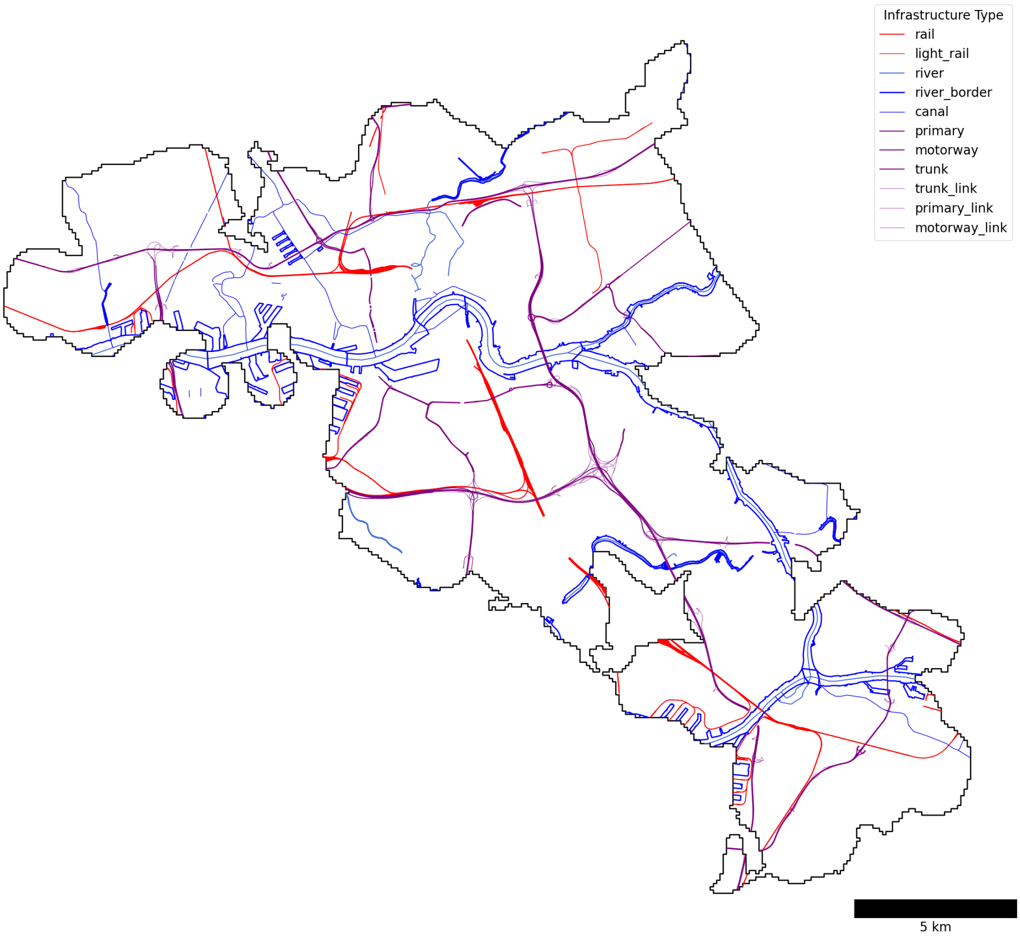


Figure 2.5: Lines extracted for the Rotterdam AUC

3 Methodology

In this chapter, we outline our methodological approach, which is summarized in Figure 3.1. The methodology is structured into three main stages: generating the patterns, evaluating their similarity, and conducting more detailed evaluations of selected cities. The first two stages compose the quantitative portion of our research. Here, we generate spatial patterns based on the data sources presented in the previous chapter. These patterns are then compared using mutual information, a similarity measure to compare data partitions. This similarity analysis involves the creation of a set of synthetic fragmentation patterns to account for any potential similarities that could arise by random chance between the original patterns. Following the quantitative analysis, we select a small set of cities for qualitative exploration to understand the influence of local dynamics on its spatial segregation pattern and its interplay with infrastructure. This mixed-methods approach allows us to apply a generalizable framework across a broad set of cities, while still providing the opportunity for a more detailed exploration to account for the local context of each case.

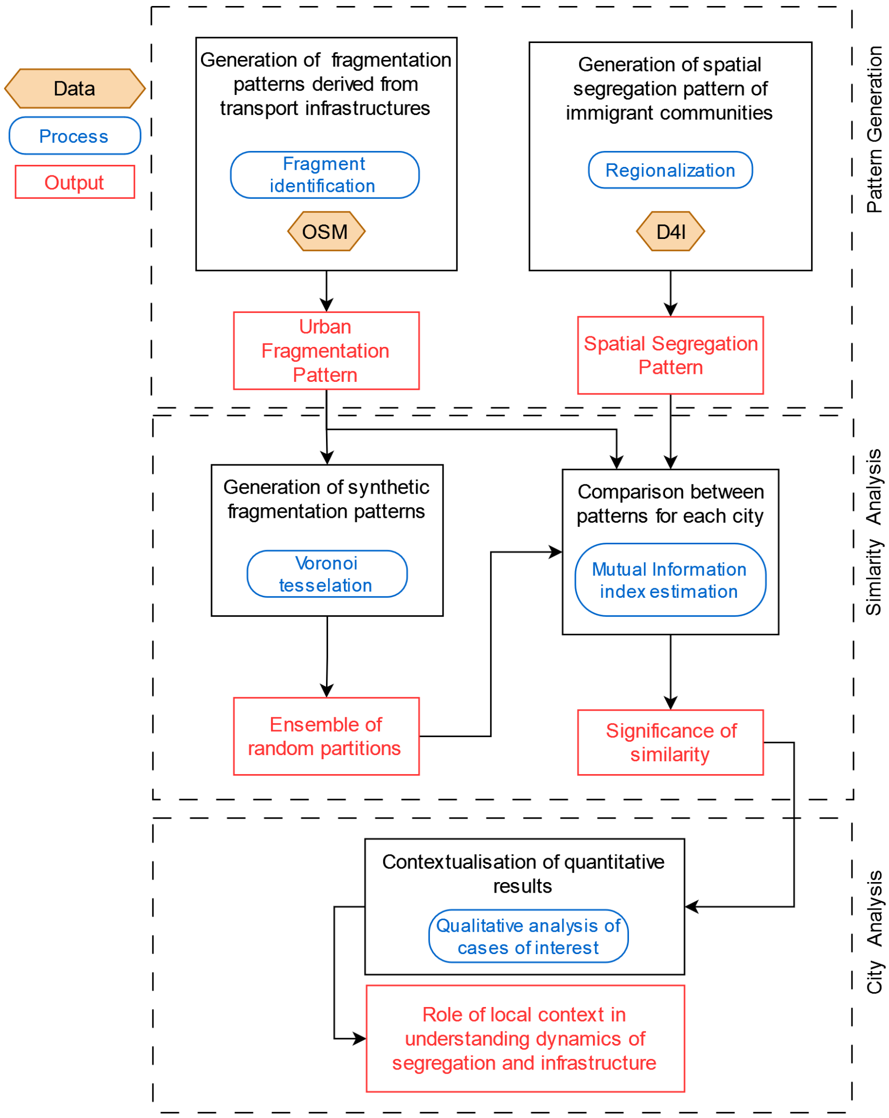


Figure 3.1: The approach presented by our methodology as a sequential set of processes.

3.1. Urban Fragmentation Patterns

The urban fragmentation patterns are defined as the spatial patterns resulting from the partition of urban space by the presence of physical barriers. In this instance, physical barriers refers to the transportation infrastructures and waterways as discussed in Chapter 2. These infrastructures, represented as line geometries, intersect one another as they transverse the urban space. The result of these interactions is that portions of the urban space become 'surrounded', or 'enclosed', by physical barriers. However, not all enclosed areas are of analytical relevance. For example, the middle of a roundabout is a spatial unit completely surrounded by roads. Therefore, the classification of an area as an urban fragment depends on the presence of a population within its boundaries. Since the research makes use of a standard grid for the distribution of the population, an urban fragment can be defined as the collection of populated cells that fall within an enclosed-region that has physical barriers as boundaries. The AUC is divided into n polygons, each polygon representing a space enclosed by a set of infrastructural lines. Each populated cell is assigned a fragment ID based on its belonging to one of these polygons. First, we verify if a cell geometry fall completely within the boundaries of one of these polygons. Cells that overlap with two fragments are assigned to the fragment with the largest overlap.

Despite its simplicity, the cell assignment process is complicated by limitations in the OSM data and the use of a standard grid. In OSM, a two-way road, such as a motorway, is depicted using two line geometries, each representing traffic flowing in one direction, rather than a single line for both directions, despite their immediate proximity. The area between these two lines would be defined as an enclosed area. These polygon geometries have been termed face artefact by Fleischmann and Vybornova (2023). In theory, this should not be problematic, since an urban fragment, to be defined as such, requires the presence of a population. However, there are cases where populated cells overlap with these face artefacts and are erroneously assigned to such polygons, despite them being a 'irrelevant' fragments. A similar issue is produced by the use of river borders as barrier lines. Populated cells may be assigned to a fragment that in reality represent the river polygon geometry. These issues are addressed by applying extra filters to the cell assignment process. We filter out any fragments that contain only less than four cells and its fragment ID to limit the emergence of micro-fragments. In the case of rivers, we reassign any cell that intersects with the river to the fragment of the nearest cell that does not intersect the river.

Incomplete boundaries can be another recurrent issue. Occasionally, gaps are present in the trajectory of an infrastructure. This may be caused by the exclusion of short underpasses, since underground elements are excluded in the OSM feature extraction, or by tag misclassification in OSM. As a result, despite the clear visual and conceptual presence of enclosed regions, since the infrastructural lines that represents the boundaries contain a small gap, fragments that should be treated separately are merged together. The solution was to implement a conditioned spatial snap function. This function combines lines that are between a certain tolerance from one another, allowing for the completion of boundaries. In our case, we used a maximum tolerance of 150 metres. Implementing these additional filters and restrictions improved the cell assignment to their respective urban fragments, resulting in more precise urban fragmentation patterns.

[1] Different colours represent different fragments. However, for adjacent fragments that do not have adjacent populated cells, the colour may be the same for both fragments.

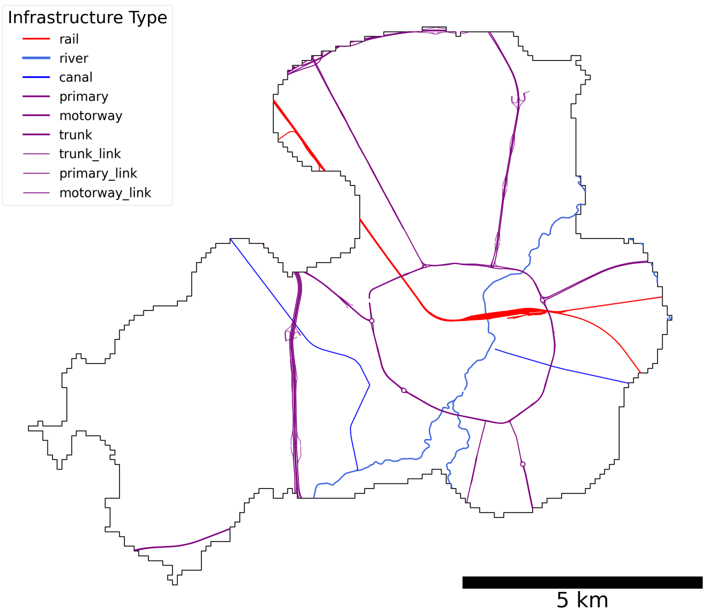


Figure 3.2: Infrastructure and waterways across the Eindhoven AUC.

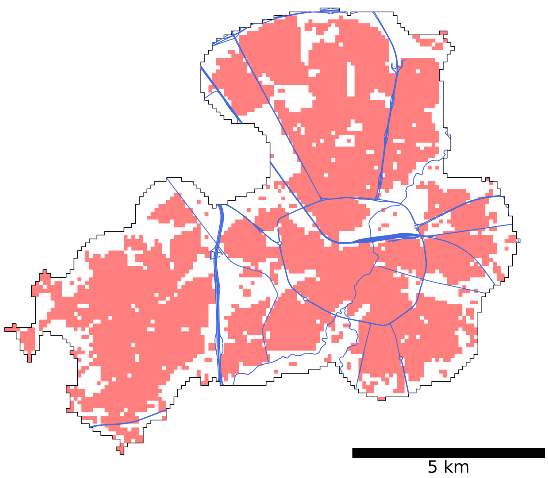


Figure 3.3: Populated grids and infrastructural lines across the Eindhoven AUC.

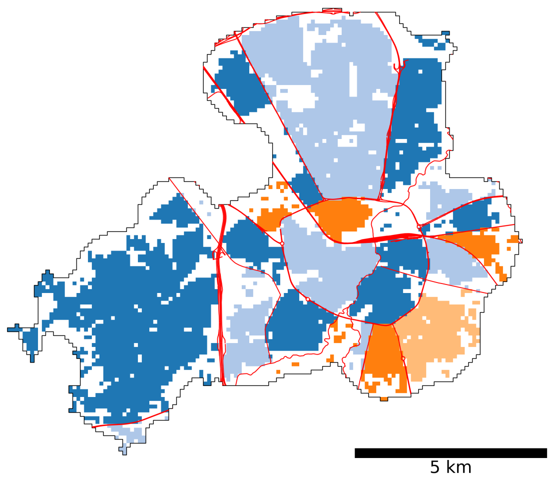


Figure 3.4: Urban fragmentation pattern of the Eindhoven AUC. [1]

3.2. Segregation Patterns

While urban fragmentation patterns describe how space is physically divided, segregation patterns represent the uneven distribution of populations across space. These are the patterns of socio-spatial fragmentation, a partition resulting from the demographic variables and group characteristics. Defining segregation patterns is inherently more challenging than delineating urban fragmentation patterns, as the latter relies on pre-existing physical boundaries. In contrast, demographic data often exhibits variability and noise, which complicates the establishment of distinct boundaries between fragments. Chodrow (2017) argued that identifying the spatial structure of segregation is a process of aggregating spatial units to boundaries that represent 'demographic transitions', a regionalization task. Regionalization is a type of spatially constrained clustering algorithm that can be used to identify regions with homogenous internal characteristics (Wei, Rey, & Knaap, 2021). For this research, we adopt the regionalization method presented by Spierenburg, van Cranenburgh, and Cats (2022, 2023, 2024), using the percentage of resident with a non-EU immigration background as the variable of interest.

As discussed in Spierenburg et al. (2022), traditional regionalization methods are susceptible to small-scale fluctuations in the data, resulting in chaotic borders and overfitting. Therefore, prior to the agglomerative clustering process, it is necessary to filter out these fluctuations by means of a weighted averaged. This process requires the definition of a new variable, the concentration coefficient (con_coeff). The value of the coefficient is determined by the percentage of non-EU residents in the cell and its surrounding area. Each grid cell, including those without any population, is assigned a concentration coefficient score. This assignment guarantees that spatially continuous regions with 'smooth' borders can be obtained during the clustering process.

$$con\_coeff_i = \sum_{i}^{j} w_{ij} \tag{3.1}$$

$$w_{ij} = \begin{cases} 1 \cdot noteu\_perc_i & : \ d_{ij} = 0 \\ 1250/d^2 \cdot noteu\_perc_j & : \ d_{ij} > 0 \end{cases} \tag{3.2}$$

Equations 3.1 and 3.2 present the mathematical definition of the coefficient. The influence of cell j on the score of cell i is inversely proportional to the square of the Euclidean distance between cell pair ij[2]. We only account for the set of cells $J = \{1, 2, ...j\}$, whose centroids are within a 850-metre radius from the centroid of cell i. Figure 3.5 shows the results of the calculations for The Hague AUC. Comparing these results with Figure 3.6, which shows the unfiltered input, we can observe that the concentration coefficient presents smoother transitions between regions with low-high scores.

Once the concentration coefficient have been computed, it is possible to proceed to the agglomerative clustering stage. This process involves merging adjacent cells into clusters based on a 'agglomeration criterion' (Tokuda, Comin, & Costa, 2022). The criterion regulates the selection of cells, or regions, to be merged and ensures that only those with the most similar characteristics according to the defined metric are combined. In our case, we use the Ward distance, as in Spierenburg et al. (2022, 2023), which involves merging adjacent cells into larger regions, such that the within-region variance is minimized. The merging process stops once a dissimilarity threshold has been exceeded. This threshold was tuned empirically, and set at $\beta \cdot n_{city}$, where n_{city} represents the number of cells in the AUC. The constant β

[2] Since c/d^2 is not defined at $d = 0$, we define $c = 1250$ to match both parts of the equations. If $c = 1250$ and $d = d_{ref} = 50/\sqrt{2}$, then the second part of the equation is equal to 1. A cell with sides $d_{ref} \cdot 2$ would have half the area of the original cell.

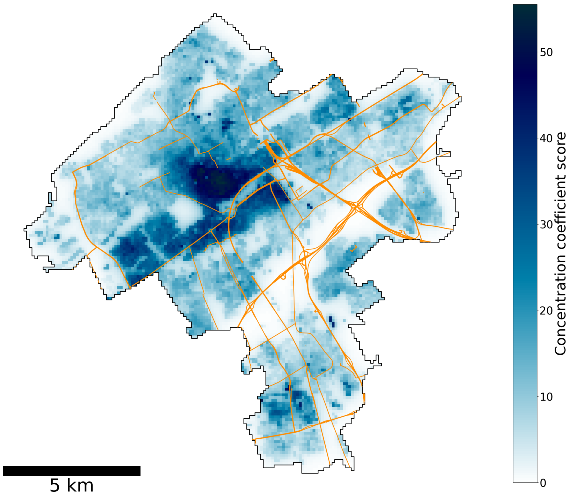


Figure 3.5: Concentration coefficient score across The Hague AUC.

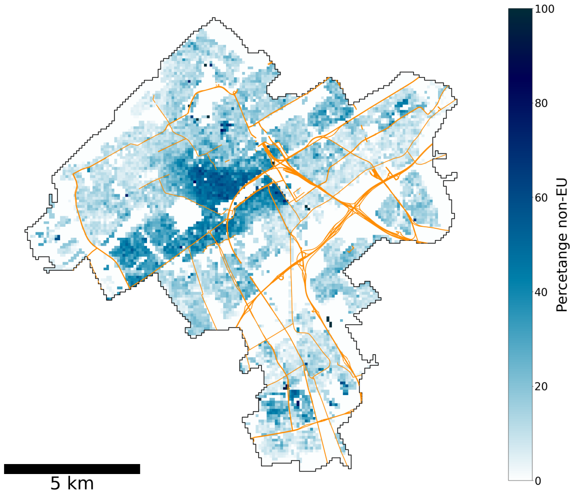


Figure 3.6: Percentage of non-EU residents across The Hague AUC.

is adjusted inversely with n_{city}, as shown in Table 3.1. Adjusting the threshold is necessary to prevent larger cities from being overly consolidated into fewer, larger regions, thereby preserving a meaningful distinction between regions. Figure 3.7 shows the resulting regions from the clustering process. These regions have the characteristic of being homogeneous in terms of the demographic variable, the concentration coefficient (Spierenburg et al., 2024). As can be noted, the AUC presents a high-level of fragmentation. However, it must be noted that some of these regions simply represent the 'gradient' effect resulting from the spatial distribution of the concentration coefficient. In other words, the structure of the regions show a 'inner-outer' ring behaviour centred around areas with high concentration scores.

Table 3.1: Dissimilarity threshold constant.

n_{city}	β
<20,000	0.0032
20,000-60,000	0.0012
>60,000	0.0007

Given the regions obtained from the agglomerative clustering, the subsequent step involves classifying each region into one of three classes: high concentration (1), mixed (0), and low concentration (-1). For this purpose, we compute the population-weighted average percentage of non-EU residents for each region i, as delineated in Equation 3.3. Note that we use $noteu\_perc$ rather than con_coeff for classification. The concentration coefficient was needed during the clustering process to handle fluctuations and avoid chaotic borders. However, the demographic variable of interest remains the percentage of non-EU residents. Since the regions have been properly delineated, we can default back to the original variable. The classification is based on the comparison between the calculated average against the upper and lower thresholds defined in Equation 3.4. The variable α, set at 0.13, is a manually tuned constant initially calibrated for a representative city and reapplied across the dataset. The term μ_{city} represents the fraction of the total population in the AUC with non-EU background. The square root component of the equations captures the variance of a binomial distribution, since the probability of encountering a non-EU resident in subsequent random samples from the population adheres to such distribution. The use of the variance of the binomial distribution in the thresholds is de-

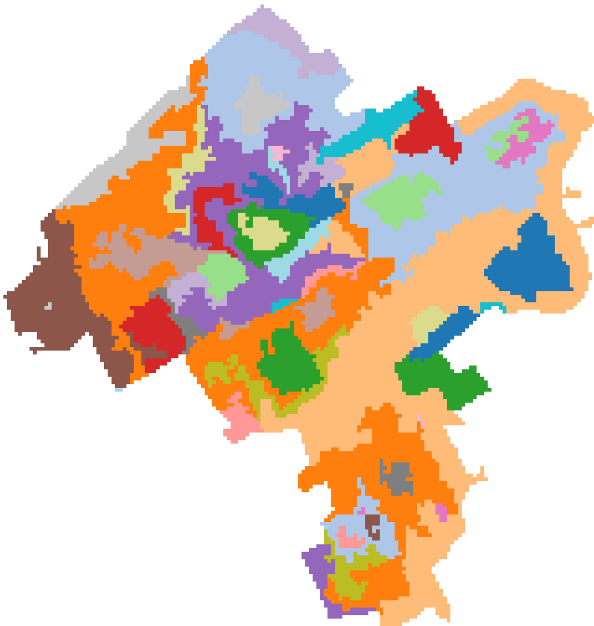


Figure 3.7: Agglomerative clustering results for The Hague AUC.

signed to capture significant deviations from the city's average. Given that the distribution of *noteu_perc* is right-skewed —indicating that most cells have a percentage below the average— the regions exceeding the upper threshold are significantly marked by a higher concentration of non-EU residents.

$$noteu\_perc^{i}_{avg} = \frac{\sum_j noteu\_perc_j \cdot tot\_pop_j}{\sum_j tot\_pop_j} \tag{3.3}$$

$$T_{\text{upper}} = \mu_{\text{city}} + \alpha\sqrt{\mu_{\text{city}} \cdot (1 - \mu_{\text{city}})} \tag{3.4}$$

$$T_{\text{lower}} = \mu_{\text{city}} - \alpha\sqrt{\mu_{\text{city}} \cdot (1 - \mu_{\text{city}})} \tag{3.5}$$

where $\alpha = 0.13$

Once each region has been classified, we merge those adjacent regions that have the same classification. Cells without any population are filtered out, similarly as with urban fragments. The result is a segregation pattern as presented in Figure 3.8. Since the original regions are spatially continuous, it is possible for populated cells that are not adjacent to correspond to the same region. This is made possible by the filtered-input approach, which defines the concentration coefficient for cells across the entire grid. Finally, each populated cell is assigned a corresponding cluster ID based on its region.

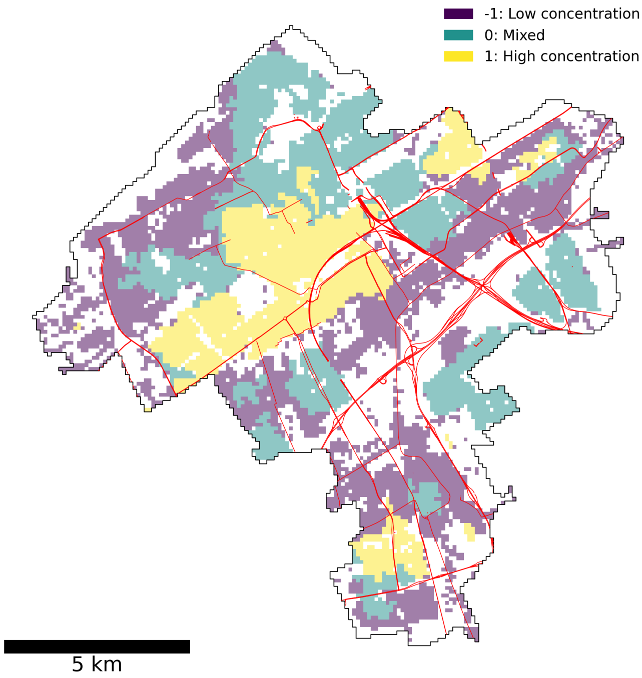


Figure 3.8: Segregation pattern for The Hague AUC.

3.3. Similarity Analysis

Once the urban fragmentation pattern and segregation patterns have been properly defined, the next challenge becomes quantifying the similarity between them. One way to (re)conceptualize this task is by viewing both sets of patterns as two distinctive partitions of the same set of cells. Each partitions constructs clusters of cells based on different process.[3] Therefore, we could view the urban fragmentation pattern as a partition F and the segregation pattern as a partition D. This perspective is beneficial because the similarity comparison of different partitions has been extensively studied in the literature, with a variety of metrics already developed for this purpose. In the following subsection, we introduce some of these metrics and their underlying concepts. Later, we present our approach to quantifying the similarity between both patterns by means of generating a set of synthetic fragmentation patterns.

3.3.1. Similarity Measures

External comparison metrics can be used to assess the similarity between two partitions, U and V, on the same dataset (van der Hoef & Warrens, 2019). In particular, these measures are used to validate the goodness of a partition V in relation to a 'ground thruth' (Romano, Vinh, Bailey, & Verspoor, 2016). Comparison measures are most commonly classified into three groups: pair-counting, information theoretic and set-matching (Hennig, Meila, Murtagh, & Rocci, 2015; Schroten et al., 2019). Measures based on pair-counting focus on the relationships between pairs of data points that are assigned to the same or different clusters across U and V. Information theoretic measures, on the other hand, evaluate the amount of shared information between the two partitions. They use concepts from information theory, such as entropy and mutual information, to assess how much knowing the cluster assignment of U reduces uncertainty about V, and vice versa (Meilă, 2007; Vinh, Epps, & Bailey, 2010). We restrict ourselves to these two categories, excluding set-matching measures due to their

[3]The term partition and clustering are used interchangeably. For clarification, a clustering/partition can be understood as a collection of clusters.

inability to account for unmatched elements between clusters, which complicates comparisons across partitions with differing numbers of clusters (Vinh et al., 2010; Warrens & van der Hoef, 2022).

Among the variety of pair-counting and information-theoretic measures available, the most commonly used are the Rand Index and the Mutual Information Index, respectively (Romano et al., 2016). The Rand Index (RI) can be intuitively understood as a ratio between pairs of data points that are consistently assigned in both partitions. For a dataset with n elements, the overlap between partitions U and V can obtained by calculating the number of pairs assigned to the same cluster in both U and V (N_{11}) and the number of pairs that are in different clusters in both U and V (N_{00}). In addition, we need to know the number of pairs that appear together in U but not in V, and vice versa, N_{10} and N_{01} (Meilă, 2007). The formula for the Rand Index can be defined as the proportion of agreement between both clusterings.

$$RI = (N_{00} + N_{11})/(N_{00} + N_{11} + N_{01} + N_{10}) \tag{3.6}$$

The Mutual Information Index (MI) quantifies the amount of information shared between two partitions, reflecting their mutual dependence (Vinh et al., 2010). The concept underlying MI is entropy, a measure of uncertainty or randomness within a dataset. The entropy of each partition, $H(U)$ and $H(V)$, represent their respective levels of randomness. $H(V|U)$ is the conditional entropy of V given U, it represents the uncertainty in V that remains once we know U, similarly for $H(U|V)$. The MI is calculated as the reduction in entropy/uncertainty from one partition given knowledge of the other. MI has a lower bound of zero, but no upper bound (Imaizumi et al., 2020). Therefore, it is more common to work with the Normalized Mutual Information (NMI) with a range [0,1]. Different versions of the NMI exist, depending on the normalization factor (Vinh et al., 2010). In our case, we use NMI_{max} as defined in Equation 3.8.

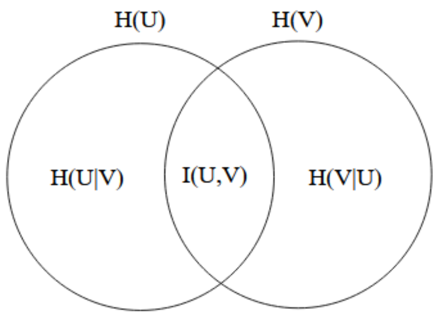


Figure 3.9: Venn Diagram representation of MI components. Adapted from Vinh, Epps, and Bailey (2010).

$$MI = I(U, V) = H(V) - H(V|U) = H(U) - H(U|V) \tag{3.7}$$

$$NMI = \frac{I(U, V))}{max\,\{H(U), H(V)\}} \tag{3.8}$$

Both the NMI and RI range from 0 to 1, where a score of 1 indicates perfect agreement between the two partitions, and a score of 0 suggests complete independence. However, the distribution of RI scores is not uniform across this range, and the RI score between two random partitions does not obtain a value of zero (Hennig et al., 2015; Wagner & Wagner, 2007). Similarly, the NMI can also show non-zero values even when the clustering assignments are made randomly. This indicates that both metrics can sometimes reflect ‘agreement by chance’ rather than genuine correspondence between partitions. Ideally, these measures should have a baseline property that corrects for the agreement by change. This means that a value of zero would imply that the agreement between the clusterings is no different from what would be expected by random coincidence (Vinh et al., 2010). For such purpose, adjusted measures have been developed that aim to correct for such limitation. Adjusted indexes subtract the baseline value, represented by the expected score of the index, as shown in Equation 3.9 and 3.10 (Gates & Ahn, 2017; Hennig et al., 2015).

$$Adjusted\ RI = \frac{RI - E(RI)}{1 - E(RI)} \tag{3.9}$$

$$Adjusted\ MI = \frac{MI - E(MI)}{max\,\{H(U), H(V)\} - E(MI)} \tag{3.10}$$

The key aspect of the formulation is the concept of the *expected value* of the index. As discussed by Gates and Ahn (2017), the expected value originates from assessing similarity in the context of a *random ensemble of clusterings*. Traditionally, the ARI and AMI utilize a ‘permutation model’ that assumes that both partitions to be drawn from a set of random partitions with identical number of clusters and size distribution (Gates & Ahn, 2017; Vinh et al., 2010; Wagner & Wagner, 2007). The use of this model allows for an analytical derivation of the expected value. However, as demonstrated by Gates and Ahn (2017), altering the model and its underlying assumptions can change the result of the similarity comparison, implying that this approach can not be universally applied and is context-dependent.

In our case, the assumptions of the permutation model are not applicable for the comparison between D and F, as the number and size distribution of the clusters in each partition do not necessarily match. Furthermore, as highlighted by Gates and Ahn (2017), assuming both partitions to be drawn from the same random model is not ideal if we consider that one of the two partitions represents a ground-truth. In such cases, it should be assumed that the structure of the reference partition remains fixed and is present in all comparisons against partitions from the random model. Given that D and F are the product of two distinct clustering process, our comparison should treat one as the reference partition, rather than assuming both to be drawn from the same random model.

The limitations inherent to the traditional ARI and AMI, which rely on the permutation model, make them unsuitable for our purposes. However, defining our own random model to allow for the analytical derivation of the expected value would be overly complex and beyond our capabilities. Consequently, we opt for an alternative approach: generating a random ensemble of partitions to *estimate* the expected value of the index. This method involves setting either D or F as the reference partition and obtaining the adjusted index under the assumption that the remaining partition is drawn from our random ensemble of partitions with the same number of clusters and similar size distributions. This method, while less precise than an analytical derivation, operates under assumptions more suitable for our analysis. Nevertheless, it raises the question about which clustering should be considered the ground truth and how to construct a representative ensemble of random partitions. These issues will be addressed in the following subsection, which will discuss the creation of the synthetic fragmentation patterns.

3.3.2. Synthetic Fragmentation Patterns

Prior to the construction of the random ensemble of partition, we must decide which pattern will be used as the reference partition and which will be ‘immitated’ in the ensemble. Conceptually, either D or F could serve as the reference partition. F might seem more suitable as the ground truth because it is based on tangible physical barriers, unlike D, which is derived from a more complex regionalization process using demographic thresholds. However, the main concern should be that the random set of partitions in the ensemble are a proper representation of its original counterpart. As noted by Gates and Ahn (2017), the random model should be random enough to not encode all features of the original clustering, yet not so random as to become unrepresentative. In this context, it is simpler to create synthetic sets of urban fragmentation patterns rather than segregation patterns. This is because segregation patterns involve spatial autocorrelation, where cells with similar demographic characteristics—such as high or low concentrations of immigrants—are likely to be adjacent. Therefore, using traditional methods like bootstrapping to construct new partitions is not suitable, as these methods would not preserve the spatial autocorrelation inherent to the original pattern. Conversely, urban fragmentation patterns, which represent spatial partitions based on set physical boundaries, are easier to simulate. Any form of spatial clustering would capture the property that adjacent cells have a higher probability of belonging to the same cluster. Therefore, as long as there is a reasonable level of similarity between the original and synthetic urban fragmentation patterns, these synthetic partitions should form an appropriate ensemble for estimation purposes.

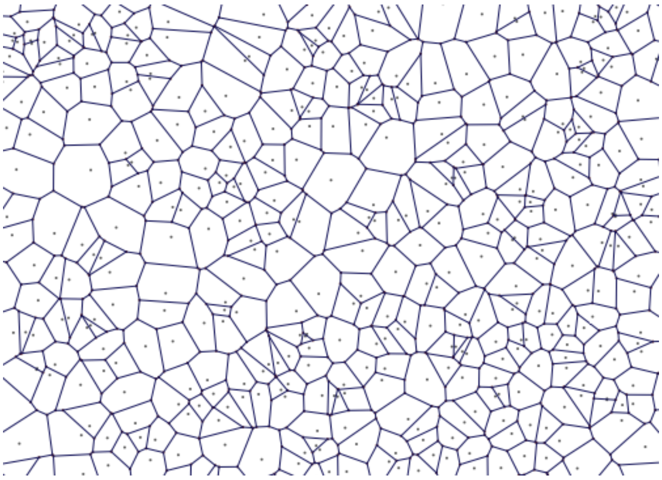


Figure 3.10: Visual representation of a Voronoi tessellation and its seed points (Belmonte, n.a.).

For the construction of the synthetic fragmentation, we employ the concept of 'tessellation', specifically Voronoi tessellation. A tessellation divides 2D space into non-overlapping subregions (Daisy Phillips, 2014). Voronoi tessellation, in particular, partitions space into n polygons that represent each representing the area of influence of one of the n 'seeds points'. Each polygon contains the points that are closest to the seed point (Fleischmann, Feliciotti, Romice, & Porta, 2020; Daisy Phillips, 2014), as shown in Figure 3.10. The application of Voronoi tessellation offers certain advantages. Firstly, it has been previously utilized in urban studies for various forms of analysis (Abellanas & Palop, 2008; Fleischmann et al., 2020; Usui & Asami, 2018). Notably, Usui and Asami (2018) commented that the size distribution of Voronoi tessellations, when seeds are uniformly selected— also known as a Poisson Voronoi—has similar properties as the size distribution of urban blocks. Secondly, the construction of Voronoi polygons is computationally efficient, which is of great importance for generating a sufficiently large ensemble of synthetic clustering for each city in the dataset. Nevertheless, the most import factor in the selection of the Voronoi tessellation is that we can adjust its construction to obtain an ensemble of clusterings that is representative of the original pattern. Since the construction of the tessellation uses a fixed number of seed points, we can control for the number of resulting polygons. Therefore, we can ensure that the number of fragments always matches that of the urban fragmentation pattern.

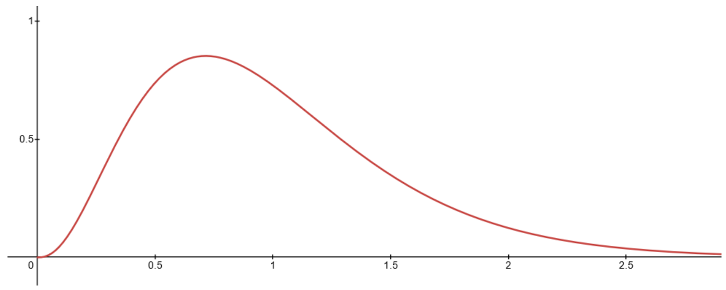


Figure 3.11: Normalized polygon size distribution of a Poisson Voronoi tessellation as estimated by Ferenc and Néda (2007).

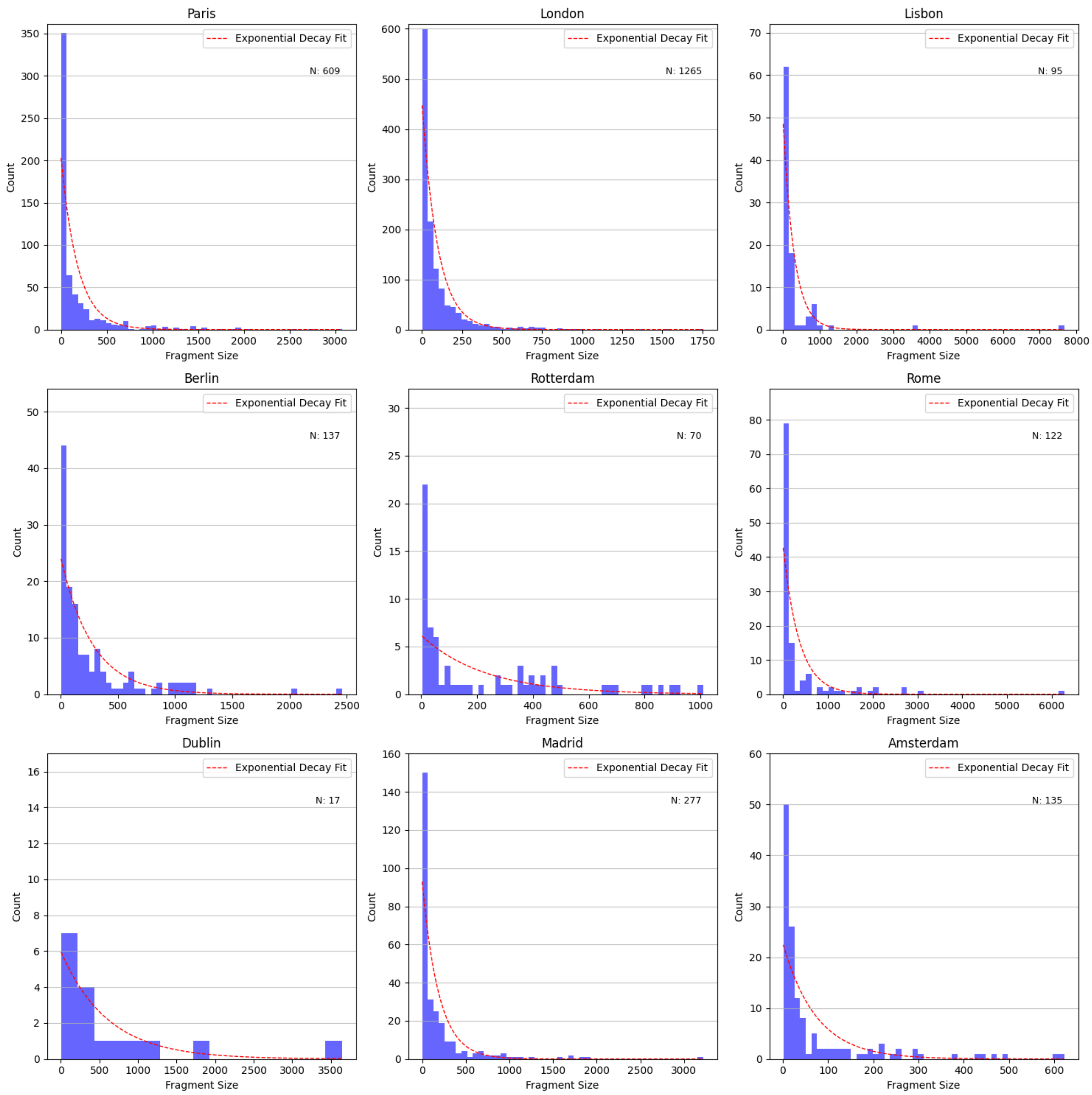


Figure 3.12: Histogram for the urban fragment size distribution and corresponding exponential decay fit.

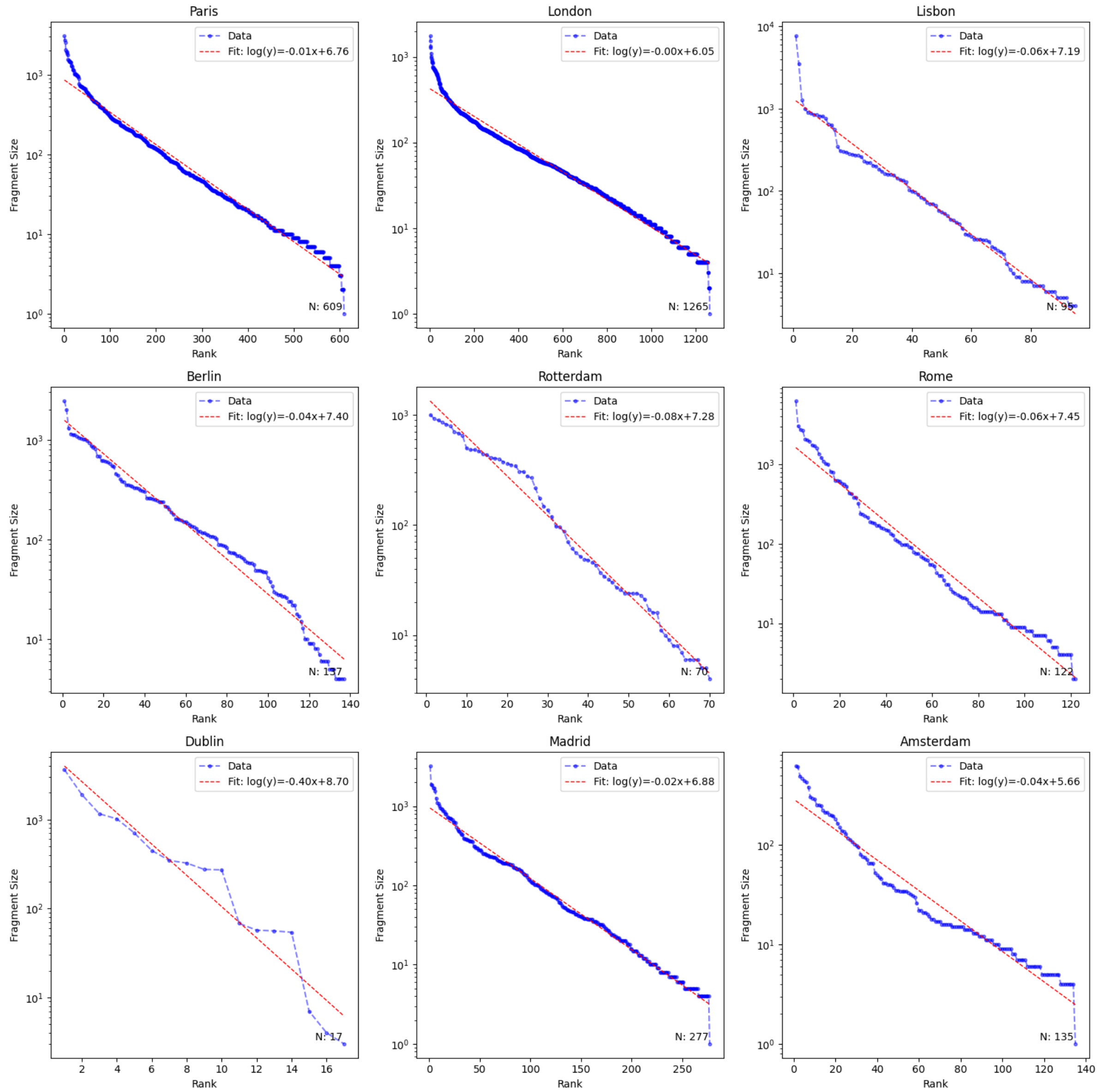


Figure 3.13: Rank size plot for the urban fragment size distribution. Notice the log-scale on the y-axis.

The more challenging aspect involves replicating a size distribution similar to that observed in the original urban fragmentation pattern. Research has shown that the size distribution of polygons in a Poisson Voronoi tessellation typically follows a right-skewed gamma distribution (Ferenc & Néda, 2007) (Figure 3.11). However, the size distribution of urban fragmentation patterns, when measured by the number of populated cells per fragment, matches that of an exponential decay, as seen in Figure 3.12 and Figure 3.13. Therefore, using a uniform selection of seed points would not adequately match the size distributions of the synthetic cases to the original ones. For that purpose, we utilize the GSTool package to generate sets of spatial random fields (Heße, Prykhodko, Schlüter, & Attinger, 2014; Müller, Schüler, Zech, & Heße, 2022). The random fields define a value ω_i for each cell, which would be used as a weight for the selection of points. However, the issue remained identifying the set of parameters for the random field that would lead to the desired fragment size distribution. For that purpose, we fixed the parameters used for the construction of the Gaussian random field (Müller et al., 2022) and take the resulting ω_i values to an exponential k. We test 100 values of k evenly spaced between 2 and 20, and generate a Voronoi tessellation for each iteration, as in Figure 3.16. These tessellations are used to assign populated cells to synthetic fragmented, in the same manner as with the urban fragments. For each instance, we compute the linear fit for the rank-size distribution, similarly to Figure 3.13. By repeating this process across the range of k, we observe a clear trend that higher values of k lead to more negative slopes, illustrated in Figure 3.15. A linear regression can be fit into this trend and given that we know the slope of the original urban fragment size, we can derive the optimal k value for each city. Once identified, we use the corresponding k power of each city to generate 500 synthetic fragmentations per city. These set of fragmentations serve as the ensemble of random cases for the estimation of the expected index value. This method ensures that the synthetic cases closely match the size distribution of the original urban fragments, thereby fulfilling the necessary assumptions for the random ensembles.

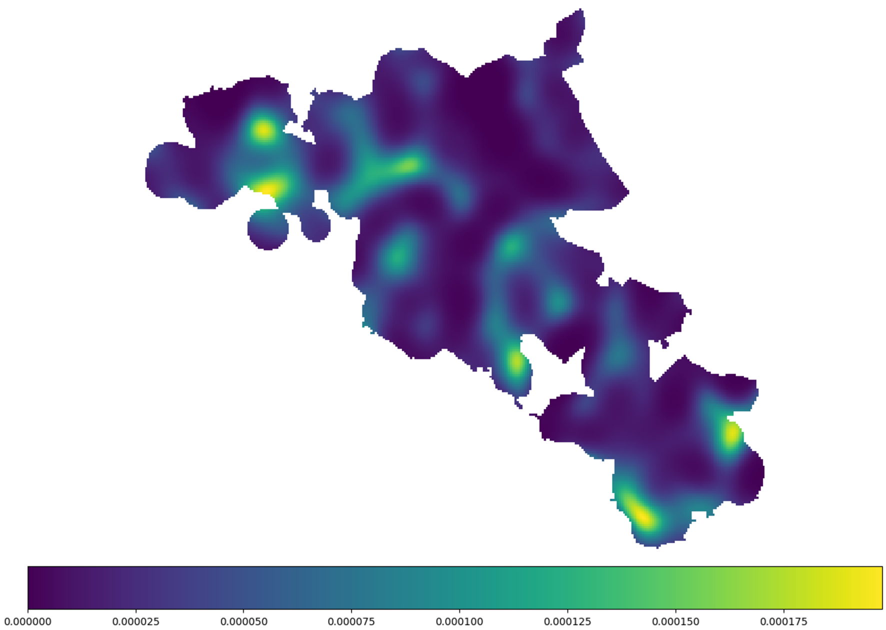


Figure 3.14: Synthetic field for Rotterdam AUC (var=400, len_scale=1400, k=4).

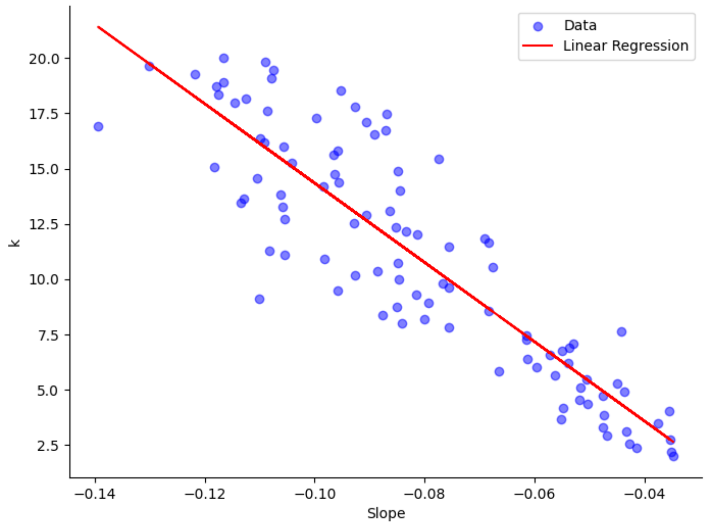


Figure 3.15: Linear regression - power k to slope for the Rotterdam AUC. (100 points)

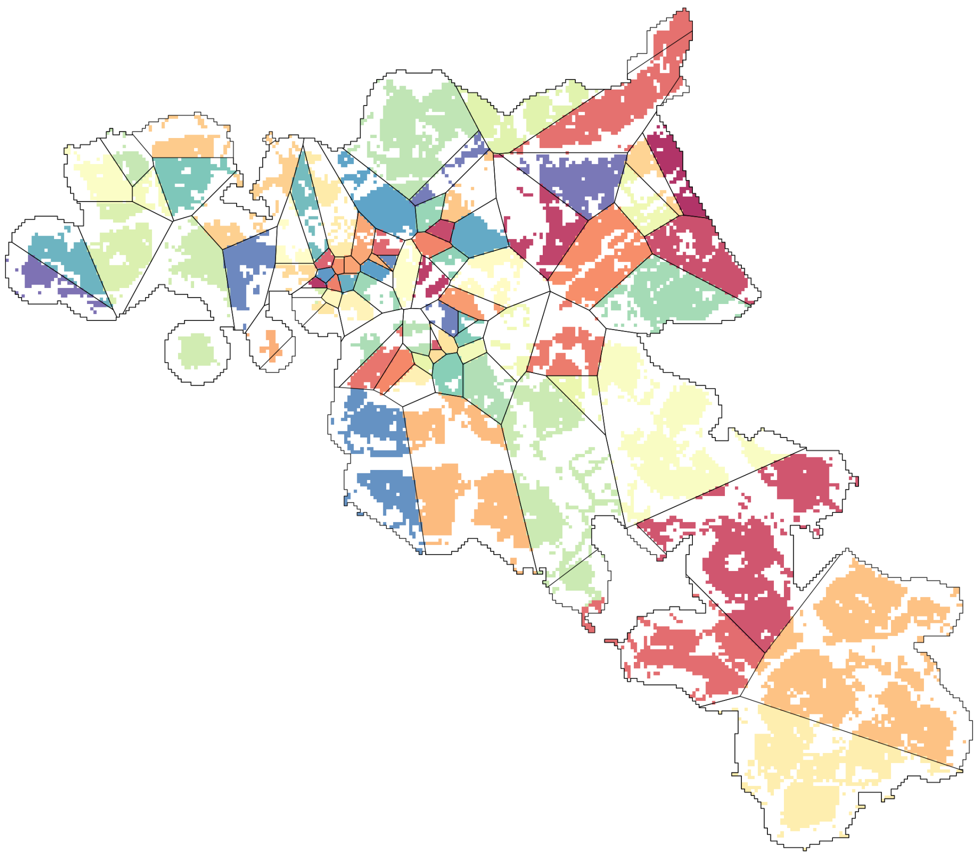


Figure 3.16: Example of a Voronoi synthetic fragmentation for the Rotterdam AUC

3.3.3. Index Estimation

Once the random clustering ensemble have been selected for each city, it is possible to proceed with the estimation of the expected index value. Previously, we introduced two of the most popular comparison measures, the Rand Index and the Mutual Information Index. Although it is not uncommon to use both measures simultaneously, as in the case of Spierenburg et al. (2022). As Romano et al. (2016) argues, ARI is suited for scenarios where the reference clustering consists of large, equally-sized clusters. On the other hand, AMI is better for handling cases with unbalanced cluster sizes and small clusters. In our case, the segregation pattern D, which serves as our reference clustering, tend to exhibit cluster size imbalance, making MI the preferred metric. Additionally, MI is also advantageous for its ability to capture non-linear relationships in the data (van der Hoef & Warrens, 2019). Therefore, it was decided to limited ourselves to the use of MI for the similarity evaluation.

$$\widetilde{MI}_{adj} = \frac{MI - \widetilde{E}(MI)}{max\,\{H(U), H(V)\} - \widetilde{E}(MI)} \tag{3.11}$$

$$\widetilde{E}(MI) = \frac{1}{n}\sum MI(D, S_n) \tag{3.12}$$

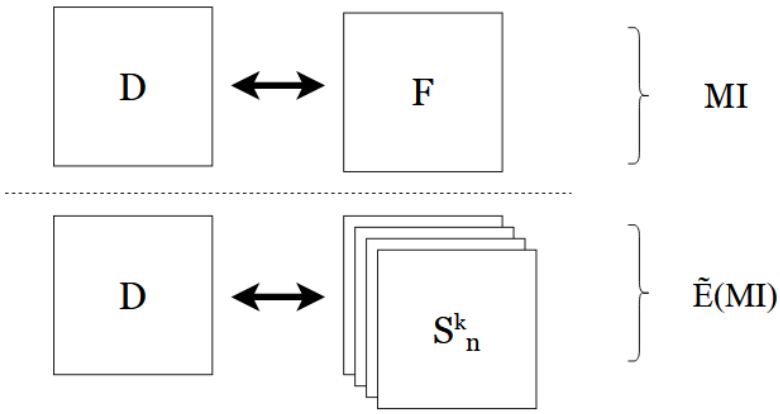


Figure 3.17: Comparisons required to obtain components of $\widetilde{MI}_{adj}$

We define our estimated adjusted Mutual Information Index, $\widetilde{MI}_{adj}$, as outlined in Equation 3.11. It should be noticed that this is the same formulation as Equation 3.10, the only difference being the expected value component. The value of MI is obtained by the 'original' comparison between our actual demographic D and urban fragmentation F patterns. Comparing D and the ensemble of synthetic fragmentations S_n will produce a distribution of MI scores, as shown in Figure 3.18. The estimated expected value is thus calculated as the mean of the MI scores from this distribution, Equation 3.12. Once these elements have been computed, we can obtain the value of $\widetilde{MI}_{adj}$ for each city. As with other adjusted indices, scores close to zero indicate no relation between both patterns, beyond what is possible by random chance. Positive scores indicate varying levels of agreement, while negative scores, which can also occur, signify more disagreement than expected by chance (Gates & Ahn, 2017). The results of the analysis will be presented in the following chapter.

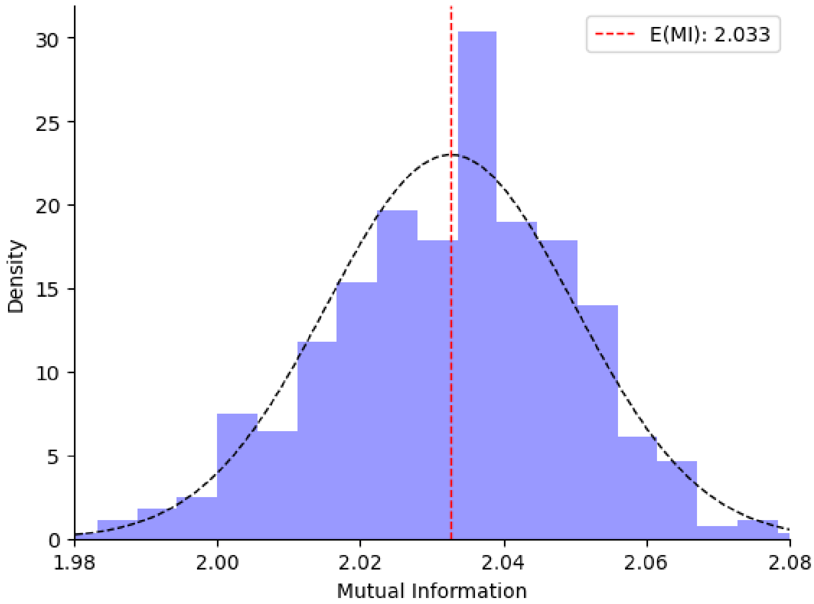


Figure 3.18: Distribution of the MI score for the London AUC, the largest city in the study. As it may be observed, the set of comparison between the synthetic fragmentations and the spatial segregation pattern generate a distribution of scores for the mutual information. The mean of said distribution is defined as the estimated expected value.

3.4. City Analysis

The benefit of our approach is that by constructing the spatial patterns for each case, we gain the ability to explore results at the city level. This allows for a more detailed inspection of cases of interest and to consider the influence of local context. Due to the large range of cities included in the study, it is not practical to examine each case individually. Instead, we aim to select a diverse set of cities that represent different contexts. The selection of cities is based on the outcomes of the quantitative analysis, with an emphasis on including cities from across the different countries in the study to contrast local dynamics under different national contexts. Priority is given to cities that show significant correlation between urban fragmentation and spatial segregation, since the connection between these patterns is the main focus of the study. In choosing the cities, we compare their levels of fragmentation and segregation to the national median, aiming to include a mix of different scenarios. The qualitative exploration consist on examining areas of high concentration and analysing the local dynamics that may explain the resulting pattern of segregation. In cases with significant similarity, we further examine the spatial distribution of the infrastructure and consider the potential roles that urban fragmentation plays in such contexts. For cities without a clear correlation between fragmentation and segregation, we explore alternative processes that may drive concentration, which could be independent of infrastructural aspects or other physical elements of the urban environment. The aim of the qualitative exploration is not to provide definitive explanations for why segregation occurs in specific locations, but rather to illustrate how the initial findings from the quantitative analysis might be interpreted differently once the local context of each case is taken into consideration.

4

Results and Analysis

4.1. Urban Fragmentation as Predictor of Segregation

Prior to presenting the results of the similarity analysis, we aim to contest the generalizability of previous results from the literature. As mentioned in the introduction, studies suggest that urban fragmentation can act as a robust and unbiased predictor of segregation (Ananat, 2011; Tóth et al., 2021). Although these studies applied the concept of urban fragmentation to different scenarios – with Ananat (2011) examining the black-white divide in American cities and Tóth et al. (2021) focusing on inequality in Hungarian towns – both cases employ a consistent measure, the Separation of Physical Barriers (SPB)[1]. Given the effectiveness of this measure in those instances, the question arises whether its applicability can be extended to a predictor of segregation in our case. Therefore, we decide to examine the value of urban fragmentation as a predicator for the level of segregation of immigrant communities in European cities. To measure the level of segregation, we computed both the dissimilarity index (DI), as originally used by Ananat (2011), and the multigroup entropy index (H), a similar segregation metric widely used in the literature (Iceland, 2004; Monkkonen & Zhang, 2014; Spierenburg et al., 2023). In assessing urban fragmentation, in addition to the SPB, we included another set of metrics used in the literature, such as the effective mesh size (m_{eff}) (Jaeger, 2000; Schumacher & Deilmann, 2019) and the infrastructure fragmentation index (IFI) (De Montis, Martín, Ortega, Ledda, & Serra, 2017). The inclusion of various metrics was intended to confirm that the relationship between both phenomena was not biased by the type of indicators selected. For a detailed description of each metric, the reader is directed to Appendix D.

The regression analysis shown in Table 4.1 demonstrates that none of the urban fragmentation metrics attained statistical significance. This lack of relation is also evident from Figure 4.1 and 4.2, where no discernible relationship is observed between the two sets of measures. These findings suggest that the relation between urban fragmentation and the segregation of immigrant communities is practically non-existent in the European context. However, these sorts of analyses suffer crucial limitations. First, they do not implicitly consider the spatial distribution of the patterns of segregation and urban fragmentation, only their degree. Second, these results do not permit us to contextualize them in terms of the dynamics of each city. The regression model's assumption that the relationship is consistent across cities might produce misleading conclusions, such as implying that no city exhibit a correlation between these patterns. The results from the similarity analysis, based on the methodology described in the previous chapter, will help to determine the actual extent of this relationship by examining

[1] Ananat (2011) originally named the metric the 'Railway Division Index', since their study only accounted for railway lines. Nevertheless, the general formulation of the measure is the same in both instances.

the connection between both spatial patterns individually for each city, while still allowing for a detailed analysis of any case of interest.

Table 4.1: Urban fragmentation metrics as predictors of level of segregation.

		β	t-value	P
H				
	SPB	-0.0034	-0.073	0.942
	m_{eff}	8.196e-6	1.081	0.282
	IFI	5.736e-8	0.800	0.426
DI				
	SPB	-0.0605	-0.490	0.490
	m_{eff}	1.982e-5	1.399	0.165
	IFI	5.433e-8	0.403	0.688

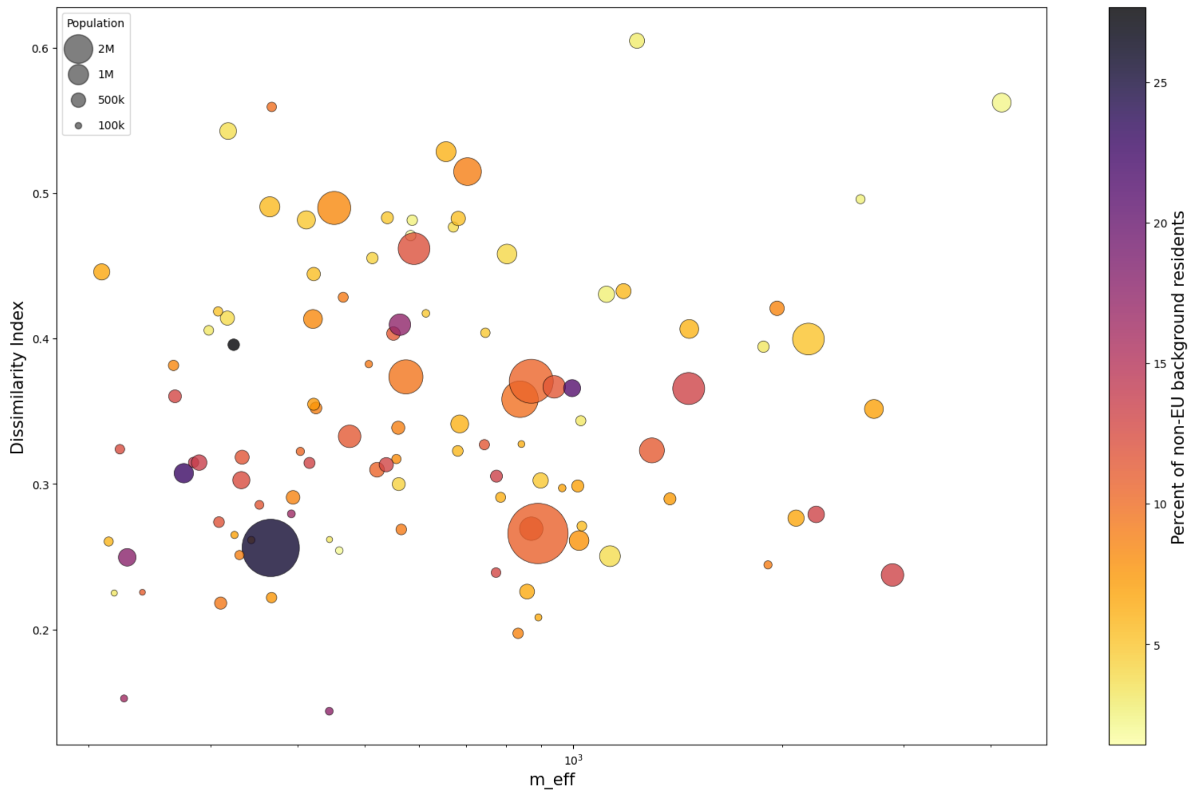


Figure 4.1: Dissimilarity Index DI - Effective Mesh Size m_{eff}

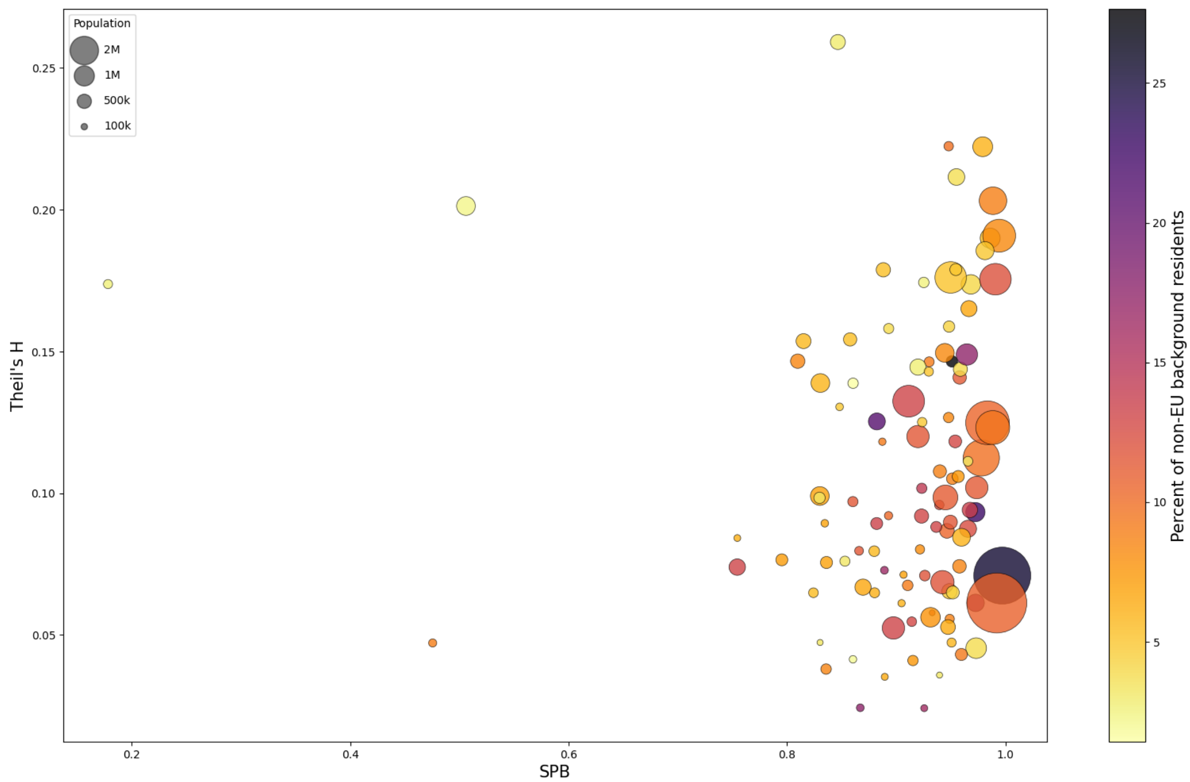


Figure 4.2: Multigroup Entropy Index H - Separation of Physical Barriers SPB

4.2. Similarity Analysis Results

We performed the similarity analysis and obtained the corresponding $\widetilde{MI}_{adj}$ score for each city. As depicted in Figure 4.3, there is a noticeable concentration of cities with scores near zero. However, before drawing any conclusions, it is important to consider that $\widetilde{MI}_{adj}$ depends on the difference between the original comparison score and the estimated expected value, $MI - \widetilde{E}(MI)$ in Equation 3.11. Since $\widetilde{E}(MI)$ is derived from the mean of a distribution, as shown in Figure 3.18, we need to verify whether the value of the original comparison significantly deviates from the such mean. This check is important because otherwise we cannot make the assertion that $MI \neq \widetilde{E}(MI)$. In addition, in the absence of a significant deviation, it is reasonable to conclude that $\widetilde{MI}_{adj}$ is essentially equal to zero, indicating no similarity between both patterns beyond what is expected by random chance.

In order to determine whether a significant deviation exists, we analysed the quantile position of the original MI score relative to the distribution. Scores that fall on the upper and lower quantiles – 0.05 and 0.95 – demonstrate a substantial deviation from the distribution mean, $\widetilde{E}(MI)$. As shown in Figure 4.4, the vast majority of cities do not fall within these quantiles. Out of the 106 cities analysed, only 33 exhibited statistically significant MI scores, as detailed in Table 4.2 and Figure 4.6.[2] Therefore, we can argue that for the majority of European cities included in the study, there is no indication that the patterns of spatial segregation experienced by immigrant communities relate to the fragmentation caused by infrastructure.

However, focusing on those cities with significant MI scores, we are confronted with surprising results. As shown in Figure 4.5, cities can exhibit both negative and positive $\widetilde{MI}_{adj}$ values. This indicates that the correlation between urban fragmentation and spatial segregation patterns can be either positive *or* negatively. Positive $\widetilde{MI}_{adj}$ values indicate a similarity between urban fragmentation and spatial segregation beyond that expected by random chance. Using the terminology of mutual information, observing one patterns reduces our uncertainty on the structure of the other. Negative $\widetilde{MI}_{adj}$ values mean that the synthetic fragmentation patterns 'consistently' outperform the actual urban fragmentation patterns, implying that it is more likely for a synthetic scenario to resemble the segregation patterns than the actual urban fragmentation itself. In those cases, the actual patterns are spatially 'divorced', reflecting a disconnect between social and spatial fragmentation.

Contrary to the regression analysis, the similarity analysis provided more nuanced results, as it is disaggregated at the city level. For the most part, the similarity analysis corroborated the findings of the regression analysis, indicating that urban fragmentation generally does not serve as a good predictor of the level of spatial segregation, as most cities showed no relationship between the two patterns. However, this does not mean that all cities conform to the same behaviour. Indeed, while a generalizable approach such as regression indicates no overall relationship, the city-specific results from the similarity analysis reveal that urban fragmentation does correlate with spatial segregation in a meaningful number of cities. In addition, the analysis also uncovered a negative correlation in a small set of cities, a counterintuitive result. These contrasting results suggest that more complex underlying phenomenon must be considered. Simply observing the presence or absence of a connection between urban fragmentation and spatial segregation is insufficient for a comprehensive understanding of their interplay.

[2]For a detailed description of the results of similarity analysis for each city, please refer to Appendix C.

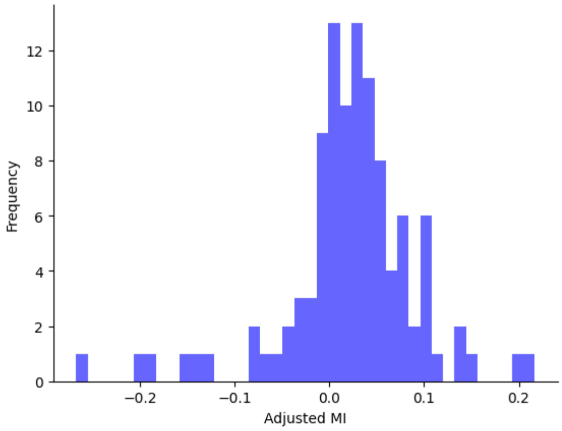


Figure 4.3: $\widetilde{MI}_{adj}$ score across the cities.

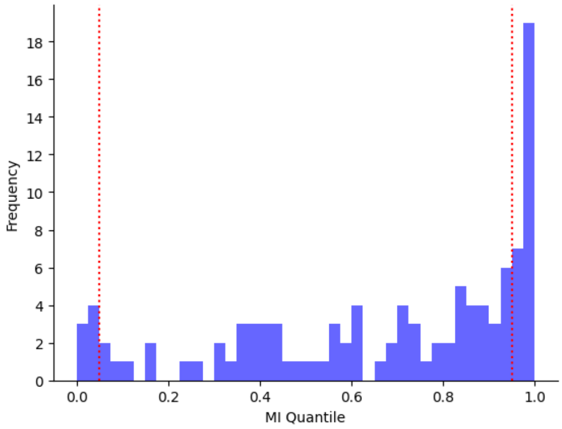


Figure 4.4: Quantile of MI scores.

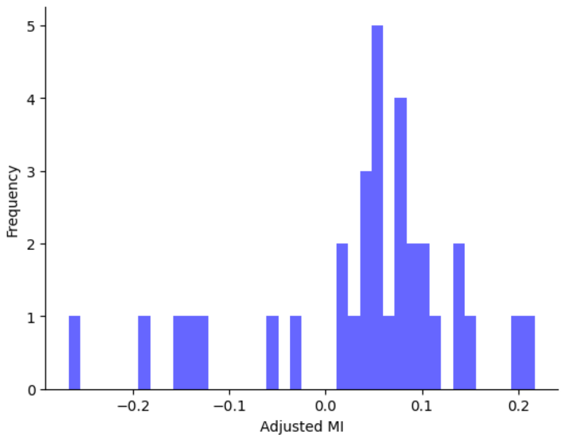


Figure 4.5: $\widetilde{MI}_{adj}$ score for cities with significant deviation from $\widetilde{E}(MI)$.

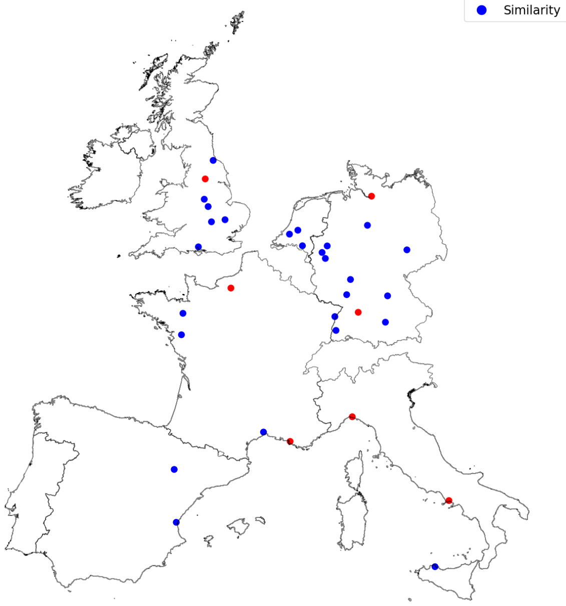


Figure 4.6: Geographical distribution of cities with significant correlation between both patterns

Table 4.2: Cities that show significant (dis)similarity between urban fragmentation and segregation patterns. Rows in green indicate that the city has been included in the qualitative analysis.

City	Country	$\widetilde{MI}_{adj}$	MI	$\widetilde{E}(MI)$	*Quantile*
Freiburg im Breisgau	DEU	0.217	1.282	0.964	0.990
Augsburg	DEU	0.201	1.561	1.229	0.998
Eindhoven	NLD	0.150	1.116	0.894	0.994
Leicester	GBR	0.143	1.618	1.343	0.998
Rotterdam	NLD	0.140	1.632	1.318	1.000
Frankfurt am Main	DEU	0.117	2.065	1.818	1.000
Hanover	DEU	0.108	1.279	1.084	0.970
Valencia	ESP	0.101	1.624	1.435	0.970
Dusseldorf	DEU	0.093	1.915	1.733	0.990
Milton Keynes	GBR	0.093	0.975	0.771	1.000
Southampton	GBR	0.081	1.518	1.349	0.976
Derby	GBR	0.079	1.075	0.903	0.956
Mannheim-Ludwigshafen	DEU	0.079	1.478	1.320	0.966
Saragossa	ESP	0.072	1.372	1.187	0.994
Utrecht	NLD	0.071	1.029	0.844	1.000
Cambridge	GBR	0.059	0.688	0.555	0.996
Nuremberg	DEU	0.058	1.321	1.173	1.000
Strasbourg	FRA	0.056	1.154	1.009	0.994
Middlesbrough	GBR	0.051	1.000	0.870	0.984
Rennes	FRA	0.049	0.647	0.508	0.992
Montpellier	FRA	0.047	0.411	0.300	0.974
Cologne	DEU	0.045	2.088	1.994	0.954
Nantes	FRA	0.036	0.498	0.388	0.996
Palermo	ITA	0.035	0.258	0.183	0.984
Ruhr	DEU	0.022	1.904	1.839	0.992
Leipzig	DEU	0.017	0.271	0.215	0.964
Leeds	GBR	-0.031	1.310	1.419	0.000
Hamburg	DEU	-0.057	1.340	1.460	0.030
Rouen	FRA	-0.128	0.457	0.669	0.008
Naples	ITA	-0.141	0.124	0.272	0.030
Marseille	FRA	-0.151	0.668	0.895	0.026
Stuttgart	DEU	-0.191	1.473	1.755	0.032
Genoa	ITA	-0.267	0.742	1.026	0.024

4.3. City Analysis

In this section, we present the qualitative analysis of the selected cities. Table 4.3 lists the nine cities chosen for further exploration, spread across seven countries. Ireland is the only country not represented, as Dublin–its only city included in the study–showed no correlation. The selection process began with cities exhibiting dissimilarity, since these are the least common cases and the more counterintuitive. This was followed by cities showing similarity and, finally, those with no correlation. Cities were chosen based on their degree of segregation and/or fragmentation relative to other cities in their respective countries. The two British cases are an exception, since these were selected to contrast alternative processes of concentration. This final selection provides a diverse set of contexts which allow for a comprehensive analysis on how local dynamics influence their respective spatial patterns of segregation and urban fragmentation.

Table 4.3: Cities selected for qualitative examination

City	Country	Correlation	Segregation[1]	Fragmentation[1]
Naples	ITA	–	+	–
Marseilles	FRA	–	+	–
Augsburg	DEU	+	+	–
Saragossa	ESP	+	+	+
Rotterdam	NLD	+	+	+
Utrecht	NLD	+	=	+
Lisbon	PRT	0	+	=
Oxford	GBR	0	–	–
Guildford	GBR	0	–	=

[1] Relative comparison to national median.

4.3.1. Naples

Naples offers an interesting analysis case as it combines low urban fragmentation–one of the lowest in the whole study–, high degree of segregation and significant dissimilarity level. From the map shown in Figure 4.7 , it is evident that the western side of the city shows minimal fragmentation, while most fragmented areas are located in the north-east. Furthermore, we notice that most regions of high concentration are clustered on the vicinity of railway station. The dissimilarity is the result of the spatial mismatch between these patterns. Although fragmentation itself does not provide much information on the formation of these patterns of segregation, other spatial mechanism may serve to better understand the result pattern of segregation. A partial answer may be found by considering the area around Napoli Centrale. Since the 80s, the area has attracted immigrant communities due to its cheap rents and its purpose as a commercial area (Dines, 2002). However, these neighbourhoods have also been subject to a strong process of urban decay. The area has been described as a *'badly lit, decaying and menacing nightmare thick with graffiti, grime and filth'* (Pardo, 2019). In addition to the poor social conditions, the housing stock does not bear much better, being composed mostly of old tenement blocks (Dines, 2002). In the case of Naples, there seems to be clear overlap with the presence of urban decay and the concentration of immigrant communities.

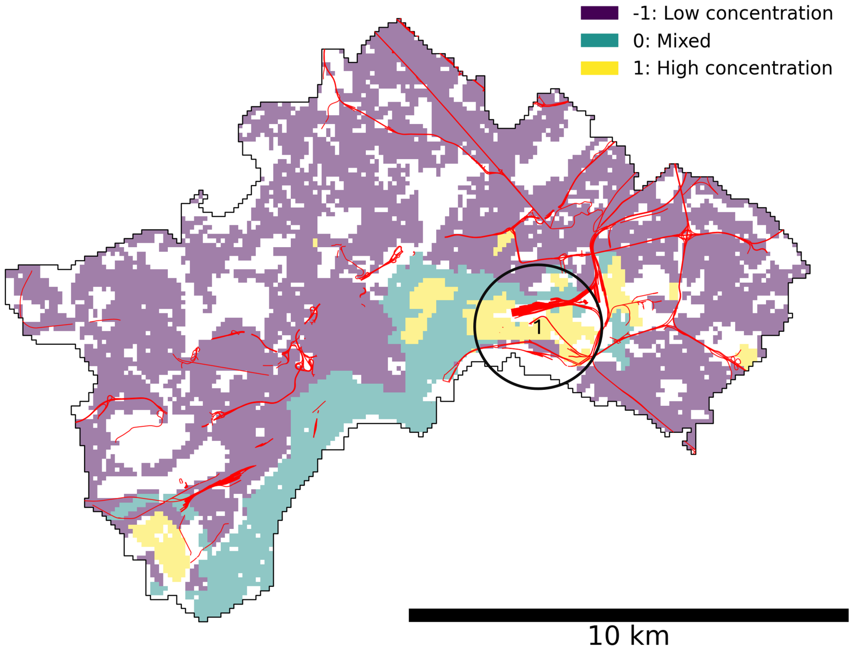


Figure 4.7: Naples - Infrastructure and patterns of segregation. 1) Napoli Centrale and Piazza Garibaldi

4.3.2. Marseilles

Marseilles is France's the second-largest city, its principal port, and the city with the highest degree of segregation. Observing Figure 4.8, the port's location in the north-west becomes evident from the dense concentration of infrastructure, such as highways and railways. However, despite the significant presence of infrastructure, the similarity analysis reveals a significant dissimilarity between patterns of segregation and urban fragmentation. Notably, the concentration of infrastructure also overlaps with a region of high immigrant concentration. This area is known as the *'triangle of poverty'* (Grzegorczyk, 2012), a combination of districts that composed the former industrial portion of the city. Originally inhabited by the industrial working class, these districts consist predominantly of high-rises and represent the poorest portion of the city. Currently, the area is characterized by a large immigrant population and high levels of deprivation (Gripsiou & Bergouignan, 2022; Grzegorczyk, 2012).

Interestingly, the infrastructure within the triangle of poverty does not serve to define its boundaries. Instead, the triangle of poverty extends beyond the urban fragments, indicating that there is no 'wrong side of the tracks', as both sides correspond to the same overarching region of concentration. Within the triangle of poverty, regardless of the urban fragment, these neighbourhoods are generally unattractive and suffer from urban decay and abandonment. However, the concentration of infrastructure in this region may also indicate another type of relation. Historically, the wealthier classes of Marseilles withdrew from the city centre to the southern and eastern parts of the city, leaving the working class and later immigrant communities closer to the port area (Mitchell, 2011). Examining Figure 4.8 shows that urban fragmentation is concentrated in the triangle of poverty, while the southern and eastern parts of the city exhibit limited fragmentation. This pattern raises questions about whether the infrastructure expansion in the triangle of poverty could have been influenced by a general disregard for the traditionally underprivileged residents of these districts.

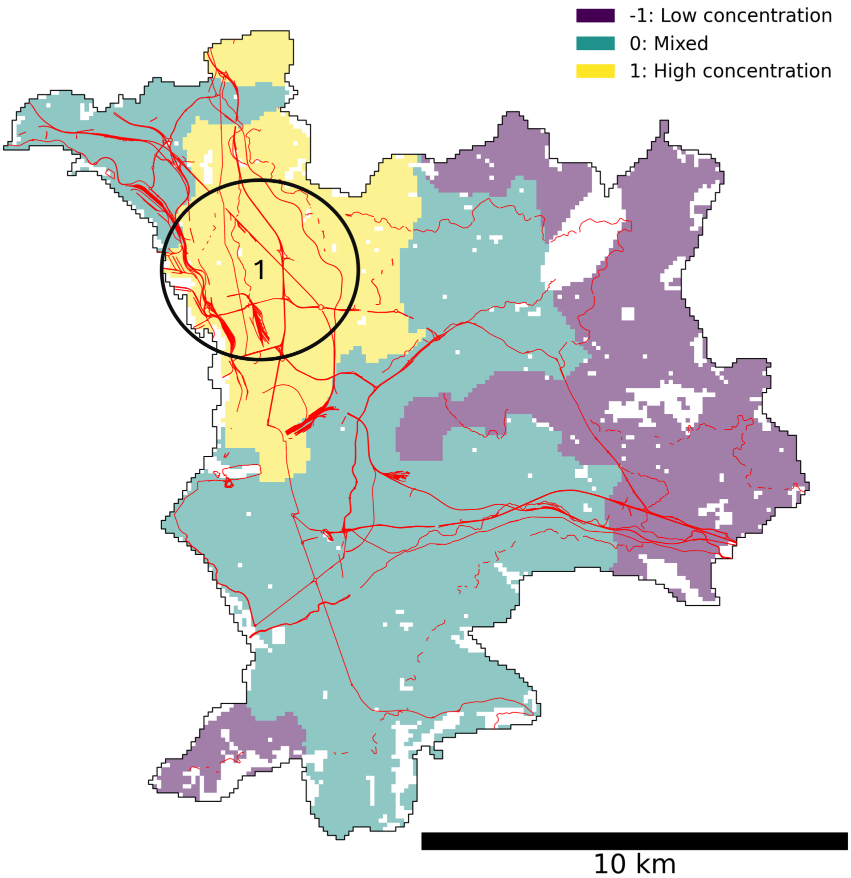


Figure 4.8: Marseilles - Infrastructure and patterns of segregation. 1) Triangle of Poverty

4.3.3. Augsburg

Augsburg, among all cities studied, exhibited the second-highest magnitude of $\widetilde{MI}_{adj}$, indicating a 'stronger' relation between both patterns. Even though another German city had higher magnitude, Freiburg im Breisgau, we decided to examine Augsburg due to its higher level of segregation. Among districts in Augsburg, Oberhausen in the norther part of the city, is notable for its pronounced concentration of immigrants, both in terms of percentage and numbers, the highest in the city (Stadt Augsburg, 2024). In addition, the district can be characterized by its surrounding 'barriers', with a river on the right and railway tracks on the left. Historically, Oberhausen developed around the industrial complex of the 'Gaswerken', which currently serves as a cultural centre (Gaswerk Augsburg, n.d.). Despite the industry's decline, its influence on the spatial structure of the district is still evident. Most of the current housing stock still dates back to the industrialization period at the end of the 19th century (Stadt Augsburg, n.d.-b). It is evident that processes of deindustrialization have affected the district, both spatially and socially. The original native working-class population of the district have gradually abandoned the area and have been substituted by immigrant communities, who may have been attracted to affordable housing options in the area. The old housing stock has lead to signs of urban decay, which have prompted the local government to adopt initiatives aimed at urban revitalization (Stadt Augsburg, n.d.-a).

Even though the infrastructural barriers largely coincide with the demographic boundaries of the neighbourhood, its connection seems more spurious than direct. The observed alignment likely stems from a historical path dependency, where both industrial and urban development

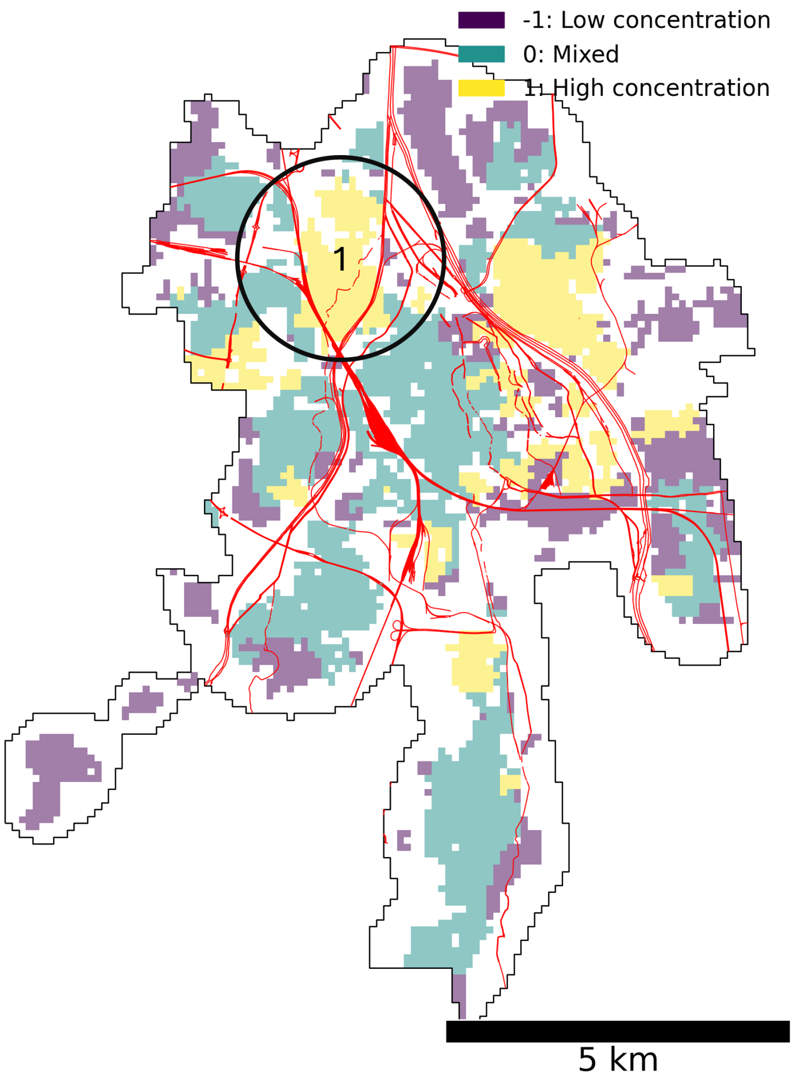


Figure 4.9: Augsburg - Infrastructure and patterns of segregation. 1) Oberhausen

mutually influenced each other. Initially, the Gaswerken attracted workers to its vicinity due to employment opportunities. The railway track, which served the factory as means of connectivity, also created a physical division between the industrial complex and the residential areas. As the industrial activity declined, the area underwent a demographic transformation, becoming a hub for immigrant populations. The location of the railway tracks are a legacy of spatial processes dating back to the industrialization of the city, rather than active contributors to the current concentration of immigrants. Instead of infrastructure shaping segregation patterns, it is more probable that other characteristic of the built environment, such as the quality of the housing stock, have resulted in the concentration of immigrants in the area.

4.3.4. Saragossa

Among Spanish cities, both Saragossa and Valencia exhibited significant levels of similarity in our study. We chose to focus on Saragossa, the largest city in the landlocked province of Aragon, due to its higher degree of segregation despite a lower percentage of immigrant population. Observing the map of the city, we notice various regions of high-concentration scattered throughout. However, many of these areas, such as the large northern regions overlap with industrial and recreational districts, and feature low population densities. The high concentration in these areas may be attributed to the presence of immigrant workers in the vicinity or individuals temporarily housed within these facilities.

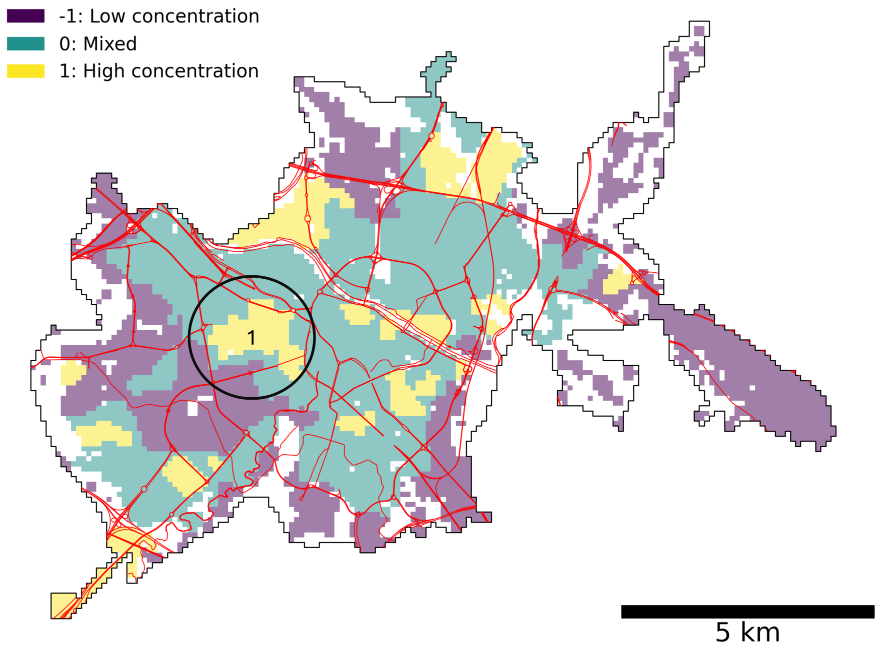


Figure 4.10: Saragossa - Infrastructure and patterns of segregation. 1) Barrio Delicias

An area that is worthy of a more detailed discussion is the district of 'Delicias' in the south-west of the city. The district is characterized by high density and by a large presence of immigrants; in 2007 23% of all foreign-born resident of Saragossa were living in the district (Sociedad Municipal de Rehabilitación Urbana de Zaragoza, 2007). The district experienced rapid development during the 60s, when internal migration of Spanish workers drawn to the city's industries led to mass construction due to insufficient housing. These large apartment buildings were constructed in small parcels in close proximity to one another (Zaragoceando, 2021). Currently, the urban fabric of the district has become subject to processes of urban decay characteristic of urban peripheries, with a substantial portion of housing stock being obsolete (Revitasud-Interreg, 2005). Notably, Delicias has a large percentage of abandoned housing, usually the older constructions, reflecting the general state of decay of portions of the building-stock. Recent housing developments have prompted some residents to transition from renters to homeowners, making rental properties available to immigrants who have come to replace the departing residents (Sociedad Municipal de Rehabilitación Urbana de Zaragoza, 2007). It should be noted that in recent decades, Delicias has been subject to efforts in urban revitalization (Revitasud-Interreg, 2005; Sociedad Municipal de Rehabilitación Urbana de Zaragoza, 2007).

The examination of the urban dynamics of Delicias does not indicate that infrastructure influence the process of immigrant concentration. The roads that surround the district may delineate its boundaries, but these do not differ from other portions of the city's motorway network that make up the ring and axial roads. Instead, the availability, condition of housing stock and the attractiveness of the area seem more relevant factors. The process of concentration in Delicias seems to reflect similar mechanism as those present in Oberhausen, Augsburg and the Triangle of Poverty, Marseille. Housing initially intended for industrial workers is gradually vacated by the original population, with these areas consisting predominantly of older houses and representing less attractive portions of the city, being increasingly occupied by immigrants.

4.3.5. Rotterdam and Utrecht

Three cities in the Netherlands showed significant relation between spatial segregation and infrastructure: Eindhoven, Rotterdam and Utrecht. Dutch cities are particularly insightful because, while they present patterns of concentration similar to those previously discussed, they also introduce new contexts related *post-war large housing estates*. For the examination, we focus on Utrecht and Rotterdam due to their higher degree of urban fragmentation.

In Rotterdam, there seems to be a connection between unemployment, poverty and the concentration of immigrants, with large portion of these communities residing in the older and poorer neighbours of the city (van Ostaaijen, 2014). Tarwewijk and Afrikaanderwijk in Rotterdam South are such examples. These neighbourhoods emerged in the early 20th century due to internal migration and were initially populated by the working-class drawn by the port's industry (Custers & Willems, 2024; van Ostaaijen, 2014). However, similar to other industrial neighbourhoods previously discussed, the 'native' working-class population gradually withdrew from the area, making space for an influx of foreign immigrant workers. Nevertheless, this process of withdrawal is not exclusive to older neighbourhoods from the industrialization period. In the post-war period, due to significant population growth and housing shortages, Rotterdam expanded by developing neighbourhoods at the outskirts of the city, such as Pendrecht (McCarthy, 1999). These new developments were characterized by large housing estates with a significant presence of social housing and higher density dwellings. Although Pendrecht was originally considered an attractive place to live, by the 90s, processes of decay in the housing stock made the area unappealing for most but the least privileged (van Ostaaijen, 2014). Over time, Pendrecht and other 'garden city' developments in Rotterdam have since been classified as one of the most deprived neighbourhoods in the country, earning a place on the list of the 40 Vogelaarwijken (KEI Kenniscentrum Stedelijke Vernieuwing, 2008).

Utrecht has experienced similar processes of concentration in its post-war housing developments, such as Kanaleneiland, Overvecht and Nieuw-Hoograven. These neighbourhoods are characterized by the presence of large housing states, constructions meant to address housing shortages during the population growth of the post-war years (Van Beckhoven & Van Kempen, 2006). These developments had an emphasis in multifamily dwellings, such as apartment blocks, and have a large presence of social housing providers (Aalbers, van Beckhoven, van Kempen, Musterd, & Ostendorf, 2003; Van Beckhoven & Van Kempen, 2006). Despite originally being considered attractive places to live, these estates have since suffered from *relative* and *absolute* decline (Aalbers et al., 2003). Absolute decline refers to lack of proper maintenance of the housing stock and its surrounding area, leading to urban decay. Relative decline refers to the emergence of more attractive housing options in others of the city, making these estates unattractive in comparison. These processes of degradation have rendered these housing estates less popular among Dutch households, reducing competition for dwellings and thereby facilitating the concentration of immigrants in these areas (Van Beckhoven & Van Kempen, 2006).

In both cities, the relationship between urban fragmentation and segregation patterns appears to be closely tied to the era in which the neighbourhoods were developed. The post-war housing projects were typically constructed on the outskirts of the city, often in areas that had little to no urban development. For example, Overvecht was agricultural land prior to its development(50 jaar gastarbeiders, n.d.). Since these neighbourhoods are positioned at the periphery, they were initially integrated through infrastructure to ensure connectivity. However, as in the case of Utrecht, these areas have remained isolated and have been described

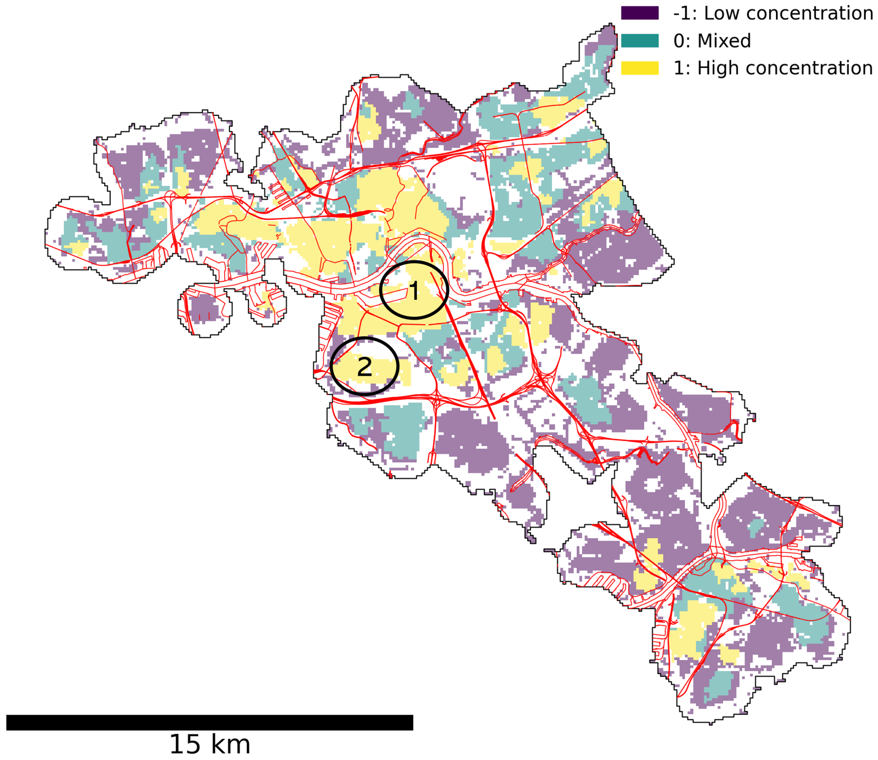


Figure 4.11: Rotterdam - Infrastructure and patterns of segregation. 1) Tarwewijk and Afrikaanderwijk 2) Pendrecht

to be '*surrounded by railway and national highways*' (Aalbers et al., 2003; Van Beckhoven & Van Kempen, 2006). Thus, the presence of these physical barriers is not directly causal to the segregation patterns, but rather an addition affliction that exacerbates the isolation of these areas.

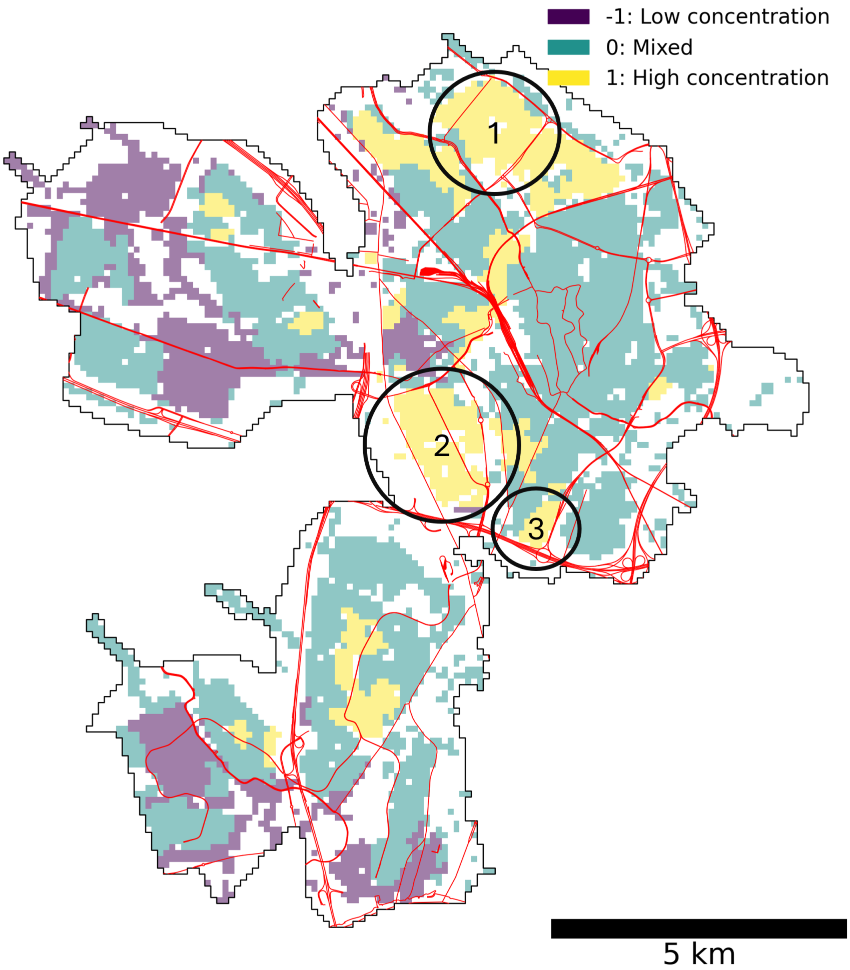


Figure 4.12: Utrecht - Infrastructure and patterns of segregation. 1) Overvecht 2) Kanaleneiland 3) Niew-Hoograven

4.3.6. Lisbon

In our study, no Portuguese city showed a clear relationship between urban fragmentation and segregation patterns. Nonetheless, examining Lisbon, the largest metropolitan area in the country, offered valuable insights into the dynamics of urban expansion. Observing Figure 4.13, we notice that despite no relation between both patterns, areas of high concentration seem to be frequently located near transportation infrastructure, particularly on the west side of the city. One such neighbourhood is 'Alto da Cova da Moura', a small settlement situated between a railway line and a highway. This area, described as a *'shanty neighbourhood'*, emerged through the illegal construction of houses during a period of large rural-urban migration in Portugal (Horta, 2006). Over time, Cova da Moura experienced a demographic shift, with many of the original Portuguese residents being replaced by immigrants, particularly from former African colonies (Horta, 2006).

The spatial process observed in Cova da Moura, including its origins and demographic transition, are not unique. Similar slums and clandestine housing emerged in the peripheries of Lisbon during the 50s and 60s as a result of internal migration (Malheiros, 2000). As foreign migration increased, dwellings originally occupied by local Portuguese were increasingly transferred to the incoming immigrants. This shift resulted in a concentration of these communities in the urban fringes and restricted inner suburbs (Malheiros, 2000). Although efforts for slum

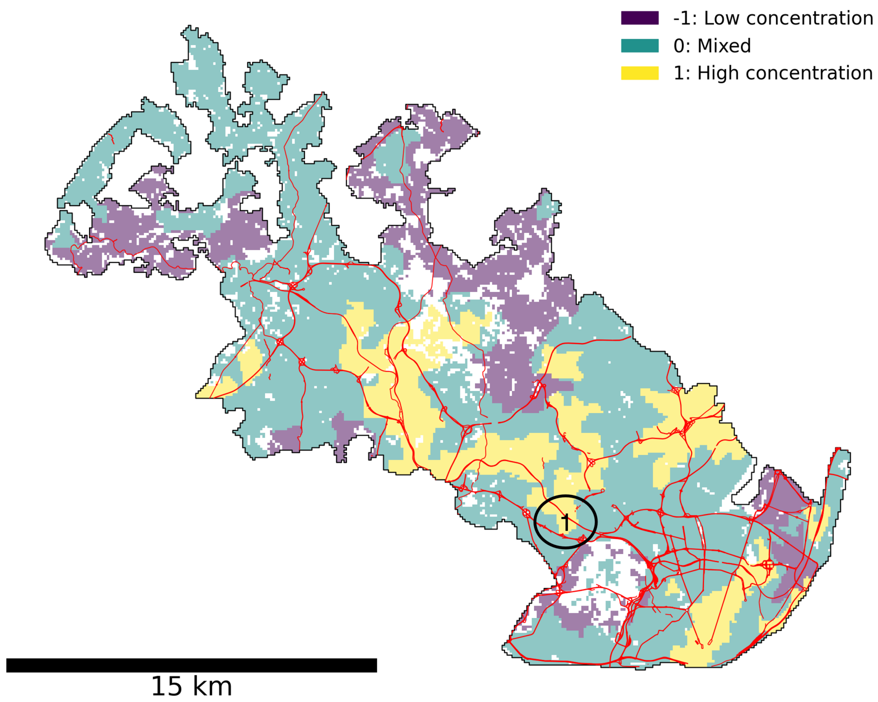


Figure 4.13: Lisbon - Infrastructure and patterns of segregation. 1) Alto da Cova da Moura

clearance have been made, they often merely relocated the population to large social housing complexes, thereby preserving the patterns of segregation (Malheiros, 2000).

Even though urban fragments may not relate to segregation patterns, it does necessitate that infrastructure does not. During the suburbanization process in the 1940s and 1960s, Lisbon's growth was accompanied by a significant expansion of the transportation infrastructure network (Santos, 2013). This apparent connection between high concentrations of population and proximity to infrastructure may be linked to the temporal emergence of these suburban 'irregular' neighbourhoods. As the city expanded, suburbs and shanty towns appeared at its periphery, and a corresponding set of infrastructures was developed in response to the mobility demands of the growing population.

4.3.7. Oxford and Guildford

In the previous cities in our analysis, we observed the appearance of a recurring theme. Neighbourhoods with high concentrations of immigrants typically represent relatively unattractive portions of the city, often characterized by poorer housing conditions. However, it is worth highlighting that this is not always the case, and immigrant concentration can result from diverse dynamics. Although Oxford and Guildford do not exhibit any particular relationship between urban fragmentation and segregation patterns, these cities still offer valuable insights due to their demonstration of an alternative concentration mechanism influenced by the process of globalization. Both cities are characterized by the presence of knowledge institutions, Oxford University and the University of Surrey, which serve as major attractors for international students and researchers, thereby fostering a concentration of highly skilled immigrants in their vicinity. In Figure 4.14, we observe that Guildford presents two regions of high concentration on the west side of the city, these correspond to the location Surrey's main campus and Surrey Research Park, Figure 4.15. The additional region in the north corresponds to Hazel Farm, a student housing complex within a resident area (University of Surrey, n.d.). A similar spatial concentration process can be observed in Oxford. The city contain various colleges, international schools, medical research centres, and student housing complexes, which spatially concentrate a significant percentage of the knowledge-based immigrants. For the example, the northernmost region of concentration can be attributed to a graduate student accommodation, Figure 4.16 and Figure 4.17. The observations from Oxford and Guildford illustrate that the concentration of immigrants should not automatically be associated with poor housing conditions, unattractive neighbourhoods, or broader issues of inequality. Furthermore, we observe how knowledge institutions and modern labour dynamics can reshape the spatial and demographic composition of cities in the process of attracting talent from abroad.

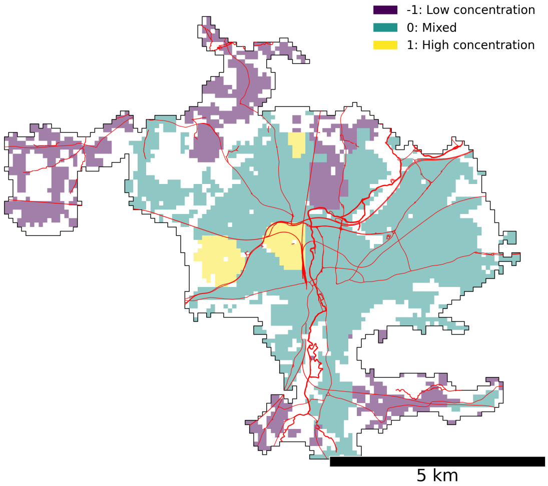


Figure 4.14: Guildford - Infrastructure and patterns of segregation

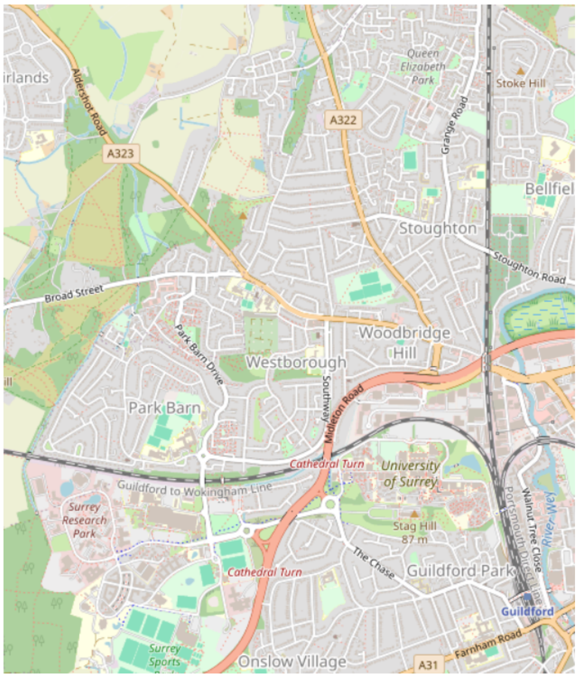


Figure 4.15: Map of Guildford

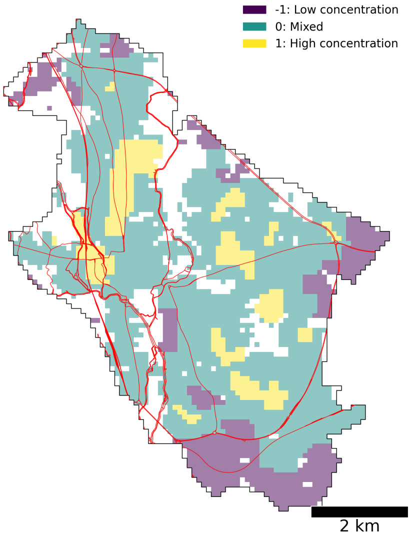


Figure 4.16: Oxford - Infrastructure and patterns of segregation

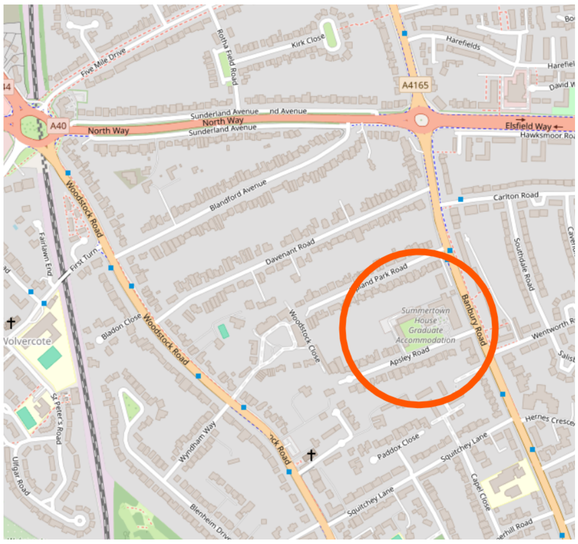


Figure 4.17: Summertown Graduate Accommodation in northern Oxford

5

Discussion & Conclusion

In this research, we aimed to address the connection between urban fragmentation and spatial segregation patterns in the European context, focusing specifically on the role of transportation infrastructures and the spatial distribution of non-EU immigrant groups. The purpose of our study was not only identify the existence of a connection, but to contextualize these relations in terms of the local dynamics of each city. Previous studies have indicated that urban fragmentation could serve as a robust predictor of segregation, a notion influenced by findings in the American case, where barriers resulting from infrastructure have served to reinforce separation between social groups. However, these relations cannot be translated to other instances, since each city corresponds to its own unique context. Our research challenged the notion of urban fragmentation as a generalizable measure for evaluating segregation and highlighted the importance of considering cases individually in more detailed. This final chapter summarizes the main contributions and implications of our research, discusses its limitations, and suggests directions for future studies.

5.1. Contributions and Implications

In terms of our results, the primary implication is that a connection between urban fragmentation and the spatial segregation patterns of immigrants does not exist as a generalizable phenomenon in the European context. Less than one-third of the cities in the study exhibited any statistically significant relationship between these patterns. Furthermore, the nature of these relationships varies, with some cities displaying positive correlations and others negative. Importantly, even where significant similarities exist, infrastructural barriers do not seem to actively shape segregation patterns. Instead, these connections are more likely influenced by other dynamics related to each city's urban development and historical context. Our qualitative exploration of specific cases provided insights into the types of spatial processes at play. A recurring theme is the transformation of areas that once housed lower-class industrial workers into neighbourhoods now marked by urban decay and high concentrations of immigrant residents. This observation suggests a potential link between the historical path dependency of cities and their current segregation patterns. Just as the presence of deprived neighbourhoods on the east side of industrial cities has been associated with historically uneven exposure to pollution from factories (Heblich, Trew, & Zylberberg, 2021), the concentration of immigrants in certain areas may also be tied to their historical roles as zones predominantly occupied by the urban lower classes.

Our approach provides a generalizable methodology while still enabling a detailed examination of individual cities through their unique geographies. This contrasts with previous research into the segregation of immigrant communities across Europe, which has often relied on single segregation metrics, as those presented in Chapter 4.1 (Benassi, Naccarato, Iglesias-Pascual, Salvati, & Strozza, 2023; Lichter et al., 2020), or studies that regress the degree of urban fragmentation against the degree of segregation, (Ananat, 2011; Tóth et al., 2021). Such methodologies, while useful for observing general trends, cannot capture elements unique to the local dynamics of each city. Our study emphasizes the importance of understanding segregation through its geographies, as advocated by Nelson et al. (2024), which led to the development of unique urban fragmentation and spatial segregation patterns for each case. This was the crucial process that enable the recontextualization of our quantitative results. The city analysis showed how the interpretation of the similarity analysis can vary once we account for such dynamics. For example, Utrecht and Saragossa both showed significant similarity between patterns, however, each case corresponds to different histories of urban development. In addition, our study uncovered both positive and negative correlations between urban fragmentation and segregation patterns. These contrasting results cannot be fully appreciated without recontextualizing them in terms of each city's spatial processes. Even in instances where the relation is negative, as in Marseilles, or non-existent, as in Lisbon, transportation infrastructure may still have connections to the patterns of segregation beyond its resulting urban fragmentation.

These results offer valuable insights for those involved in urban planning and transport policy design. The lack of a generalizable relation between urban fragmentation and segregation suggests that infrastructural removal is not an effective means of addressing segregation between communities. On the contrary, land revalorization around areas of highway removal can even result in the displacement of marginalized groups (Stehlin, 2023). Although the removal of infrastructural barriers may still offer benefits in terms of increased local mobility, it should not be considered a standalone solution for addressing segregation. Since relations vary by context, policy approaches cannot be generalized either. Even under the same national context, cities can exhibit significantly different relation, from similarity to dissimilarity or no correlation at all. This diversity underscores that our understanding of spatial segregation and urban fragmentation must adapt to local dynamics, indicating that policy-makers should focus on *localized* solutions rather than one-size-fit-all policies. Additionally, our qualitative exploration highlights that neighborhoods suffering from urban decay deserve special attention from planners, particularly because these areas often concentrate immigrant communities across different contexts. This focus is necessary because, as noted by Andersen (2002), areas of decay often experience self-perpetuating cycles and are unlikely to recover through their own means. Lastly, although the eras of aggressive highway and railway expansion in Europe may be foregone, future projects could still inadvertently lead to the separation of social groups. Due to their size and longstanding nature, planners should make a conscious effort to minimize the fragmentation caused by these infrastructures. Even if they are not explicitly designed to act as barriers, demographic shifts and future urban development might mean that certain groups become affected by these physical elements. The city analysis showed the strong effect that historical path depence can have in relation to the patterns of segregation and urban fragmentation. Therefore, it is better to try to minimize these negative impacts since their inception.

5.2. Limitations

Concerning our methodology, there are two aspects are worth addressing. As Spierenburg et al. (2024) detailed, the variability in the percentage of immigrants across cities means that definition of low and high concentration can vary greatly between cities. The regionalization approach used by Spierenburg et al. (2024) normalized the demographic variable of interest to account for this variation and make the resulting regions more comparable across cities. The implementation time that would have been needed to incorporate this normalization would have negatively impacted the developments of other portions of the projects, such as the urban fragmentation and the synthetic cases, and was therefore not adopted in this project. This more precise delineation of region is unlikely to impact the overall results of the similarity analysis. However, better region classification could improve future qualitative analysis by having a better identification of areas of interest.

The second issue concerns the synthetic fragmentation patterns. As mentioned in Chapter 3.3.2, we used Voronoi tessellation to produce a set of random fragmentation patterns, aiming to preserve the number of fragments and their size distribution of the original urban fragmentation pattern. However, questions remain about whether these synthetic cases are sufficiently representative for estimating the expected value of the mutual information. For instance, Voronoi polygons always exhibit ‘sharp boundaries’, whereas real infrastructural boundaries take more complex shapes, including curves and other diverse geometries. Additionally, the boundaries presented by rivers should remain constant even in the synthetic cases, since they are ‘permanent’ elements of the urban form. Yet, our current approach was not capable of incorporating such constrains. Future efforts could explore alternative forms of tessellation, such as Manhattan Voronoi (Wang, Xing, & Zhang, 2023), which, although still featuring sharp boundaries, results in polygons that are less triangular and more block-like, potentially better mimicking urban layouts. Additionally, these efforts could experiment try to preserve different properties of the original fragmentation patterns, such as the presence of certain barriers.

5.3. Further Research

The results from this study present a foundation for future research to further our knowledge on segregation in the European context. One promising direction is the implementation of longitudinal studies, to account for infrastructural developments and demographics shifts. As it stands, we can only assess the level of similarity at a single time period. However, in a city, neither its population nor its urban form remain static; both are subject to changes over time. Although infrastructures tend to be stable and long-lasting elements, the spatial distribution of populations is much more dynamic. Therefore, even if a road was developed with the intent to divide, it does not necessitate that it remains a boundary. For instance, despite highways being used to divide black and white communities in Atlanta, this did not prove to be a long-term barrier as the black population would still permeate to ‘the other side’ Bayor (1988). The absence of historical analysis limits our ability to determine causal mechanisms in the relationship between both patterns. The qualitative analysis was intended to partially address this issue by exploring the potential spatial mechanisms that are involved in spatial segregation. Nevertheless, without proper longitudinal analysis, these observations remain only partial.

Another opportunity for future research would be to compare the performance of urban fragmentation against other patterns derived from the built environment. The insights from the city analysis suggests that in relation to physical urban characteristics, the quality of dwelling units and the material conditions of the building stock may serve as better spatial predictors for the concentration of immigrant communities. New spatial patterns could be constructed based on variables such as the average age of dwelling units or real-estate prices, which may act as proxies for the overall state of the building stock. These patterns could then be compared to the spatial segregation patterns using the same principles of the similarity analysis applied in this study. The results from this new comparison could be directly contrasted with those concerning urban fragmentation presented in this report. In essence, we could evaluate which patterns derived from elements from the built environment exhibits a higher degree of similarity to the spatial segregation patterns. Extending the similarity analysis to include these additional patterns could help determine if the significant relationships observed in some cities might be explained by spurious associations with these other urban characteristics.

Lastly, the relation between spatial segregation and infrastructure could be reconsidered under different analytical frameworks. In our case, we focused on urban fragmentation resulting from infrastructure. However, the impact of infrastructure extends beyond creating divides; it also introduces negative externalities such as noise and pollution, which may diminish the attractiveness and liveability of neighbourhoods on 'both sides of the border'. Research by Mahajan (2024) in the American context indicate that these disamenities could be connected to the ethnic composition of neighbourhoods near highways. Additionally, while our study considered immigrant communities as our target demographic, other disadvantaged groups in Europe might also be disproportionately affected by such infrastructures. For instance, the spatial segregation patterns of the urban poor could show a stronger correlation with urban fragmentation patterns compared to those of immigrants. The methodological approach used in our study, including the regionalization technique, could be adapted to analyse other demographic groups if data is available, potentially revealing that the connection between urban fragmentation and segregation not only varies based on the context but also on the demographic group.

5.4. Final Remarks

Infrastructures are crucial components of modern cities, providing important benefits in terms of connectivity and reduced travel times. However, these benefits should not compromise the wider integration of vulnerable groups into society. In our evaluation of the relationship between urban fragmentation and spatial segregation of immigrants, we focused on fragmentation caused by prominent infrastructures that act as physical barriers to local mobility. While the general absence of a strong connection might be seen positively, indicating a thoughtful approach to infrastructural development in Europe, it also highlights the complexity of understanding the spatial configuration of segregation. Although other characteristics of the built environment, such as urban decay, may offer a better chance at capturing the underlying structure of spatial segregation, the challenge remains large. For instance, the boundaries that divide communities may much more subtle than we assume. As commented by Stefanizzi and Verdolini (2019), deprived areas may be separated from affluent areas by *'one single street'*. This observation suggests the presence of *'imaginary boundaries'* that may not necessarily be explained simply through the composition of the physical space. The implication is profound; even if we alter our physical environments to remove barriers, and even if urban revitalization projects target areas of decay, segregation may persist if these boundaries remain in the imaginary of the communities inhabiting these places.

Nevertheless, despite the complexities and challenges that spatial segregation presents, it is crucial that we continue our efforts to study and understand it. Cities are not static; they are always evolving. This dynamism presents opportunities to reshape our urban environments for the better, making them more inclusive and equitable for all their residents. As Jane Jacobs (1961) famously stated:

> *'Cities have the capability of providing something for everybody, only because, and only when, they are created by everybody.'*

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A

List of FUA

Table A.1: Cities included in the study

FUA	Country	Population
Aachen	DEU	534,000
Aberdeen	GBR	477,000
Amsterdam	NLD	2,751,000
Augsburg	DEU	648,000
Barcelona	ESP	4,746,000
Bari	ITA	711,000
Berlin	DEU	4,952,000
Bilbao	ESP	930,000
Blackburn with Darwen	GBR	289,000
Blackpool	GBR	309,000
Bologna	ITA	758,000
Bonn	DEU	897,000
Bordeaux	FRA	1,190,000
Bremen	DEU	1,234,000
Brighton and Hove	GBR	429,000
Bristol	GBR	918,000
Cambridge	GBR	376,000
Cardiff	GBR	901,000
Catania	ITA	620,000
Cheshire West and Chester	GBR	485,000
Coimbra	PRT	271,000
Colchester	GBR	307,000
Cologne	DEU	1,951,000
Coventry	GBR	697,000

Continued on the next page

Table A.1: Cities included in the study (continued)

FUA	Country	Population
Derby	GBR	487,000
Doncaster	GBR	311,000
Dresden	DEU	1,316,000
Dublin	IRL	1,825,000
Dundee City	GBR	258,000
Dusseldorf	DEU	1,519,000
Edinburgh	GBR	842,000
Eindhoven	NLD	736,000
Exeter	GBR	450,000
Florence	ITA	773,000
Frankfurt am Main	DEU	2,577,000
Freiburg im Breisgau	DEU	630,000
Genoa	ITA	665,000
Glasgow	GBR	1,786,000
Grenoble	FRA	660,000
Guildford	GBR	262,000
Hamburg	DEU	3,173,000
Hanover	DEU	1,271,000
Ipswich	GBR	349,000
Karlsruhe	DEU	733,000
Kingston upon Hull	GBR	590,000
Leeds	GBR	2,577,000
Leicester	GBR	867,000
Leipzig	DEU	971,000
Lille	FRA	1,472,000
Lincoln	GBR	303,000
Lisbon	PRT	2,925,000
Liverpool	GBR	1,484,000
London	GBR	11,982,000
Lyon	FRA	2,016,000
Madrid	ESP	6,612,000
Malaga	ESP	816,000
Manchester	GBR	3,293,000
Mannheim-Ludwigshafen	DEU	1,139,000
Marseille	FRA	1,248,000
Medway	GBR	263,000
Middlesbrough	GBR	554,000

Continued on the next page

Table A.1: Cities included in the study (continued)

FUA	Country	Population
Milan	ITA	4,762,000
Milton Keynes	GBR	264,000
Montpellier	FRA	686,000
Muenster	DEU	526,000
Munich	DEU	2,823,000
Nantes	FRA	922,000
Naples	ITA	3,293,000
Newcastle upon Tyne	GBR	447,000
Nice	FRA	1,013,000
Northampton	GBR	465,000
Norwich	GBR	392,000
Nottingham	GBR	892,000
Nuremberg	DEU	1,298,000
Oxford	GBR	528,000
Palermo	ITA	963,000
Paris	FRA	12,794,000
Plymouth	GBR	393,000
Porto	PRT	1,265,000
Portsmouth	GBR	510,000
Preston	GBR	254,000
Reading	GBR	310,000
Rennes	FRA	672,000
Rome	ITA	4,142,000
Rotterdam	NLD	1,805,000
Rouen	FRA	685,000
Ruhr	DEU	5,020,000
Saarbrucken	DEU	794,000
Saint-Etienne	FRA	475,000
Saragossa	ESP	748,000
Seville	ESP	1,489,000
Sheffield	GBR	1,164,000
Southampton	GBR	664,000
Stoke-on-Trent	GBR	470,000
Strasbourg	FRA	805,000
Stuttgart	DEU	2,659,000
Sunderland	GBR	265,000
Swansea	GBR	378,000

Continued on the next page

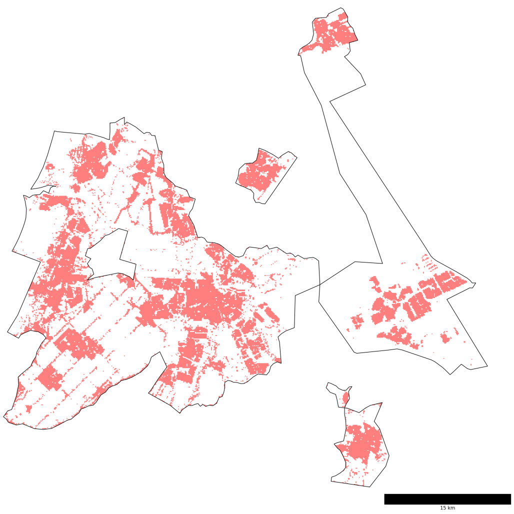
Table A.1: Cities included in the study (continued)

FUA	Country	Population
The Hague	NLD	1,052,000
Toulon	FRA	535,000
Toulouse	FRA	1,391,000
Turin	ITA	1,741,000
Utrecht	NLD	875,000
Valencia	ESP	1,629,000
Venice	ITA	506,000
West Midlands urban area	GBR	3,020,000

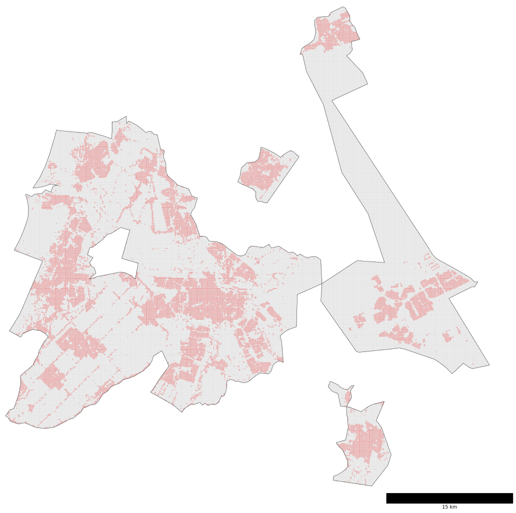
B

Adjusted Urban Cores (AUCs)

The issue of discontinuity and (over)aggregation are the motivations for the redefinitions of the boundaries of urban cores of the selected FUA. The objective is to generate a single continuous spatial unit that captures the most relevant portions of the original urban core. The redefinition process adheres to a replicable set of rules, mirroring the methodology originally employed to define the urban cores (Alessandrini et al., 2017). The first step involves the construction of a full grid to cover the extent of the original urban core. The original boundaries of the urban cores were obtained from OECD's official sources (OECD, n.a.). Based on the coordinates provided by the demographic data, we identify which populated cells are within the boundaries of the urban core. Using these coordinates and based on the fact that these lay in a standard grid of 100x100m cells, we construct the rest of the grid to cover the whole extent of the urban core. This process can be observed in Figure B.1.



(a) Populated cells in the urban core of the Amsterdam FUA



(b) Grid with full coverage of the urban core

Figure B.1: Construction process of the grid

As can be noted from Figure B.1a the distribution of the population is uneven and discontinuous. It is apparent that some of these populated cells could be grouped into separate, distinct regions. However, even though some cells may not be directly connected to other populated cells, their proximity indicates belonging to the same 'area of influence'. Therefore, to properly delineate these regions, we construct a 'heatmap' based on the distribution and concentration of population across cells.

In the heatmap, each cell in the entire grid is assigned a density coefficient (den_coeff) score, reflecting the magnitude of its own population and that of its surroundings. The density coefficient is equal to the summation of the weights of all Origin-Destination (OD) pairs ij for a given cell i (Equation B.1). The weight of each OD pair is determined by its distance and the population of the destination cell. Weights are inversely proportional to the distance, reflecting the decreasing influence of cells further apart (Equation B.2[1])

These weights are computed using the Euclidean distance from the centroid of a cell i to the centroid of any cell j within a radius of 850. It should be noted that the radius of 850 is an arbitrary selection based on the memory limitations presented by the number of computations required for large grids. This method assigns higher weights to neighbouring cells that are closer and have larger populations, thereby capturing the influence of population density in the surrounding area. In addition, even if a cell has no population but remains sufficiently close to populated cells, its density coefficient will be non-zero.

$$den_coeff = \sum_{i}^{j} w_{ij} \tag{B.1}$$

$$w_{ij} = \begin{cases} 1 * tot\_pop_i & : \ d_{ij} = 0 \\ 1250/d^2 * tot\_pop_j & : \ d_{ij} > 0 \end{cases} \tag{B.2}$$

The computation of the density coefficient produces a heatmap as observed in Figure B.2. The red portions of the map represent cells with $den_{coeff} < 1$. These are cells that not sufficiently close of any (densely) populated area, and its inclusion in the urban core is of limited contribution. The heatmaps highlights the existence of 'islands'. Each island is a continuous region that represent the agglomeration of (populated) cells sufficiently close to be considered under the same area of influence. The term island from the fact that these regions are separated by a 'sea' of cells with insufficient density scores. From the heatmap, it also becomes apparent that among these islands, some have higher density score and/or concentrate a larger number of people.

Once the density islands have been defined, the final part of the process is to select a single island to obtain the boundaries of the adjusted urban core (AUC). In our case, we select the island that contains the largest number of people. Figure B.3 to Figure B.11 show the AUC for all the cities included in the study. In must be noted that there are three special instances of the AUC. Liverpool and Portsmouth contain two regions rather than one. The reason being that the original shape file of the urban core excluded the river that separated these regions. Nevertheless, these regions remain sufficiently close to be categorized as parts of the same continuous area of influence. The last exception is Venice, that is composed of the urban area in the mainland and its islands.

[1]The constant value of 1250 was chosen to ensure that when $d = 50/\sqrt{2}$, the weight $w_{ij} = 1$. The distance value of $50/\sqrt{2}$ serves as a reference distance to align both parts of the equation, which allows for the handling of cases where the distance is zero, since c/d^2 is undefined at zero. A cell with sides $d_{ref} * 2$ would have half the area of the original cell.

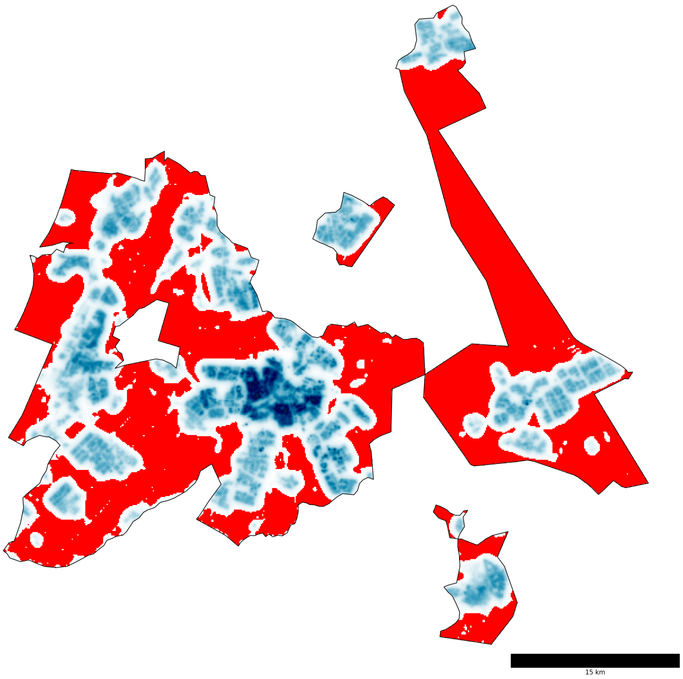


Figure B.2: Density coefficient heatmap for Amsterdam


Bremen
10 km
Hanover
5 km
Freiburg im Breisgau
5 km
Frankfurt am Main
10 km
Berlin
15 km
Hamburg
25 km
Stuttgart
10 km
Leipzig
5 km
Dusseldorf
5 km
Nuremberg
5 km
Augsburg
2 km
Bonn
5 km
Northing (m)
Easting (m)

Figure B.3

Karlsruhe
Saarbrucken
Muenster
Aachen
Munich
Dresden
Cologne
Mannheim-Ludwigshafen
Ruhr
Valencia
Bilbao
Seville
Northing (m)
Easting (m)
5 km
10 km
25 km
2 km

Figure B.4

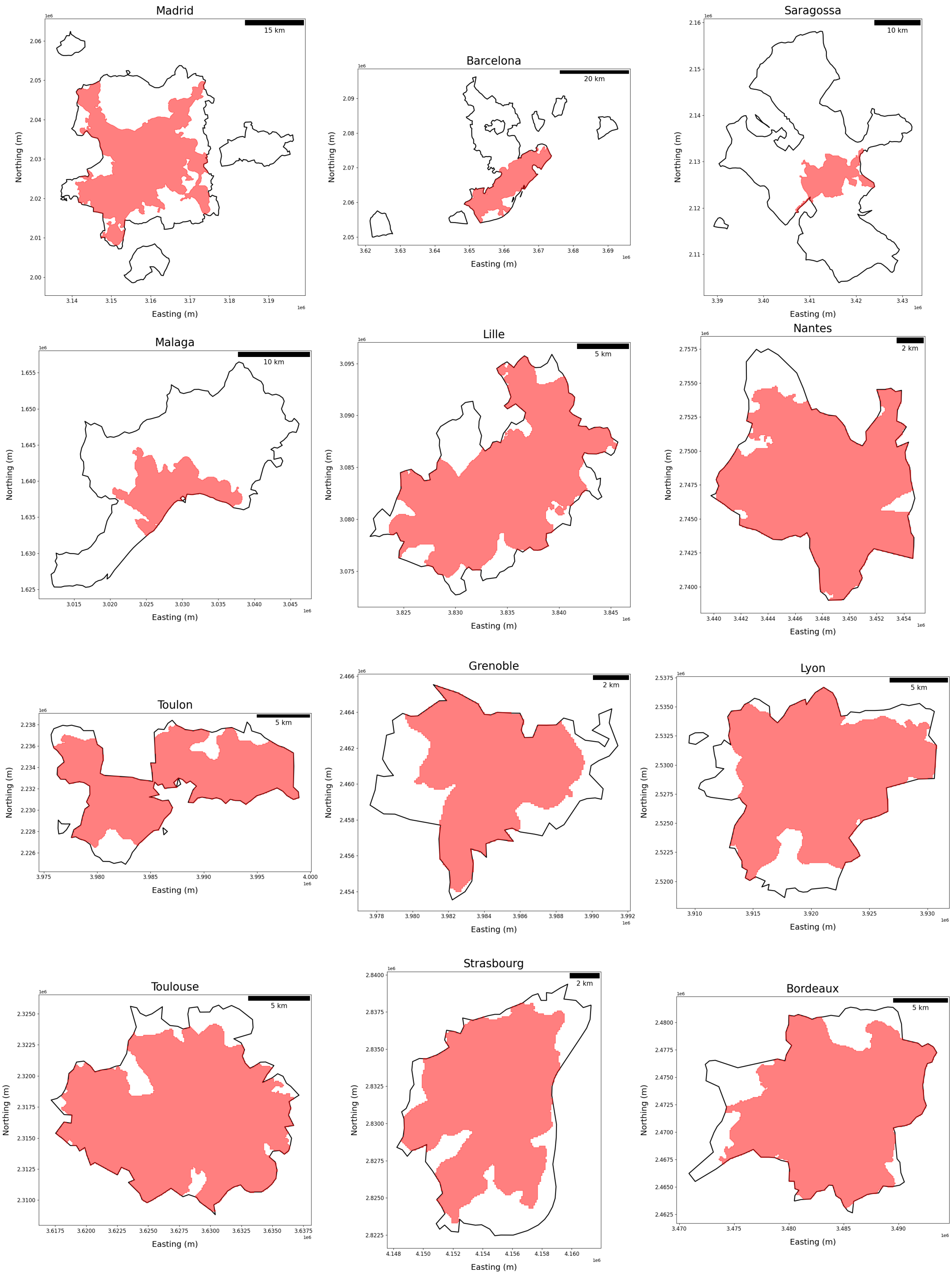

Madrid
Barcelona
Saragossa
Malaga
Lille
Nantes
Toulon
Grenoble
Lyon
Toulouse
Strasbourg
Bordeaux
Easting (m)
Northing (m)

Figure B.5

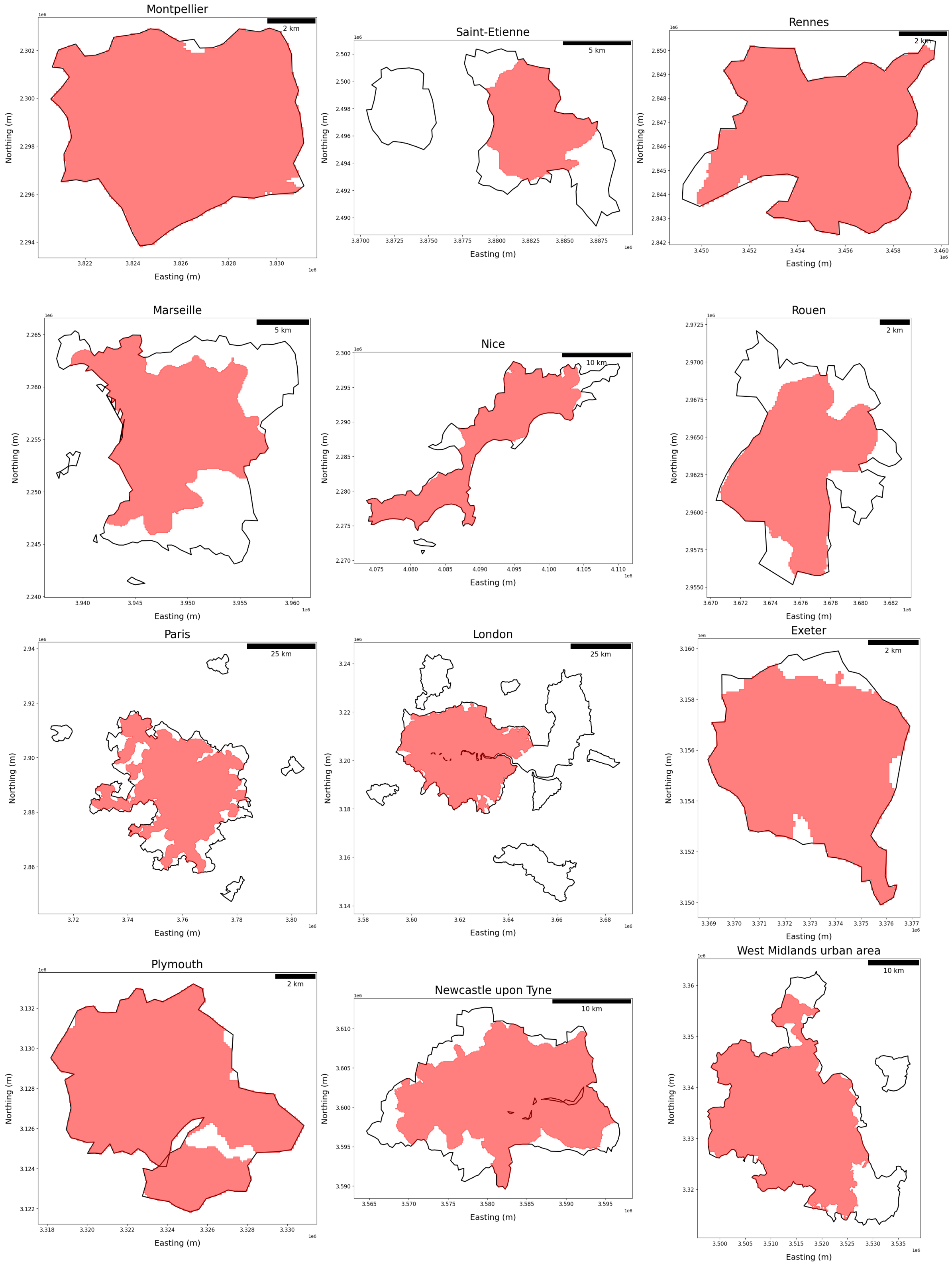

Montpellier
2 km
Saint-Etienne
5 km
Rennes
2 km
Marseille
5 km
Nice
10 km
Rouen
2 km
Paris
25 km
London
25 km
Exeter
2 km
Plymouth
2 km
Newcastle upon Tyne
10 km
West Midlands urban area
10 km
Northing (m)
Easting (m)

Figure B.6

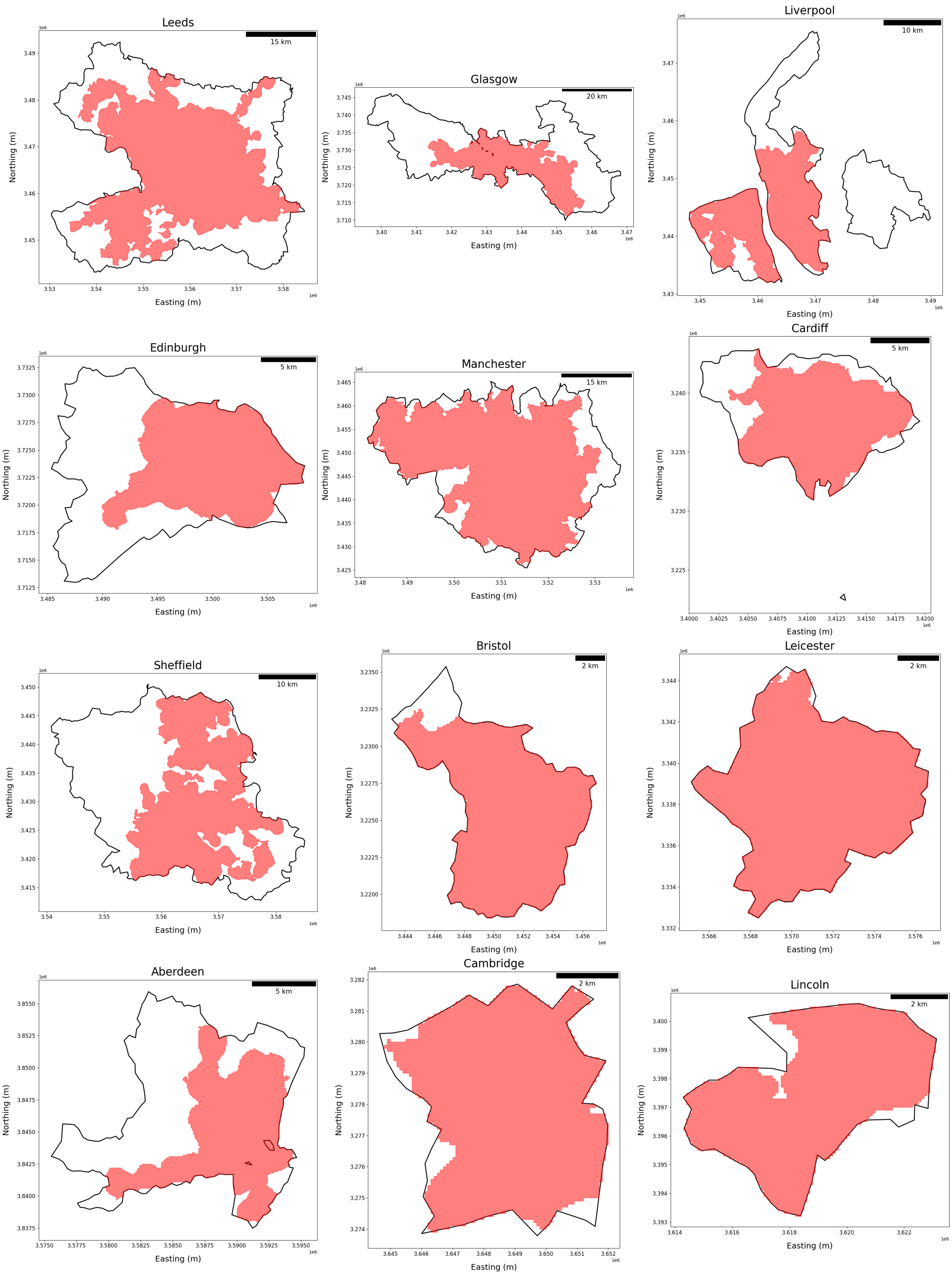

Leeds
15 km
Northing (m)
Easting (m)
Glasgow
20 km
Liverpool
10 km
Edinburgh
5 km
Manchester
15 km
Cardiff
5 km
Sheffield
10 km
Bristol
2 km
Leicester
2 km
Aberdeen
5 km
Cambridge
2 km
Lincoln
2 km

Figure B.7

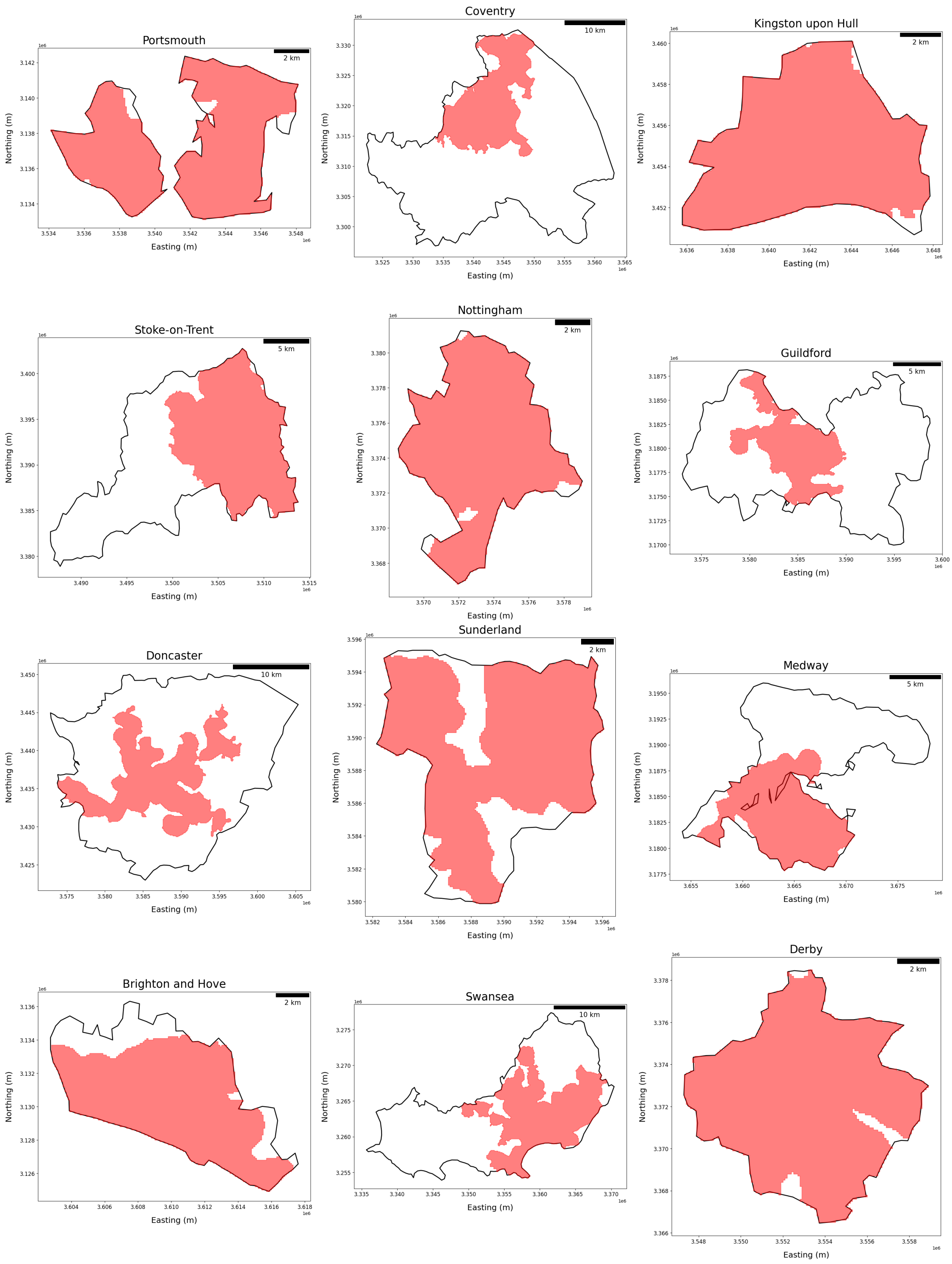

Portsmouth
2 km
Northing (m)
Easting (m)
Coventry
10 km
Northing (m)
Easting (m)
Kingston upon Hull
2 km
Northing (m)
Easting (m)
Stoke-on-Trent
5 km
Northing (m)
Easting (m)
Nottingham
2 km
Northing (m)
Easting (m)
Guildford
5 km
Northing (m)
Easting (m)
Doncaster
10 km
Northing (m)
Easting (m)
Sunderland
2 km
Northing (m)
Easting (m)
Medway
5 km
Northing (m)
Easting (m)
Brighton and Hove
2 km
Northing (m)
Easting (m)
Swansea
10 km
Northing (m)
Easting (m)
Derby
2 km
Northing (m)
Easting (m)

Figure B.8

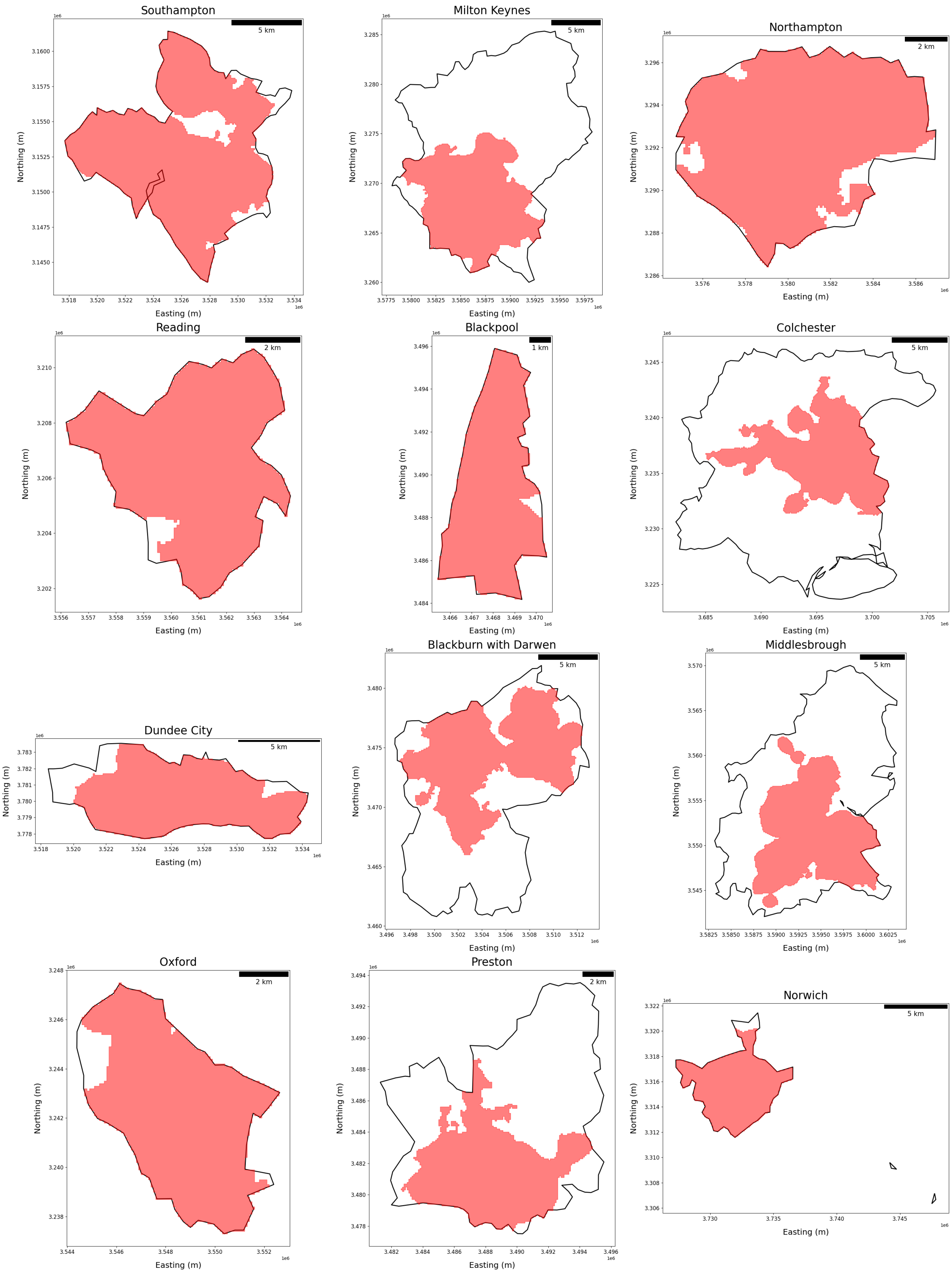

Southampton
5 km
Milton Keynes
5 km
Northampton
2 km
Reading
2 km
Blackpool
1 km
Colchester
5 km
Blackburn with Darwen
5 km
Middlesbrough
5 km
Dundee City
5 km
Oxford
2 km
Preston
2 km
Norwich
5 km
Northing (m)
Easting (m)

Figure B.9

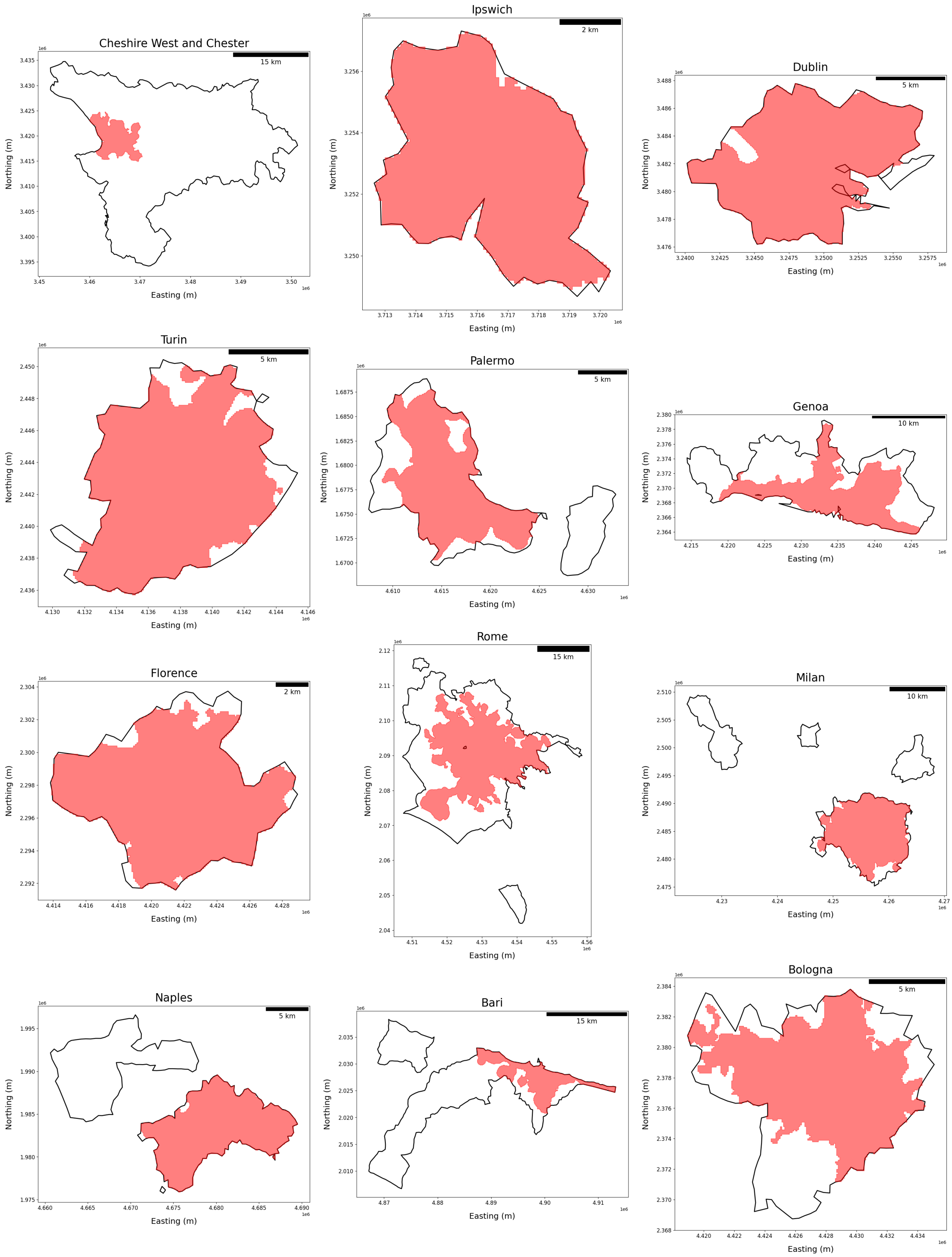
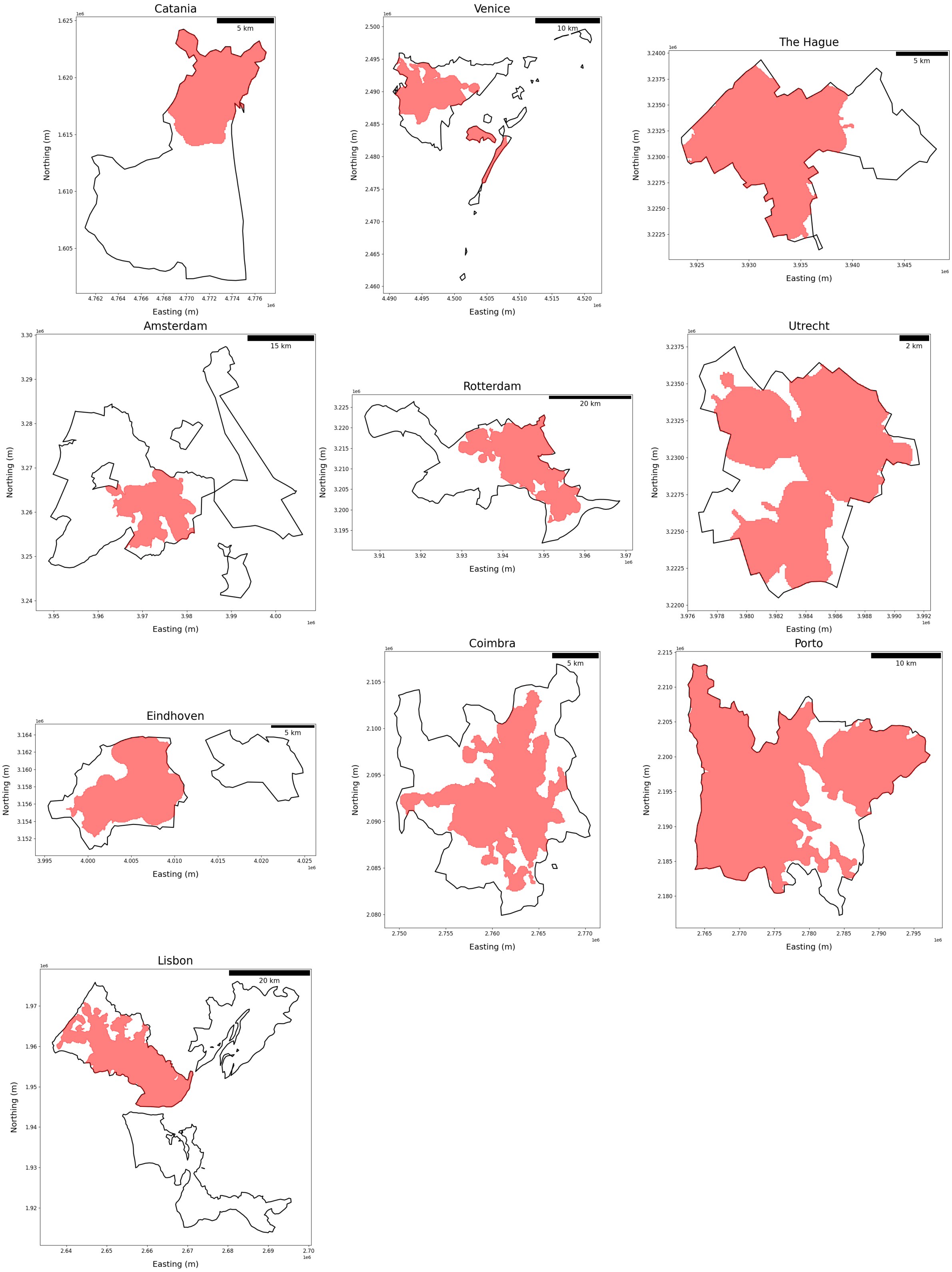

Cheshire West and Chester
15 km
Northing (m)
Easting (m)
Ipswich
2 km
Northing (m)
Easting (m)
Dublin
5 km
Northing (m)
Easting (m)
Turin
5 km
Northing (m)
Easting (m)
Palermo
5 km
Northing (m)
Easting (m)
Genoa
10 km
Northing (m)
Easting (m)
Florence
2 km
Northing (m)
Easting (m)
Rome
15 km
Northing (m)
Easting (m)
Milan
10 km
Northing (m)
Easting (m)
Naples
5 km
Northing (m)
Easting (m)
Bari
15 km
Northing (m)
Easting (m)
Bologna
5 km
Northing (m)
Easting (m)

Figure B.10



Catania
5 km
Venice
10 km
The Hague
5 km
Amsterdam
15 km
Rotterdam
20 km
Utrecht
2 km
Eindhoven
5 km
Coimbra
5 km
Porto
10 km
Lisbon
20 km
Northing (m)
Easting (m)

Figure B.11

C

Similarity Analysis Results

Table C.1: Results for the similarity analysis for the cities included in the study

City	$\widetilde{MI}_{adj}$	MI	$\widetilde{E}(MI)$	$s^2(MI)$	$CI^{95\%}_{lower}$	$CI^{95\%}_{upper}$	$Quantile$
Aachen	0.039	0.851	0.761	0.0064	0.754	0.768	0.912
Aberdeen	0.070	1.350	1.238	0.0273	1.223	1.253	0.718
Amsterdam	0.049	1.794	1.679	0.0073	1.672	1.687	0.946
Augsburg	0.201	1.561	1.229	0.0326	1.213	1.245	0.998
Barcelona	-0.033	1.410	1.460	0.0155	1.449	1.471	0.258
Bari	0.015	0.296	0.266	0.0042	0.260	0.272	0.658
Berlin	0.026	1.745	1.679	0.0023	1.675	1.683	0.95
Bilbao	0.004	0.848	0.841	0.0163	0.830	0.852	0.442
Blackburn with Darwen	0.015	1.148	1.114	0.0057	1.107	1.120	0.622
Blackpool	0.014	0.609	0.586	0.0270	0.572	0.601	0.422
Bologna	0.011	0.845	0.825	0.0076	0.818	0.833	0.516
Bonn	0.055	1.126	1.039	0.0084	1.031	1.047	0.836
Bordeaux	0.033	0.775	0.691	0.0060	0.684	0.698	0.89
Bremen	0.097	1.752	1.590	0.0150	1.580	1.601	0.95
Brighton and Hove	-0.006	0.576	0.586	0.0118	0.577	0.596	0.406
Bristol	0.034	0.729	0.642	0.0076	0.634	0.649	0.864
Cambridge	0.059	0.688	0.555	0.0051	0.549	0.561	0.996
Cardiff	0.028	0.946	0.871	0.0069	0.864	0.878	0.844
Catania	-0.195	0.126	0.303	0.0122	0.293	0.312	0.076
Cheshire West and Chester	0.007	0.093	0.070	0.0004	0.068	0.072	0.87
Coimbra	0.016	0.290	0.250	0.0017	0.246	0.253	0.846
Colchester	0.011	0.729	0.708	0.0058	0.702	0.715	0.568
Cologne	0.045	2.088	1.994	0.0042	1.988	2.000	0.954
Coventry	0.020	1.200	1.149	0.0058	1.142	1.155	0.724

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Table C.1: Results for the similarity analysis for the cities included in the study (continued)

City	$\widetilde{MI}_{adj}$	MI	$\widetilde{E}(MI)$	$s^2(MI)$	$CI^{95\%}_{lower}$	$CI^{95\%}_{upper}$	$Quantile$
Derby	0.079	1.075	0.903	0.0165	0.891	0.914	0.956
Doncaster	0.002	0.198	0.192	0.0013	0.189	0.195	0.542
Dresden	-0.026	0.221	0.291	0.0014	0.287	0.294	0.05
Dublin	0.097	0.856	0.732	0.0241	0.718	0.746	0.788
Dundee City	0.102	0.720	0.567	0.0198	0.555	0.579	0.866
Dusseldorf	0.093	1.915	1.733	0.0081	1.725	1.741	0.99
Edinburgh	0.025	0.608	0.533	0.0045	0.527	0.539	0.894
Eindhoven	0.150	1.116	0.894	0.0220	0.881	0.907	0.994
Exeter	-0.020	0.501	0.529	0.0140	0.518	0.539	0.362
Florence	-0.075	0.682	0.776	0.0137	0.766	0.787	0.17
Frankfurt am Main	0.117	2.065	1.818	0.0080	1.810	1.826	1.0
Freiburg im Breisgau	0.217	1.282	0.964	0.0351	0.948	0.981	0.99
Genoa	-0.267	0.742	1.026	0.0116	1.016	1.035	0.024
Glasgow	0.003	1.117	1.105	0.0011	1.102	1.108	0.606
Grenoble	0.061	0.654	0.515	0.0102	0.506	0.524	0.926
Guildford	0.020	0.820	0.773	0.0104	0.764	0.782	0.616
Hamburg	-0.057	1.340	1.460	0.0032	1.455	1.465	0.03
Hanover	0.108	1.279	1.084	0.0188	1.072	1.096	0.97
Ipswich	0.027	0.350	0.285	0.0047	0.279	0.291	0.814
Karlsruhe	0.076	1.556	1.439	0.0161	1.428	1.450	0.822
Kingston upon Hull	0.008	0.858	0.842	0.0160	0.831	0.853	0.444
Leeds	-0.031	1.310	1.419	0.0010	1.416	1.422	0.0
Leicester	0.143	1.618	1.343	0.0220	1.330	1.356	0.998
Leipzig	0.017	0.271	0.215	0.0013	0.212	0.218	0.964
Lille	-0.018	0.448	0.505	0.0028	0.500	0.509	0.152
Lincoln	-0.002	0.083	0.087	0.0010	0.084	0.089	0.474
Lisbon	-0.082	1.334	1.472	0.0058	1.465	1.478	0.052
Liverpool	0.001	1.123	1.119	0.0010	1.116	1.122	0.48
London	0.005	2.054	2.033	0.0003	2.031	2.034	0.904
Lyon	-0.009	1.354	1.371	0.0111	1.362	1.381	0.37
Madrid	0.025	2.263	2.201	0.0035	2.196	2.206	0.846
Malaga	-0.019	1.134	1.166	0.0077	1.158	1.173	0.316
Manchester	-0.000	1.215	1.216	0.0005	1.214	1.218	0.418
Mannheim-Ludwigshafen	0.079	1.478	1.320	0.0129	1.310	1.330	0.966
Marseille	-0.151	0.668	0.895	0.0085	0.887	0.903	0.026
Medway	0.034	0.594	0.526	0.0102	0.518	0.535	0.732
Middlesbrough	0.051	1.000	0.870	0.0063	0.863	0.877	0.984

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Table C.1: Results for the similarity analysis for the cities included in the study (continued)

City	$\widetilde{MI}_{adj}$	MI	$\widetilde{E}(MI)$	$s^2(MI)$	$CI^{95\%}_{lower}$	$CI^{95\%}_{upper}$	$Quantile$
Milan	0.038	1.182	1.107	0.0101	1.098	1.116	0.786
Milton Keynes	0.093	0.975	0.771	0.0096	0.763	0.780	1.0
Montpellier	0.047	0.411	0.300	0.0044	0.295	0.306	0.974
Muenster	0.076	1.390	1.243	0.0139	1.233	1.254	0.918
Munich	0.071	1.610	1.476	0.0101	1.468	1.485	0.942
Nantes	0.036	0.498	0.388	0.0030	0.383	0.393	0.996
Naples	-0.141	0.124	0.272	0.0050	0.266	0.278	0.03
Newcastle upon Tyne	-0.001	1.000	1.003	0.0026	0.998	1.007	0.428
Nice	0.017	1.144	1.116	0.0099	1.107	1.125	0.554
Northampton	0.037	0.823	0.728	0.0088	0.720	0.737	0.856
Norwich	0.036	0.720	0.645	0.0071	0.637	0.652	0.832
Nottingham	0.039	1.194	1.113	0.0180	1.101	1.124	0.684
Nuremberg	0.058	1.321	1.173	0.0046	1.167	1.179	1.0
Oxford	-0.006	0.621	0.633	0.0073	0.625	0.640	0.388
Palermo	0.035	0.258	0.183	0.0019	0.179	0.187	0.984
Paris	-0.002	1.819	1.826	0.0007	1.824	1.828	0.374
Plymouth	-0.009	0.420	0.435	0.0140	0.425	0.445	0.398
Porto	0.003	0.626	0.617	0.0005	0.615	0.619	0.622
Portsmouth	0.045	0.944	0.862	0.0116	0.853	0.872	0.76
Preston	0.041	0.914	0.839	0.0122	0.829	0.849	0.744
Reading	0.103	1.046	0.866	0.0284	0.851	0.881	0.89
Rennes	0.049	0.647	0.508	0.0062	0.502	0.515	0.992
Rome	-0.062	1.680	1.785	0.0072	1.778	1.793	0.106
Rotterdam	0.140	1.632	1.318	0.0124	1.308	1.327	1.0
Rouen	-0.128	0.457	0.669	0.0061	0.662	0.675	0.008
Ruhr	0.022	1.904	1.839	0.0012	1.835	1.842	0.992
Saarbrucken	0.027	1.063	1.020	0.0190	1.007	1.032	0.564
Saint-Etienne	-0.039	0.520	0.557	0.0276	0.542	0.572	0.376
Saragossa	0.072	1.372	1.187	0.0110	1.178	1.196	0.994
Seville	0.053	1.063	0.935	0.0115	0.925	0.944	0.938
Sheffield	0.005	1.467	1.453	0.0021	1.449	1.457	0.598
Southampton	0.081	1.518	1.349	0.0135	1.339	1.359	0.976
Stoke-on-Trent	0.016	0.859	0.815	0.0051	0.809	0.821	0.718
Strasbourg	0.056	1.154	1.009	0.0068	1.001	1.016	0.994
Stuttgart	-0.191	1.473	1.755	0.0171	1.743	1.766	0.032
Sunderland	-0.006	0.093	0.109	0.0009	0.106	0.111	0.316
Swansea	0.010	0.238	0.210	0.0016	0.206	0.213	0.732

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Table C.1: Results for the similarity analysis for the cities included in the study (continued)

City	$\widetilde{MI}_{adj}$	MI	$\widetilde{E}(MI)$	$s^2(MI)$	$CI^{95\%}_{lower}$	$CI^{95\%}_{upper}$	$Quantile$
The Hague	0.033	1.338	1.288	0.0109	1.279	1.297	0.682
Toulon	-0.038	0.751	0.801	0.0117	0.791	0.810	0.236
Toulouse	0.044	1.028	0.926	0.0098	0.917	0.935	0.892
Turin	0.031	0.613	0.567	0.0136	0.557	0.578	0.598
Utrecht	0.071	1.029	0.844	0.0065	0.837	0.851	1.0
Valencia	0.101	1.624	1.435	0.0190	1.423	1.447	0.97
Venice	0.034	1.340	1.276	0.0094	1.268	1.285	0.716
West Midlands urban area	-0.003	1.556	1.566	0.0012	1.563	1.569	0.332

D

Urban Fragmentation and Segregation Measures

SPB is bounded between zero and one, with higher values indicating more fragmentation. For m_{eff}, higher values indicate a lower degree of fragmentation. Higher values of IFI indicate higher fragmentation.

$$SPB = 1 - \sum_{i=1}^{n} \left(\frac{A_i}{A_{pc}} \right)^2 \tag{D.1}$$

- A_{pc}... Total number of populated cells in the AUC
- A_i... Number of populated in fragment i

$$m_{eff} = \frac{1}{A_{pc}} \cdot \sum_{i=1}^{n} A_i^2 \tag{D.2}$$

- A_{pc}... Total number of populated cells in the AUC
- A_i... Number of populated in fragment i

$$IFI = \frac{(\sum_{i=1}^{n} L_i \cdot O_i) \cdot N_g \cdot P_g}{A_g} \tag{D.3}$$

- L_i... Total length of infrastructure type i
- O_i... Occlusion coefficient for infrastructure type i [1]
- N_g... Total number of fragments in the AUC
- P_g... Perimeter of the AUC
- A_g... Total area of the AUC

[1] We followed similar coefficients to those used by Ledda and De Montis (2019). 1 for motorways and railways. 0.5 for primary and trunk roads. 0.3 for canals and light-rail.

Both H and D are bounded between zero and one, with higher values indicating more segregation.

$$H = 1 - \frac{1}{T \cdot E} \sum_{j=1}^{J} t_j \sum_{m=1}^{M} \pi_{jm} \log_M \frac{1}{\pi_{jm}} \tag{D.4}$$

$$E = \sum_{m=1}^{M} \pi_m \log_M \frac{1}{\pi_m} \tag{D.5}$$

- T... Total population in the AUC
- t_j... Population in spatial unit j
- E... Total entropy in the AUC
- π_{jm}... Proportion of group m in spatial unit j
- M... Number of (demographic) groups

$$D = \frac{1}{2} \sum_{i=1}^{N} \left| \frac{X_i}{X_{total}} - \frac{Y_i}{Y_{total}} \right| \tag{D.6}$$

- X_i... Population of group X in unit i
- X_{total}... Total population of group X
- Y_i... Population of group Y in unit i
- Y_{total}... Total population of group Y

Table D.1: Urban fragmentation and segregation levels for cities in the study

City	SPB	IFI	m_{eff}	H	DI
Aachen	0.939	2.817e+03	2.219e+02	0.096	0.324
Aberdeen	0.922	1.788e+03	5.559e+02	0.080	0.317
Amsterdam	0.972	2.9998e+04	2.744e+02	0.093	0.307
Augsburg	0.923	1.392e+03	2.834e+02	0.102	0.315
Barcelona	0.911	1.4666e+04	1.468e+03	0.132	0.366
Bari	0.860	1.504e+03	5.829e+02	0.139	0.471
Berlin	0.978	3.2404e+04	8.382e+02	0.112	0.358
Bilbao	0.858	2.971e+03	4.225e+02	0.154	0.444
Blackburn with Darwen	0.948	6.112e+03	3.675e+02	0.222	0.559
Blackpool	0.860	4.736e+02	4.598e+02	0.041	0.254
Bologna	0.836	4.553e+03	1.015e+03	0.076	0.299
Bonn	0.882	3.786e+03	7.752e+02	0.089	0.305
Bordeaux	0.949	5.270e+03	8.976e+02	0.065	0.302
Bremen	0.946	8.234e+03	5.213e+02	0.087	0.310
Brighton and Hove	0.836	8.473e+02	8.329e+02	0.038	0.197

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Table D.1: Urban fragmentation and segregation levels for cities in the study (continued)

City	SPB	IFI	m_{eff}	H	DI
Bristol	0.940	3.953e+03	5.594e+02	0.108	0.339
Cambridge	0.926	5.539e+02	2.250e+02	0.024	0.153
Cardiff	0.951	6.037e+03	4.256e+02	0.105	0.352
Catania	0.178	1.269e+02	2.597e+03	0.174	0.496
Cheshire West and Chester	0.940	3.377e+03	2.178e+02	0.036	0.225
Coimbra	0.889	4.481e+03	8.909e+02	0.035	0.208
Colchester	0.835	1.747e+03	9.643e+02	0.089	0.297
Cologne	0.974	3.759e+04	4.759e+02	0.102	0.333
Coventry	0.958	7.899e+03	5.505e+02	0.141	0.403
Derby	0.930	2.641e+03	4.659e+02	0.146	0.428
Doncaster	0.966	6.488e+03	2.981e+02	0.111	0.406
Dresden	0.920	4.385e+03	1.117e+03	0.144	0.430
Dublin	0.810	1.254e+02	1.969e+03	0.147	0.421
Dundee City	0.848	5.006e+02	6.132e+02	0.130	0.417
Dusseldorf	0.966	1.075e+04	3.322e+02	0.087	0.303
Edinburgh	0.958	3.167e+03	3.944e+02	0.074	0.291
Eindhoven	0.860	1.066e+03	7.447e+02	0.097	0.327
Exeter	0.754	4.108e+02	8.421e+02	0.084	0.327
Florence	0.795	1.101e+03	1.379e+03	0.076	0.290
Frankfurt am Main	0.973	1.366e+04	2.274e+02	0.061	0.250
Freiburg im Breisgau	0.866	1.109e+03	3.527e+02	0.080	0.286
Genoa	0.815	5.793e+03	1.182e+03	0.154	0.433
Glasgow	0.986	5.787e+04	3.651e+02	0.190	0.491
Grenoble	0.915	2.787e+03	3.673e+02	0.041	0.222
Guildford	0.933	2.946e+03	2.392e+02	0.058	0.226
Hamburg	0.945	2.105e+04	1.299e+03	0.098	0.323
Hanover	0.923	1.996e+03	5.376e+02	0.092	0.313
Ipswich	0.905	8.159e+02	3.433e+02	0.061	0.261
Karlsruhe	0.926	4.362e+03	3.084e+02	0.071	0.274
Kingston upon Hull	0.893	9.632e+02	6.717e+02	0.158	0.477
Leeds	0.989	1.875e+05	7.042e+02	0.203	0.515
Leicester	0.951	1.998e+03	3.239e+02	0.146	0.396
Leipzig	0.959	2.684e+03	3.171e+02	0.144	0.414
Lille	0.960	1.295e+04	6.861e+02	0.084	0.341
Lincoln	0.830	2.433e+02	4.452e+02	0.047	0.262
Lisbon	0.897	3.056e+04	2.889e+03	0.052	0.237
Liverpool	0.968	3.697e+04	8.028e+02	0.174	0.458

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Table D.1: Urban fragmentation and segregation levels for cities in the study (continued)

City	SPB	IFI	m_{eff}	H	DI
London	0.997	4.330e+05	3.662e+02	0.071	0.256
Lyon	0.931	1.150e+04	1.020e+03	0.056	0.261
Madrid	0.984	2.728e+05	8.702e+02	0.125	0.371
Malaga	0.888	1.130e+04	6.828e+02	0.179	0.482
Manchester	0.994	2.384e+05	4.522e+02	0.191	0.490
Mannheim-Ludwigshafen	0.950	8.579e+03	3.331e+02	0.090	0.318
Marseille	0.830	5.814e+03	2.716e+03	0.099	0.352
Medway	0.880	1.940e+03	7.860e+02	0.065	0.291
Middlesbrough	0.948	5.167e+03	5.134e+02	0.159	0.455
Milan	0.920	6.883e+03	939.011	0.120	0.367
Milton Keynes	0.914	2.533e+03	7.740e+02	0.055	0.239
Montpellier	0.910	1.446e+03	5.650e+02	0.067	0.269
Muenster	0.948	1.619e+03	2.652e+02	0.127	0.381
Munich	0.942	6.801e+03	870.215	0.069	0.269
Nantes	0.952	5.031e+03	560.315	0.065	0.300
Naples	0.506	1.674e+03	4.152e+03	0.201	0.562
Newcastle upon Tyne	0.981	2.093e+04	412.248	0.186	0.482
Nice	0.870	1.330e+04	2.097e+03	0.067	0.276
Northampton	0.949	2.971e+03	330.114	0.056	0.251
Norwich	0.907	947.246	324.732	0.071	0.265
Nottingham	0.937	3.181e+03	416.570	0.088	0.314
Nuremberg	0.967	1.026e+04	288.746	0.094	0.315
Oxford	0.867	1.111e+03	444.845	0.024	0.144
Palermo	0.847	1.917e+03	1.236e+03	0.259	0.605
Paris	0.992	3.951e+05	889.718	0.061	0.266
Plymouth	0.853	863.941	1.026e+03	0.076	0.343
Porto	0.973	6.838e+04	1.130e+03	0.045	0.250
Portsmouth	0.880	2.889e+03	681.698	0.080	0.323
Preston	0.887	2.023e+03	507.265	0.118	0.382
Reading	0.889	1.094e+03	392.194	0.073	0.279
Rennes	0.951	3.520e+03	213.803	0.047	0.260
Rome	0.950	4.105e+04	2.185e+03	0.176	0.400
Rotterdam	0.965	1.609e+04	562.510	0.149	0.409
Rouen	0.824	2.280e+03	1.029e+03	0.065	0.271
Ruhr	0.988	1.616e+05	573.810	0.123	0.374
Saarbrucken	0.893	3.002e+03	404.112	0.092	0.322
Saint-Etienne	0.476	230.440	1.910e+03	0.047	0.244

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Table D.1: Urban fragmentation and segregation levels for cities in the study (continued)

City	SPB	IFI	m_{eff}	H	DI
Saragossa	0.967	1.872e+04	208.917	0.165	0.446
Seville	0.955	5.680e+03	317.934	0.212	0.543
Sheffield	0.979	4.494e+04	655.572	0.222	0.528
Southampton	0.957	5.976e+03	422.383	0.106	0.355
Stoke-on-Trent	0.955	6.641e+03	539.568	0.179	0.483
Strasbourg	0.960	6.312e+03	310.134	0.043	0.218
Stuttgart	0.754	4.056e+03	2.242e+03	0.074	0.279
Sunderland	0.925	3.226e+03	585.987	0.174	0.481
Swansea	0.924	3.916e+03	747.170	0.125	0.404
The Hague	0.882	5.144e+03	996.654	0.125	0.366
Toulon	0.830	2.161e+03	1.882e+03	0.098	0.394
Toulouse	0.947	7.808e+03	858.175	0.053	0.226
Turin	0.831	743.070	1.471e+03	0.139	0.407
Utrecht	0.954	1.072e+04	266.506	0.118	0.360
Valencia	0.944	1.499e+04	421.411	0.149	0.413
Venice	0.930	8.103e+03	307.496	0.143	0.419
West Midlands urban area	0.991	1.004e+05	589.507	0.175	0.462