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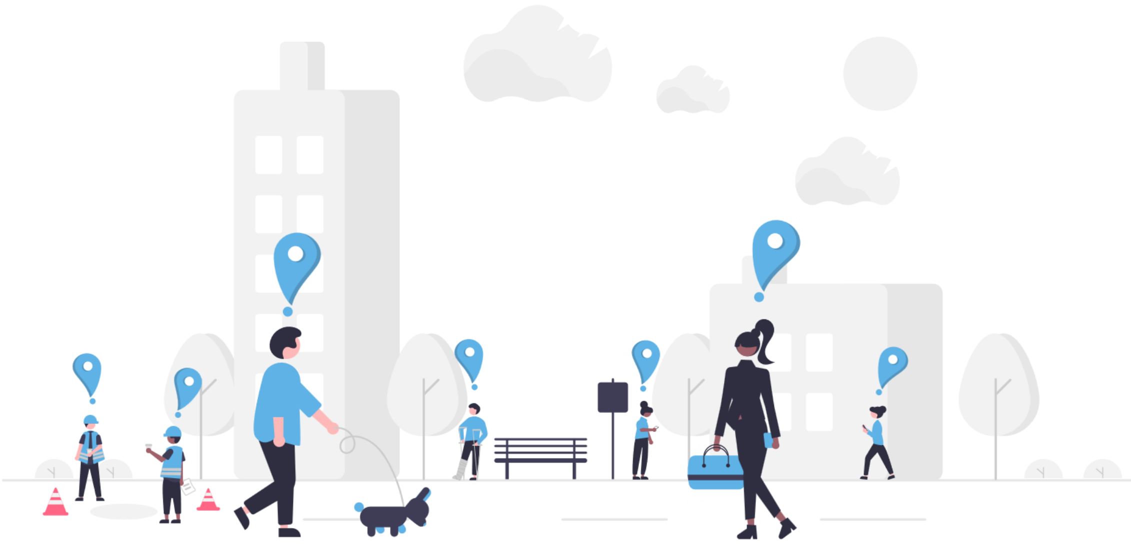

Zooming in on disparities of quality of life in urban areas

A fine spatial scale perspective on Brussels

Doctoral dissertation presented by

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in fulfilment of the requirements for the degree of doctor in sciences

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Merci !

C’est rare, dans une vie, d’avoir l’occasion d’écrire des remerciements. Et pourtant, selon une tradition bien ancrée en Géographie à l’UCLouvain, il est d’usage d’insérer une petite « thèse dans la thèse » pour remercier celles et ceux qui ont rendu ce long chemin possible. Je ne manquerai donc pas à la tradition. Après sept ans et demi de doctorat, j’ai accumulé un sacré stock de gratitude.

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1 Introduction

1.1. Quality of life in urban areas

By 2050, projections state that 68% of the global population will live in urban areas (United Nations, 2019). These areas offer numerous advantages to residents, such as proximity to services, employment opportunities, and more efficient transportation systems. However, urban environments also expose individuals to harmful factors, including air pollution, noise, a lack of green spaces, and predominantly sedentary lifestyles (Nieuwenhuijsen, 2020). In addition, the automobile-centric urban planning policies from the 1950s and 1960s, rooted in modernist ideals, prioritized functionality and vehicular accessibility. This approach transformed urban areas, focusing on individual buildings rather than cohesive public spaces and neglecting the role of cities as places for social interaction and community well-being (Gehl, 1987, 2010; Jacobs, 1961). The carbon footprint of a city is strongly shaped by its morphology: compact, high-density cities tend to have lower per capita emissions than sprawling, car-dependent urban forms (Sovacool and Brown, 2010). After decades of urban planning focused on functionality and separated from people's daily experience of living in the city, it has become obvious that this cannot address all dimensions of what makes cities liveable, in the sense that all inhabitants can live healthy and fulfilling lives. Current challenges of pollution, climate change, and chronic diseases, combined with emerging opportunities data- and method-wise have created an opportunity as well as a need to understand more finely urban living from a fine spatial scale perspective.

The dominant concerns regarding the urban environment's critical role in well-being and health have evolved over time. The management of cities' physical environments from a public health perspective has a long history. As early as the Middle Ages, efforts included waste disposal, the establishment of public latrines, and the enforcement of sanitation regulations (Rodger, 2019). Later, early hygienist social movements linked the poor living conditions of the urban working class to the degraded environments of industrial cities. They framed urban environmental management as a public health priority, focusing on waste management, housing quality, sanitation, and access to clean water (Cornut et al., 2007). Over time, this perspective on health broadened, following a shift in public health priorities. As the burden of infectious diseases declined, attention expanded to encompass noncommunicable diseases and overall well-being, a shift reflected in the WHO's 1948 definition of health: "Health is a state of complete physical, mental, and social well-being and not merely the absence of disease or infirmity."

Contemporary public health increasingly addresses a broad spectrum of health outcomes influenced by urban environments. Mental health has become a growing focus in urban public health research, with studies highlighting the role of built environment features in contributing to stress, anxiety, sleep disturbances, and overall psychological distress – particularly in relation to noise, lack of access to green spaces, or the pressures of high-paced urban living (Gruebner et al., 2017; Sullivan and Chang, 2011). In parallel, the concept of social health has gained recognition, encompassing dimensions such as social cohesion, perceived safety, and growing social inequalities – all of which shape population health outcomes in urban settings (Berke and Vernez-Moudon, 2014; Nieuwenhuijsen, 2020; Pacione, 2003).

In recent years, various approaches have emerged to better conceptualize the complex and evolving relationship between human health and the environment in general. It responds to contemporary challenges such as climate change, environmental degradation, emerging infectious diseases, and rising social and health inequalities. *One Health* promotes an integrated approach to health that recognizes the interdependence of human, animal, and ecosystems (One Health High-Level Expert Panel et al., 2022). *Planetary Health*, for its part, is based on the idea that human health depends on thriving natural systems but these are now in an unprecedented state of degradation (Whitmee et al., 2015). These paradigms challenge traditional disciplinary silos and call for a holistic and transdisciplinary understanding of health as embedded in complex socio-environmental systems. More connected to urban contexts, the notion of the *exposome* (Wild, 2005) has emerged to capture the totality of environmental exposures – physical, chemical, biological, and social – that individuals experience across the life course and how these exposures interact with biological mechanisms (Rappaport and Smith, 2010; Vineis and Barouki, 2022) (Figure 1.1). Since 70 to 90% of chronic disease risks are attributable to non-genetic factors, a better understanding of environmental determinants is essential, yet remain poorly measured and often underestimated in public health studies (Rappaport and Smith, 2010). Moreover, exposures are not randomly distributed but reflect shared social practices and environments – such as housing, workplaces, or neighbourhoods – leading to specific exposure profiles within certain populations (Vermeulen et al., 2020). In this thesis, particular attention is paid to the general external environment (Figure 1.1) – and more specifically to the urban social and physical contexts – which shape differentiated exposure profiles across urban populations.

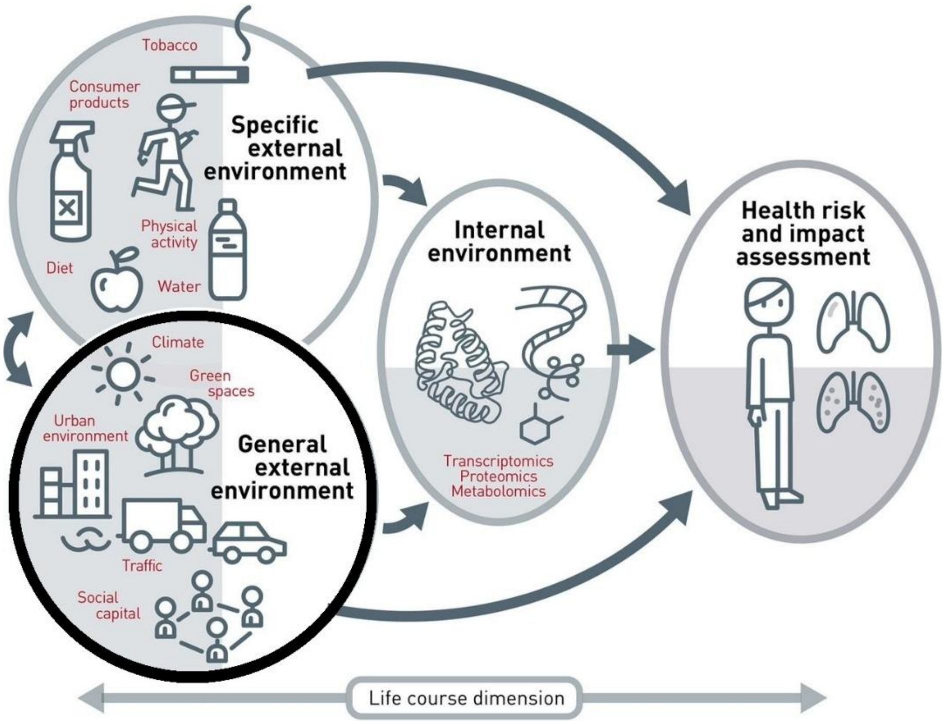


Figure 1.1. The exposome concept (Source: Vrijheid, 2014). The scope of this thesis is outlined in bold black.

Expanding the concept of health naturally leads to a broader discussion about quality of life, which extends beyond objective health indicators. Increasingly, healthcare scientific literature has sought to extend the traditional health outcome, recognizing that health status cannot be determined solely by measures of disease (Haraldstad et al., 2019). In urban planning, there is growing acknowledgment that understanding cities and quality of life is essential for sustainable development (Mouratidis, 2021; Pacione, 2003). Over the past decades, quality of life assessments have gained prominence, resulting in the development of numerous validated quality of life (Skevington et al., 2004; Ware and Sherbourne, 1992) or well-being (OECD, 2013; Ruggeri et al., 2020) measures across disciplines. However, quality of life remains a complex and multidimensional concept, interpreted in varied ways depending on the field of study (Haraldstad et al., 2019). In this thesis, we employ the concept of "quality of life" as defined by Felce and Perry (1995), as a combination of life conditions and satisfaction but emphasizes the need to take account of personal values, aspirations, and expectations (Figure 1.2). Their model identifies five key dimensions of quality of life: physical well-being, material well-being, social well-being, emotional well-being, and personal development and activity. According to their model, quality of life refers to “an overall general well-being that comprises objective descriptors and subjective evaluations of physical, material, social, and emotional well-being together with the extent of personal development and purposeful activity, all weighted by a personal set of values.” (Felce and Perry, 1995, page 60)

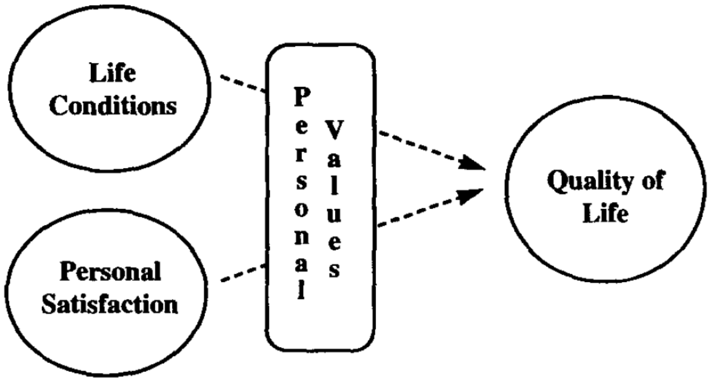


Figure 1.2. Conceptualization of quality of life as a combination of life conditions and satisfaction weighted by scale of importance (Source: Felce and Perry, 1995).

1.2. Disparities of quality of life in urban areas

Social disparities in quality of life present significant challenges in urban areas. The most vulnerable population groups are disproportionately exposed to degraded living environments, characterized for example by limited access to green spaces (Schüle et al., 2019), higher air pollution levels (Fairburn et al., 2019) and restricted access to essential services. These cumulative environmental burdens do not solely manifest in residential areas; they also extend to other key spaces of daily life, such as workplaces, transportation networks, and schools (Vallée et al., 2022). For instance, the cumulative environmental burdens that children from low socio-economic backgrounds experience at home are also present in schools (Bolte et al., 2010; Carrier et al., 2014).

Moreover, research indicates that exposure to environmental stressors – such as air pollution (Deguen and Zmirou-Navier, 2010; Landrigan et al., 2018) and limited access to green spaces (Rigolon et al., 2021) – tends to have more severe health impacts on disadvantaged populations. This heightened vulnerability is due to reduced access to alternative health-promoting resources (Deguen and Zmirou-Navier, 2010), pre-existing health conditions associated with socio-economic

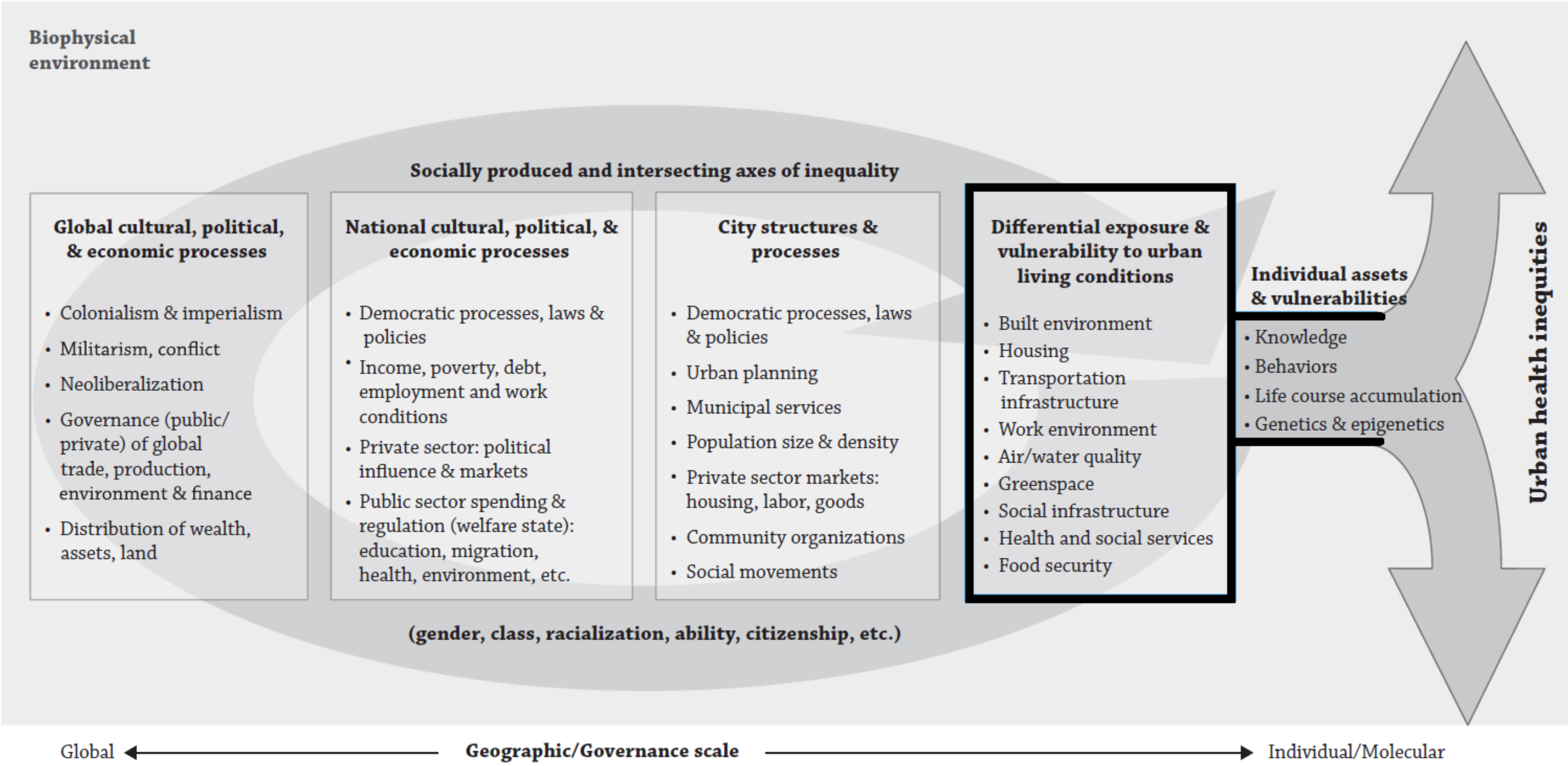


Figure 1.3. A framework for understanding the political and intersectional production of urban health inequities (Source: Brisbois et al., 2019). The scope of this thesis is outlined in bold black.

deprivation (O'Neill et al., 2003) and their greater dependence on their immediate urban environment. Their reduced mobility and limited geographic reach around their homes (Vallée et al., 2016) make them especially vulnerable to local environmental conditions. Wealthier populations, in contrast, are often better equipped to buffer the effects of detrimental exposure. They may rely on protective measures, such as air purifiers or superior healthcare; their broader living environments, including access to second homes or vacations, provide respite from urban pressures; or they possess greater knowledge and time to engage in health-promoting activities like exercise (Deguen and Zmirou-Navier, 2010).

To better understand the production of urban health inequities, Brisbois et al (2019) have proposed an analytical framework (Figure 1.3) that hierarchizes determinants across different scales – from deep-rooted causes such as colonialism, global financial structures, and militarism, to national and municipal institutions, and finally to urban living conditions and individual-level determinants. This thesis focuses specifically on proximal determinants (highlighted in bold black in the Figure 1.3), such as the characteristics of the immediate urban environment. Nevertheless, the conceptual framework serves as a reminder that these proximal factors are embedded within a broader, multi-scalar system of structural and historical forces.

1.3. A fine spatial scale perspective

The effect of urban environments on health is observed at multiple levels, ranging from broad social and economic policies to individual determinants (Kaplan, 2004; Rao et al., 2007) (Figure 1.4). This underscores the multi-scalar character of urban health and the need to examine its effects across different spatial and social scales (Galea et al., 2019). In this thesis, the focus is placed on proximal determinants, operating at levels close to the individual – ranging from the personal and household scale to the immediate living environment (Figure 1.4), including the home, the street, and the neighbourhood.

The association between urban environments and quality of life in a fine spatial scale perspective was initially explored through in-situ observations, interviews, and expert analyses (e.g. Gehl, 1987; Jacobs, 1961) and remains a key focus in contemporary research (e.g. Bereitschaft, 2017; Gehl and Svarre, 2013). Over time, other disciplines, such as psychology, contributed by designing experiments to study human responses to urban stimuli (e.g. Asgarzadeh *et al.*, 2012; Tyrväinen *et al.*, 2014). Simultaneously, fields like epidemiology, geography, and related disciplines expanded these inquiries to larger scales, with quantitative applied research examining the relationship between urban environments and well-being at the neighbourhood, city, and even national extent (e.g. Koo *et al.*, 2022; Lobaccaro *et al.*, 2021; Yang *et al.*, 2023).

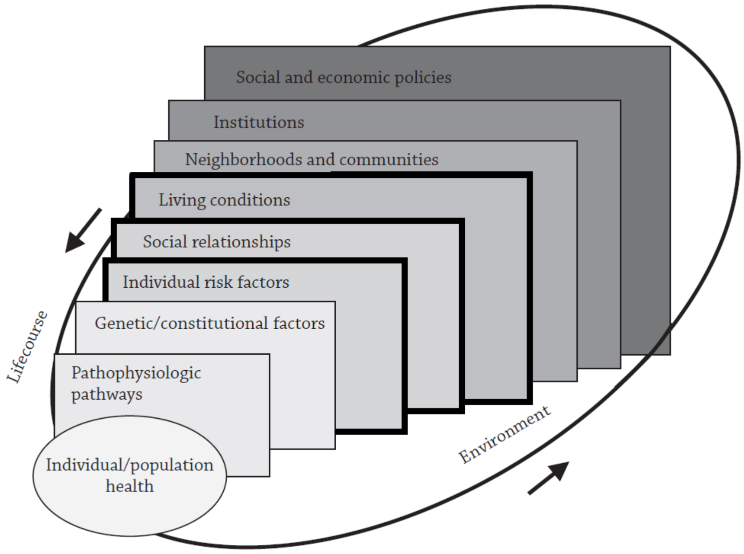


Figure 1.4. Levels of influence on the health of populations (Source: Ettman et al., 2019). The scope of this thesis is outlined in bold black.

This expansion has been made possible by the increasing availability and accessibility of large high-resolution datasets, allowing for the study of urban phenomena with greater spatial resolution. The transition from qualitative to quantitative and computational turn in human sciences was slow at first but exploded last decades (Lazer et al., 2009, 2020), moving from limited and costly data collection to an era of data abundance, albeit with persistent challenges of access, quality, and scope (Kitchin, 2013). “Big data” now plays a significant role in geography, offering diverse new data sources that extend beyond traditional government-generated information (Ferreira and Vale, 2024). However, the choice of spatial unit remains a central methodological issue.

A key challenge in this context lies in how spatial units shape both measurement and interpretation. Conventional administrative units, such as statistical sectors, are often used for practical reasons, notably their alignment with census and socio-demographic datasets. In this thesis, statistical sectors from Statbel are used in this sense: they have been created to reflect socio-economic, urban, and morphological characteristics. Although they are not centred on individuals’ places of residence, these “territorial neighbourhoods” can offer relevant estimations of access to local resources particularly when they capture long-standing social divisions (Vallée and Shareck, 2014). However, they may fall short in representing the lived experience of residents, especially for analyses focused on individual-level exposure (Chaix et al., 2009).

To address such limitations, many studies in environmental epidemiology rely on "ego-centred neighbourhoods" – typically represented by circular buffers around the residence – which aim to capture the local exposure area of individuals. Yet this approach simplifies accessibility by assuming spatial isotropy, ignoring the actual configuration of the street network and the fact that every portion of space is not equally reachable (Chaix et al., 2009). Moreover, it neglects the social and spatial mechanisms underlying unequal exposure: socially disadvantaged groups are more likely to have constrained spatial practices and reduced ability to benefit from proximal benefits (Vallée et al., 2022). Furthermore, non-residential environments are often overlooked (Chaix et al., 2009), despite their significant contribution to social disparities. Socially advantaged individuals tend to interact with broader areas around their daily activity locations, whereas disadvantaged populations typically experience more spatially constrained environments (Vallée et al., 2022).

Another alternative lies in considering the street as a relevant mid-level spatial unit (Harvey and Aultman-Hall, 2016). In contrast to the aerial perspective used in housing block analysis, streets offer a more human-centred view of the urban environment (Araldi and Fusco, 2019). They function as key social interfaces where neighbourly interactions take place (Grannis, 1998). Due to their spatial continuity and symbolic significance, streets are particularly well suited for capturing residents' relationships with their immediate surroundings. At an even finer scale, micro-scale indicators – such as architectural characteristics, building typologies, and visible vegetation – offer additional insights into the design and perceptual qualities of urban spaces.

In short, each spatial unit presents distinct strengths and limitations. Its selection should align with broader theoretical assumptions regarding what defines an individual's environment depending on the type of exposure under investigation. For example, **statistical sectors** may be more suited for capturing social context, **circular buffers** for diffuse exposures like air pollution, **street segments** for behaviour-related features such as sidewalk availability, and **micro-scale units** for visually perceived elements like greenery. Moreover, the choice of spatial unit is frequently constrained by the availability and granularity of existing data.

This thesis aims to measure the urban environment and examine its association with quality of life at a fine spatial scale perspective, using the Brussels-Capital Region as a case study. However, when moving from theory to applied research, understanding this association presents a persistent challenge. A key difficulty lies in how socio-economic and environmental inequalities combine, complicating efforts to untangle the interconnections between urban physical environments, quality of life, and urban social environment. To address these challenges, this thesis takes advantage of emerging data sources that allow for a fine spatial scale characterization of the urban environment and provide insights into individual quality of life. Rather than privileging a single spatial logic, in this thesis, it mobilizes a variety of spatial units – including buffers, statistical sectors, and street segments – selected according to the research question and data constraints. These units are not treated as interchangeable, but as complementary representations of urban space, each offering distinct analytical strengths and limitations. The research draws on a wide array of data, combining traditional administrative sources, modelled outputs, and citizen-generated inputs – many of which were not initially intended for academic use.

1.4. Conceptual framework: pathway from urban liveability to quality of life

To ground applied research of this thesis within a theoretical framework, we propose a conceptual model linking the urban environment and the quality of life (Figure 1.5), which draws on established theories (Frank et al., 2019; Galea et al., 2005; Galea and Vlahov, 2005; Pacione, 2003). This framework first examines **Urban Liveability** (Pacione, 2003), which lies at the intersection of **Urban Physical Environment** and the **Urban Social Environment** (Galea and Vlahov, 2005). By shaping and modifying the **Behaviour** (***behavioural pathway***) or via direct exposure (***exposure pathway***) (Frank et al., 2019), Urban Liveability contributes to **Quality of Life in Urban Areas**, which in turn plays a crucial role in enhancing urban health by creating environments that support physical well-being, material well-being, social well-being, emotional well-being, and personal development and activity (Felce and Perry, 1995).

1.4.1. Urban Liveability

Urban liveability can be understood as the extent to which the urban environment promotes well-being, integrating both objective conditions and the subjective experiences and perceptions of residents (Pacione, 2003). It emerges from the interaction between the **Urban Physical Environment** and the **Urban Social Environment**, underscoring that the design of urban spaces must consider not only physical infrastructure but also the social fabric that animates them. A genuinely liveable urban environment thus requires the development of liveable communities, where physical and social environments are mutually reinforcing in fostering quality of life. The vibrancy and quality of public spaces are not determined solely by their physical form, but by the presence of people, activities, and social interactions that animate urban life (Gehl, 1987).

Figure 1.5. Conceptual framework of the thesis

Urban Physical Environment

The **Urban Physical Environment** is the landscape where public life takes place in cities. The physical aspect of the street shapes how city users perceive urban spaces and, ultimately, impacts their behaviour, activities, and well-being (Gehl, 1987; Jacobs, 1961). However, characterizing its quality is challenging. How is building heights perceived? How much green space is needed to support a good quality of life? While some recommended standards exist (Konijnendijk, 2023; WHO, 2021), they are often based on expert knowledge rather than empirical evidence. Yet, cities are complex systems, where urban health outcomes depend on numerous interactions and feedback loops (Galea and Vlahov, 2005). Predicting outcomes in urban planning is fraught with difficulties, and unintended consequences are common (Rydin et al., 2012). To navigate this complexity, the Urban Physical Environment can be broken down into several broad categories.

BUILT ENVIRONMENT. Cities, by definition, are largely man-made, making the built environments a central factor in creating quality spaces that significantly impact population health (Berke and Vernez-Moudon, 2014; Evans, 2003; Frank et al., 2019; Rao et al., 2007). For example, walkability has emerged as a determinant of physical activity. Elements such as street connectivity, land-use diversity, pedestrian infrastructure, and perceived safety have consistently been associated with increased levels of walking and cycling in urban contexts (Lo, 2009; Shields et al., 2023). Conversely, car-oriented, fragmented, or aesthetically poor environments tend to discourage active mobility and contribute to sedentary behaviours, which are risk factors for obesity (Creatore et al., 2016) and cardiovascular disease (Westenhöfer et al., 2023). The quantification of urban spaces at fine spatial scale has become increasingly accessible through data collected by administrations, citizens (e.g. OpenStreetMap), street-level images (e.g. Google Street View), remote sensing technologies, and LiDAR. A significant challenge lies in leveraging this data to create meaningful indicators aligned with the specific research objectives. Several researchers have attempted to develop models with a pedestrian perspective, emphasizing the human experience of urban spaces (Araldi and Fusco, 2019; Harvey et al., 2017).

GREEN SPACES. The role of urban vegetation in enhancing quality of life is a widely discussed topic in the literature (Konijnendijk, 2023; Lee and Maheswaran, 2011; White et al., 2021), though some perspectives critically examine how discourses on urban nature, often framed as inherently positive and socially beneficial, tend to obscure important questions about who actually benefits from greening initiatives and to what extent (Angelo, 2021). Vegetation data derived from satellite imagery predominate in the literature, serving as the primary method for large-scale urban vegetation analysis. Recently, there has been growing interest among researchers in using street-level images (e.g. Google Street View) to analyse vegetation and built-up indicators. These images offer realistic 3D representations of urban streets from a pedestrian's viewpoint (Gong et al., 2018; Li et al., 2015; Richards and Edwards, 2017). However, a key challenge with vegetation data is that the choice of the database can significantly impact modelling results (Le Texier et al., 2018; Trabelsi, 2020).

POLLUTION. Pollution, whether air or noise, is perhaps one of the most recognized challenges of urban areas. However, the urban environment not only generates pollution but can also exacerbate it through its physical design. For example, the street canyon effect, where narrow streets are bordered by tall buildings, amplifies noise levels at street level (Echevarria Sanchez et al., 2016). Additionally, urban canyons worsen air quality by limiting the dispersion of traffic-related pollutants (Vardoulakis et al., 2003).

OTHER. Other features of the Urban Physical Environment, not mentioned above, also influence the quality of life. For instance, the urban heat island effect, where densely built-up areas retain heat, leads to higher temperatures compared to surrounding rural areas (Heaviside et al., 2017). This phenomenon exacerbates health risks during heatwaves, particularly for vulnerable populations such as the elderly and individuals with pre-existing health conditions. As well, the disorder effect highlights how visible signs of neglect – such as litter, vandalism, or abandoned properties – can increase perceptions of insecurity and social disorder (Kelling and Wilson, 1982). This heightened sense of insecurity contributes to stress, discourages physical activity, and reduces the use of public spaces, thereby negatively affecting both mental and physical health (Frank et al., 2019; Lorenc et al., 2012).

Urban Social Environment

The **Urban Social Environment** is a key determinant of quality of life and influence it through a multitude of pathways, shaping both individual behaviours and broader community well-being (Galea and Vlahov, 2005).

POPULATION CHARACTERISTICS. The characteristics of a population significantly influence its health outcomes. Vulnerable groups, such as older adults or economically disadvantaged populations, are more prone to health issues (Galea et al., 2005; Kirkbride et al., 2024). Additionally, factors such as education level, social background, and socio-economic status impact health literacy – the ability to access, understand, and use information to make informed health decisions.

SOCIAL RESSOURCES. Social resources refer to the networks, relationships, and social structures that can influence quality of life. These include informal social ties, social capital, and networks that provide support and cohesion (Galea and Vlahov, 2005). Social resources have both structural dimensions, referring to the size, connectivity, and characteristics of an individual’s social network, and functional dimensions, referring to the perceived quality of relationships and the specific emotional, instrumental, and informational support provided by network members (Drageset, 2021). Social resources contribute to better health outcomes by offering ongoing economic and social support and specific resources during times of stress (Drageset, 2021; Galea and Vlahov, 2005). It is associated with lower mortality, reduced crime, and improved self-reported health. In urban settings, the spatial proximity of social networks may amplify their role in shaping health behaviours and outcomes (Galea and Vlahov, 2005; Kirkbride et al., 2024).

SOCIAL DISORGANIZATION. Social disorganization refers to a community's inability to achieve shared values and maintain effective social control. It is characterized by weak or fragmented social networks – both informal, like friendships, and formal, like participation in organizations – and a lack of collective supervision over local issues (Sampson and Groves, 1989). Social disorganization, characterized by instability, disorder, and poor societal integration, creates an environment conducive to stress and adverse behaviours (Galea and Vlahov, 2005; Lorenc et al., 2012). This concept is closely related to that of anomie, which describes a broader breakdown of social cohesion and normative regulation, often resulting from the gap between societal expectations and individuals' actual means to achieve them (Merton, 1938).

INEQUALITY. Income inequality affects health not only through absolute income, but also as a reflection of the scale of social class stratification within a society. A large body of evidence supports a causal relationship between greater income inequality and worse health outcomes, including mental illness, violence, and reduced life expectancy. These effects are primarily mediated by psychosocial mechanisms – such as chronic stress, status anxiety, perceived inferiority, and weakened social cohesion – which operate across the entire population, not just among the poorest (Pickett and Wilkinson, 2015). This challenges purely materialist interpretations and points to the importance of relative position within social hierarchies. In urban contexts, the effects of inequality may be intensified by the physical proximity of wealth and poverty, a spatial pattern typical of many cities worldwide. Unlike rural areas where economic groups are more segregated, cities often concentrate contrasting living conditions side by side, making inequalities more visible and socially salient. As such, urban inequality may amplify health disparities not only through deprivation but also through daily exposure to relative disadvantage (Galea and Vlahov, 2005).

SPATIAL SEGREGATION. Inequalities are not just differences between individuals, but the result of social and spatial structures that shape them at different scales (Cottineau and Vallée, 2022). Spatial segregation acts as a key mechanism in this process, reinforcing these disparities rather than distributing them randomly. Environmental disparities are intrinsically linked to urban planning decisions, infrastructure development, and historical patterns of racial and socio-economic segregation (Coolsaet and Bullard, 2021). As a result, certain areas concentrate social disadvantages, creating self-reinforcing cycles where marginalized communities face poorer living conditions, reduced access to healthcare, lower-quality education, and fewer employment opportunities. These disparities are not static – they accumulate over time and can become intergenerational, as the spatial environment in which people live continues to shape their health trajectories, economic mobility, and overall well-being (Cottineau and Vallée, 2022).

1.4.2. Behaviour and Behavioural pathway

There are two pathways through which Urban Liveability impact Quality of Life. The first is direct (***exposure pathway***), where substances or stressors (or their positive counterparts) affect health or well-being directly, such as pollution-related illnesses or the restorative effects of green spaces. The second is indirect (***behavioural pathway***), acting through **Behaviour**, which either encourages or discourages behaviours that influence health and quality of life (Frank et al., 2019). When considering the overall quality of an urban environment, the geography and planning literature often relies on indirect measures of quality of life, such as community interaction, transportation activity, and economic factors (Harvey and Aultman-Hall, 2016). These elements can be grouped under the concept of Behaviour, as used in this context.

Collecting data on these aspects at a fine spatial scale perspective is challenging. Surveys and in-situ observations (Gehl and Svarre, 2013) are valuable but require significant time and manual data processing, limiting their applicability to small samples and reducing the generalizability of findings (Harvey and Aultman-Hall, 2016). “Big data” offers promising opportunities to overcome these limitations by providing indirect measures of Behaviour. Examples include applications like Fix My Street, which collect citizen complaints about street degradation (e.g. illegal dumping, vandalism, broken street lamps or blocked sewers), mobile phone data to investigate individual mobility patterns (Calabrese et al., 2013), and other innovative tools such as social media analysis or sensor-based technologies to monitor urban dynamics. While these methods provide scalable and complementary insights, they often rely on proxies and must be interpreted cautiously to ensure accurate and meaningful results (Ferreira and Vale, 2024; Kitchin, 2013).

Examples to illustrate the link between Urban Liveability, Quality of Life, and Behaviour can be found in the review by Frank et al. (2019), which synthesizes recent research on behavioural and exposure-based mechanisms linking the urban environment to various health outcomes. Their review reports, for instance, that higher residential density and land use mix are associated with greater walking and cycling rates; that proximity to green spaces promotes recreational physical activity and mental well-being; and that traffic-related pollution and unsafe street design are linked to increased risks of respiratory diseases and injuries. These findings emphasize how tangible urban features shape daily behaviour and perceived quality of life.

1.4.3. Quality of life in Urban Areas

Quality of Life in Urban Areas represents the outcomes of interactions between individuals and communities within their immediate urban environment. Unlike Urban Liveability, which describes the contextual conditions of the physical and social environment, Quality of Life in Urban Areas emphasis on how these conditions are perceived and experienced by individuals and communities. Drawing on Felce and Perry's (1995) multidimensional model, quality of life can be understood through five interrelated domains: physical well-being (ex. health and access to healthcare), material well-being (ex. housing quality, financial security), social well-being (ex. social networks, sense of belonging), emotional well-being (ex. mental health, life satisfaction), and personal development and activity (ex. education, leisure, and opportunities for meaningful engagement).

However, quantifying even just a part of quality of life on a large scale remains a significant challenge (Pacione, 2003). Approaches to quality of life vary depending on the field: while health sciences prioritize clinical indicators, social and environmental research often relies on perceived well-being measures, such as satisfaction and happiness outcomes (Lercher, 2003). Large-scale health surveys provide valuable insights through representative population samples, offering indicators of self-reported well-being, mental health, social cohesion, and life satisfaction. It is possible to access this data, located at the residential address, within strict conditions (Pelgrims et al., 2021). As discussed earlier, behaviour metrics – such as mobility patterns, levels of outdoor social interaction, and perceptions of safety – are often considered indirect indicators of quality of life.

1.5. Study area: the Brussels-Capital Region

The focus of this thesis is the Brussels-Capital Region (BCR). Belgium is divided into three administrative regions: the Brussels-Capital Region, Flanders, and Wallonia. The BCR, which contains the capital of Belgium, is centrally located within the country. The urban agglomeration of Brussels extends beyond the administrative boundaries of the BCR into the other two regions. However, there is no official definition of "urban agglomeration," as its delineation varies depending on the indicators and methods used (Thomas et al., 2012). In addition to its national role as capital, Brussels hosts the main institutions of the European Union, including the

European Commission, the Council of the European Union, and the European Parliament. This concentration of supranational institutions grants Brussels the status of Europe's political capital and has a profound impact on its urban form, economy, and socio-demographic dynamics.

For this research, we focus on the urban area within the administrative boundaries of the BCR. This choice minimizes issues related to inter-regional data comparisons and allows for the use of consistent and well-established datasets, such as the UrbIS vector database and remotely sensed vegetation data (Van de Voorde et al., 2010). Additionally, the Belgian Health Interview Survey (BHIS) (2008 and 2013) used in Chapter 3 included a larger sample size for the Brussels-Capital Region, further supporting the decision to limit the study to this area. For simplicity, the term Brussels will be used to refer to the BCR throughout this thesis.

The BCR is divided into 19 municipalities. It covers 161.38 km² and has 1.25 million inhabitants (source: Statistics Belgium), which means an average density of 7,697 inhabitants per square kilometre (Source: IBSA, 2024).

1.5.1. The Urban Physical Environment of Brussels

The **Urban Physical Environment** of Brussels is highly contrasted, shaped by its historical, geographical, and social structures (Figure 1.6). At its core lies the Pentagon, the historic centre, encircled by the boulevards that define its boundary. A notable physical and symbolic divide within the city is the Brussels Canal, which partially follows the Senne Valley. Over the centuries, the Senne River became an open sewer, leading to its canalization and vaulting in 1867 to prevent epidemics and flooding during high water levels. However, the blue network of waterways extends beyond the Senne, with two other tributary valleys – the Molenbeek and Woluwe – further shaping the city's landscape. Another defining spatial structure is the “poor crescent” (Figure 1.8), widely documented in the literature for both its social composition and environmental characteristics. The last major spatial structures are the Sonian Forest and the Bois de la Cambre, which are the largest and most significant green spaces in Brussels.

The **built environment** in Brussels and its spatial organization result from the long historical evolution of the city. The core of the city presents the oldest vestiges of the original settlement, enclosed within two successive ramparts (8th and 14th centuries) that can still be distinguished in the street pattern (Figure 1.6). Surrounding the historical centre, the first concentric expansion dates back to the 19th century (Figure 1.6) and is characterized by the typical Brussels townhouses: contiguous bourgeois family houses. These are recognizable by their limited width (~6 m) and “bel étage” (piano nobile), which is generally raised by 1.80 m above the sidewalk level. This creates a distance from the public street and also provides lighting in semi-basement spaces (Ledent, 2017). This type of building is still a particular feature and a specific part of the identity of the Brussels urban landscape.

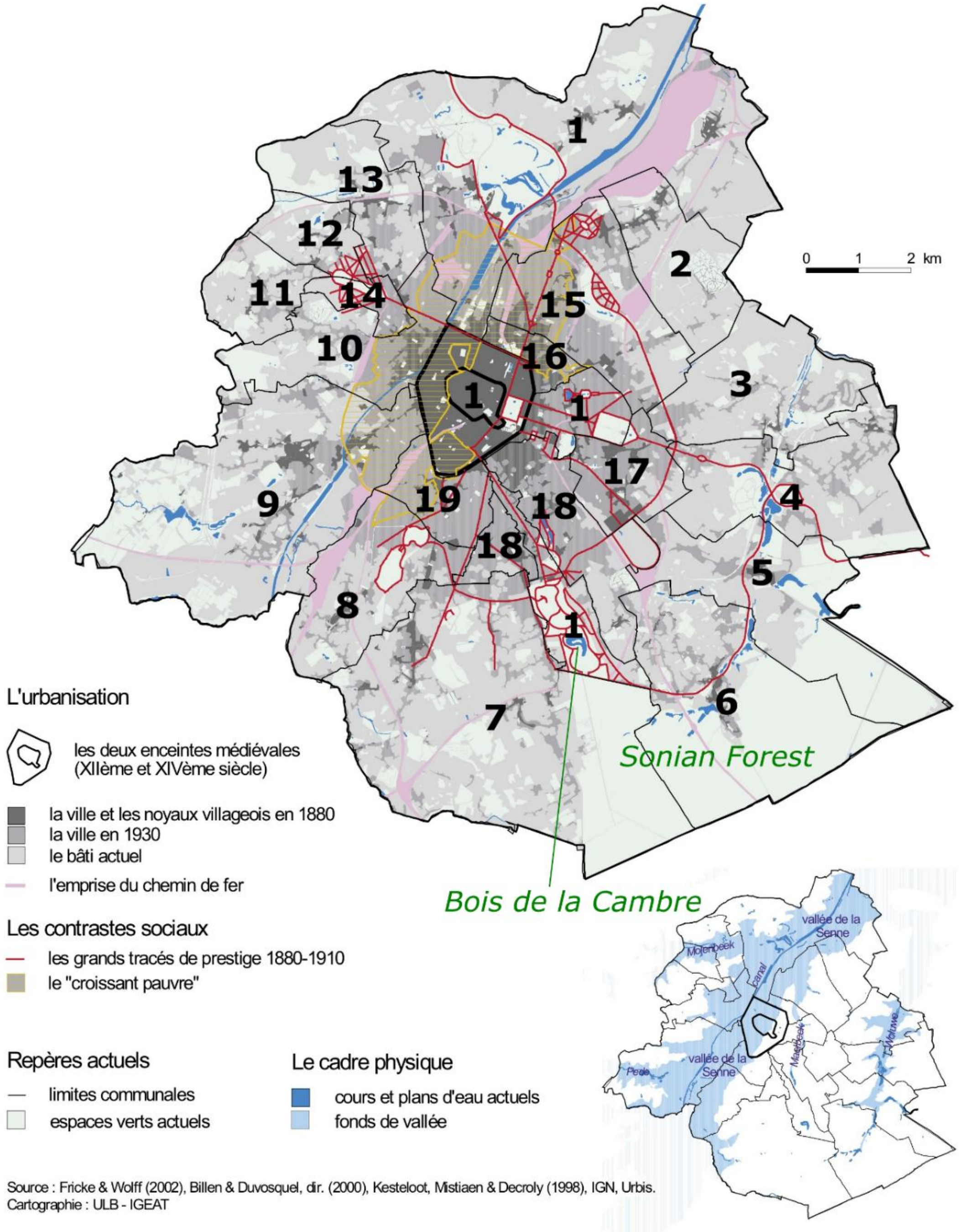


Figure 1.6. Historical legacies and socio-spatial contrasts in Brussels (modified from Roesems et al., 2006). Current municipalities: 1. Brussels, 2. Evere, 3. Woluwe-Saint-Lambert, 4. Woluwe-Saint-Pierre 5. Auderghem, 6. Watermael-Boitsfort, 7. Uccle, 8. Forest, 9. Anderlecht, 10. Molenbeek-Saint-Jean, 11. Berchem-Sainte-Agathe, 12. Ganshoren, 13. Jette, 14. Koekelberg, 15. Schaerbeek, 16. Saint-Josse-ten-Noode, 17. Etterbeek 18. Ixelles, 19. Saint-Gilles. Numbers may be repeated on the map to improve legibility and help locate fragmented or non-contiguous areas of the same municipality.

At the beginning of the 20th century, the development of garden districts (inspired by the English garden cities) shaped some of the fabric of the suburbs (Figure 1.7). Since that same period, Brusselization – the transformation of historical urban fabrics into business districts at the expense of residential areas, mixed neighbourhoods, and architectural heritage – has reshaped parts of the central city. This process, driven by the rapid growth of tertiary employment, led to the construction of new buildings and urban structures (Figure 1.9). This transformation has been accentuated by the establishment of European institutions, particularly in the Léopold district, where the concentration of EU-related offices has changed the urban morphology and increased pressure on the local property market (De Beule and Dessouroux, 2011).

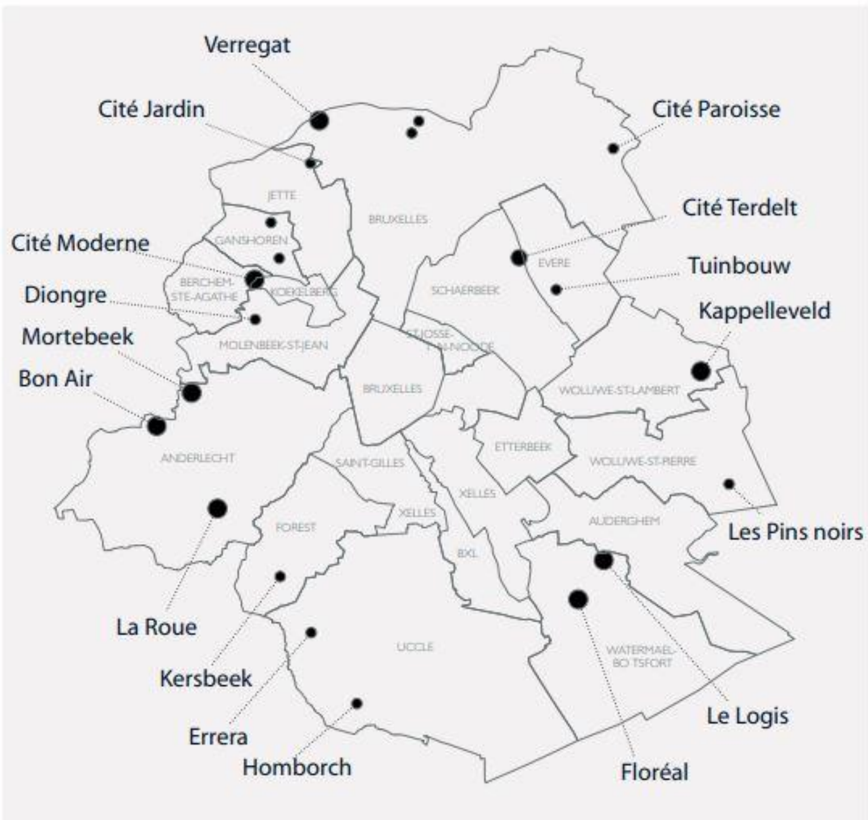


Figure 1.7. Garden cities built during the interwar period (Source: Eggericx and Hanosset, 2003).

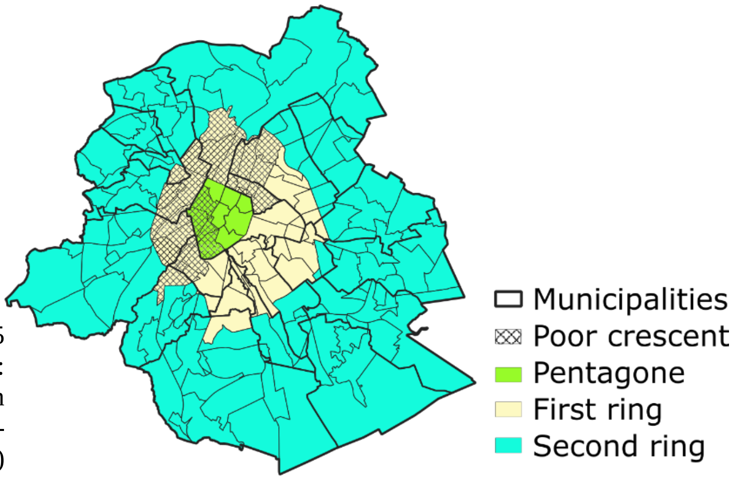


Figure 1.8. Map of 145 Brussels neighbourhoods: poor crescent and urban rings (Hermia and Treutens, 2021)

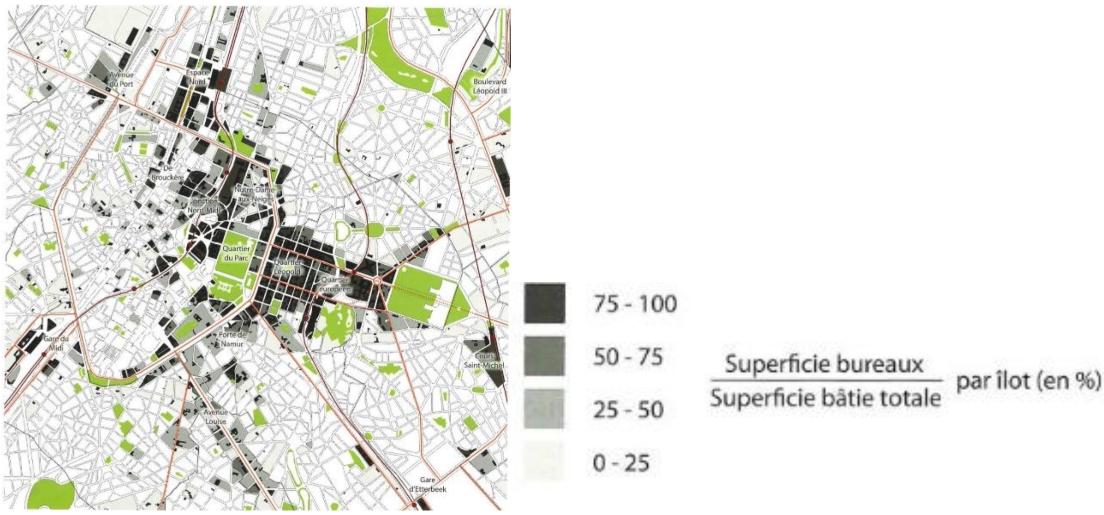


Figure 1.9. Office buildings density in the centre of Brussels (Source: De Beule and Dessouroux, 2011)

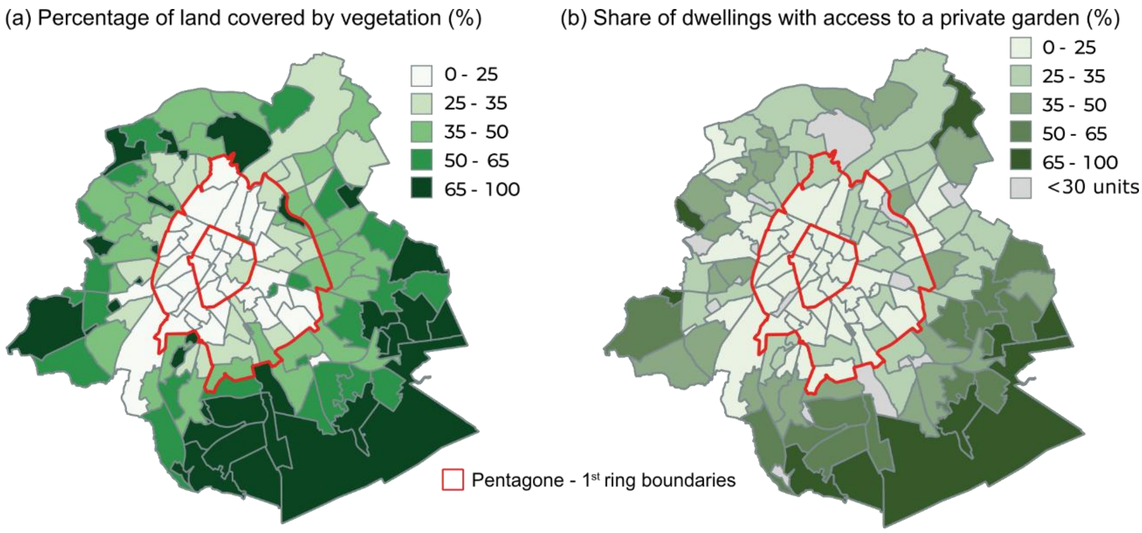


Figure 1.10. Distribution of vegetation in the Brussels-Capital Region: (a) share of land covered by vegetation in 2020 and (b) share of dwellings with access to a private garden in 2001 (Map source: Franklin, 2023).

Vegetation covers half of the Brussels-Capital Region (Franklin, 2023; Van de Voorde et al., 2010), but the spatial distribution is highly uneven across the city (Figure 1.10a). Publicly accessible green spaces make up 19% of the region's territory, but this figure drops to 10% when excluding the Sonian Forest (Franklin, 2023). Private gardens account for approximately 30% of the total green space, yet they are almost absent from the city centre (Figure 1.10b) (Franklin, 2021). The city exhibits a centre-periphery pattern, with low proximity and quality of green spaces in the central areas and greater availability and quality in the periphery. As a result, nearly two thirds of the population lacks access to high-quality green spaces (Stessens et al., 2017).

The **noise** in Brussels is largely shaped by transportation networks, with most areas experiencing Lden (Day-evening-night level) above 55 dB(A), exceeding the WHO's recommended threshold (Gamblin et al., 2024). The 2021 Multi-Exposure Noise Map (Gamblin et al., 2024) highlights that, apart from the south-eastern quadrant – including Uccle, Ixelles, Watermael-Boitsfort, Woluwe-Saint-Pierre, and Etterbeek – the Brussels-Capital Region is significantly impacted by noise pollution (Figure 1.11). The northern zone and the south-western areas of Anderlecht and Forest are particularly affected due to the high concentration of major railway lines along the North-South axis, the Ring Road in the south-west, and primary flight paths in the north.

Air pollution in the Brussels-Capital Region (BCR) varies by location, with the south-eastern areas generally experiencing lower levels of air pollution (Figure 1.12). In contrast, the most polluted areas are found around the Pentagon (historic centre), along the city's major roadways, and in the north-eastern part of the region. Regarding pollutant distribution, particulate matter ($PM_{2.5}$) is more diffusely spread across the region compared to nitrogen dioxide (NO_2), which is more directly influenced by road traffic emissions. The entire region exceeds the WHO guideline of 5 µg/m³ for PM2.5 (WHO, 2021), while only a small portion of the Sonian Forest and an adjacent neighbourhood in Auderghem remain below the WHO threshold of 10 µg/m³ for NO_2. In 2015, air pollution was estimated to contribute to 11.17% of all-cause mortality in Brussels (Andrieux et al., 2020).

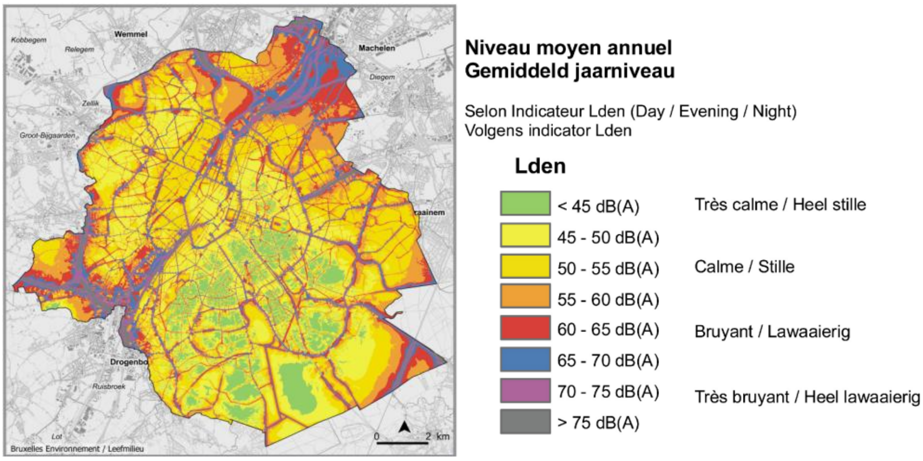


Figure 1.11. Multi-exposure noise mapping in the Brussels-Capital Region (2021). Lden global indicator Source: Bruxelles Environnement

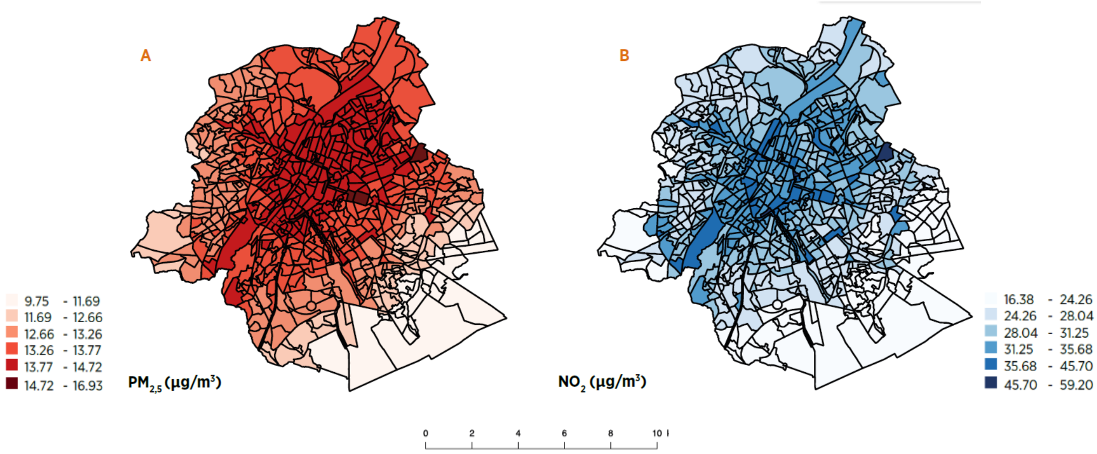


Figure 1.12. Air pollution exposure in Brussels. Annual mean (2015) of (a) $PM_{2,5}$ and (b) NO_2. Data source: IRCEL – CELINE (Source: Andrieux et al., 2020).

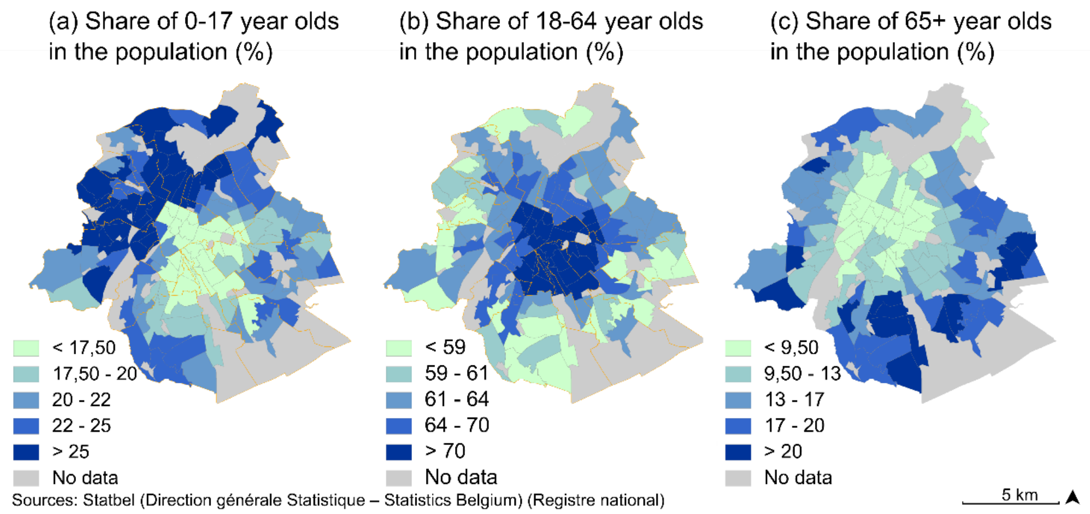


Figure 1.13. Spatial distribution of different age groups in the Brussels-Capital Region in 2023 (Source: Monitoring des quartiers, Institut Bruxellois de Statistique et d’Analyse)

1.5.2. The Urban Social Environment of Brussels

The Brussels-Capital has the highest proportion of residents of foreign origin in Belgium, with only one in four residents of Belgian origin, while 40.2% are Belgians with foreign origins and 37.2% are non-Belgians (Data source: Statbel, 2024). The population is younger than in Flanders and Wallonia, with an average age of 37.9 years, though spatial disparities exist, with more elderly residents in the periphery (Figure 1.13c), working-age individuals in the centre (Figure 1.13b), and a higher proportion of young people in the north-west (Figure 1.13a). Brussels has a lower disposable income per capita than Flanders but slightly higher than Wallonia (€24,600 vs. €28,800 in Flanders and €24,300 in Wallonia) (Lange et al., 2024) (Figure 1.14).

Social inequalities remain significant, with 6.5% of the population receiving social assistance (CPAS) and 28% living below the poverty risk threshold, a rate three times higher than in Flanders (Lange et al., 2024). There is no database mapping poverty risk at the neighbourhood level, but Lange et al. (2024) suggest using the share of the population benefiting from preferential healthcare reimbursement (Figure 1.15). Given the eligibility criteria, these individuals belong to low-income households. Around ten districts, all located in the south-east quarter of the region, have less than 10% of the population benefiting from preferential healthcare reimbursement. In contrast, this share exceeds 40% in most neighbourhoods within the “poor crescent” and some western areas. In five neighbourhoods more than one in two residents receive this support.

Brussels has stark **socio-spatial inequalities** (Costa and de Valk, 2021; Dujardin et al., 2008; Imeraj and Gadeyne, 2024; Van Criekingen, 2006; Vanneste et al., 2007). It is an urban agglomeration characterized by a pronounced socio-economic gradient, with a concentration of low-income populations mainly in its deprived central areas, in the western and northern neighbourhoods, particularly in the “poor crescent”, while wealthier areas are in the south and east (Figure 1.14 & Figure 1.15) (Costa and de Valk, 2021). These disparities are driven by socio-spatial segregation, where housing market dynamics, migration patterns, and uneven distribution of urban living environments play central roles (Haandrikman et al., 2023). Brussels reflects Belgium’s broader housing challenges, rooted in liberal housing policies that prioritize homeownership while leaving the rental market largely deregulated (De Decker, 2008). This system disproportionately affects low-income households, who are often confined to poorer-quality rental housing in disadvantaged neighbourhoods. Social housing, while a potential counterbalance to these inequalities, remains insufficient, with long waiting lists and limited

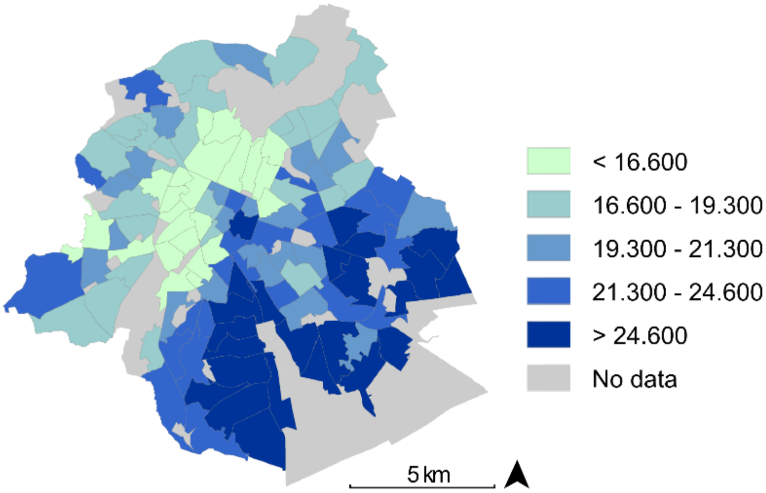


Figure 1.14. Average equivalised income per capita after tax (€) – (Source: IBSA and Statbel, 2021)

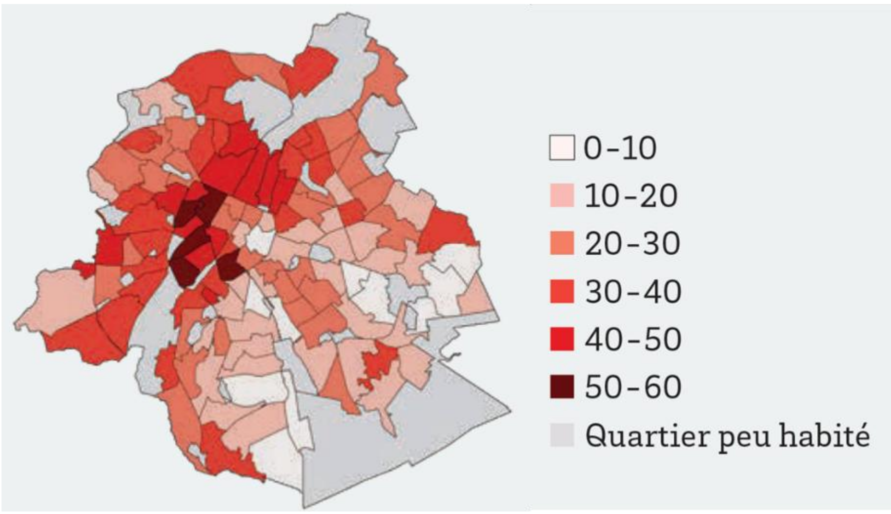


Figure 1.15. Percentage of the population benefiting from preferential reimbursement for healthcare use (bénéficiaire de l'intervention majorée) in 2023 (Source: Lange et al., 2024)

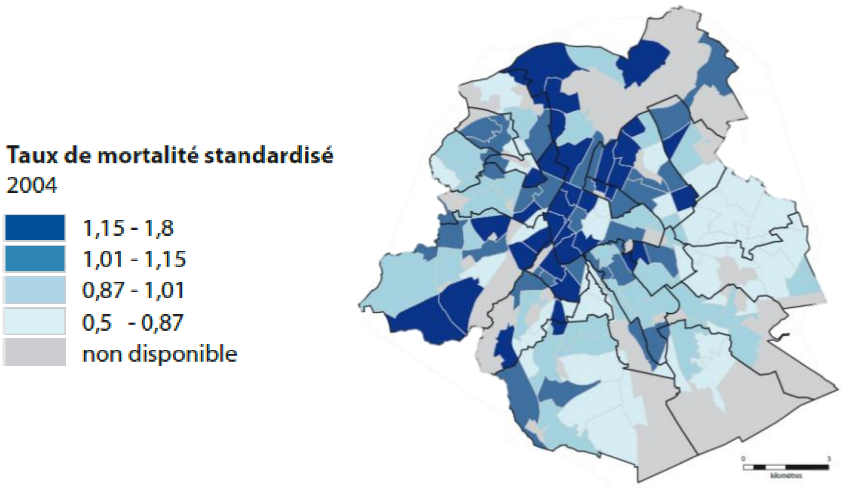


Figure 1.16. Standardized mortality (Source: Missinne et al., 2019)

availability (De Decker, 2008). Efforts to promote social mixing through area-based interventions, which often target central deprived neighbourhoods (Dessouroux et al., 2016), have been implemented. However, there is no evidence that these policies effectively reduce segregation (Haandrikman et al., 2023). Migration dynamics further amplify these inequalities. Brussels serves as a gateway city, attracting a highly diverse population, including many non-EU migrants. Ethnic and socio-economic segregation often overlap, as low-income migrants cluster in central neighbourhoods where housing is affordable but often substandard. These areas, while offering community networks and accessibility, also concentrate vulnerabilities, reinforcing patterns of exclusion. The presence of European institutions also contributes to these dynamics, by attracting a high-income international population, which can accentuate social disparities and gentrification in certain neighbourhoods (Costa and de Valk, 2021).

1.5.3. Quality of life in Brussels

Obtaining quantitative (spatially detailed) data on quality of life in Brussels is challenging, but healthcare data from the Belgian social security agency and data on original causes of death issued from death certificates provide valuable insights into certain aspects of it.

Regarding mortality data, life expectancy in Brussels (82.2 years) is slightly lower than in Flanders (83.2 years), but slightly higher than in Wallonia (80.6 years). Although no life expectancy estimates are available at the neighbourhood level, mortality rates – a related but distinct indicator – can be observed. While they do not capture the average length of life, they reflect the frequency of death within a population. Notably, mortality rates increase proportionally with the socio-economic status of the municipality of residence, highlighting significant health disparities across the region (Figure 1.16) (Missinne et al., 2019). At an individual level, data on causes of death have been used in the scientific literature to explore links between mortality and residential environment indicators (Demoury et al., 2024; Rodriguez-Loureiro et al., 2021).

Regarding healthcare data, the “Agence InterMutualiste” manages care data collected by the seven Belgian health insurance funds. They provide aggregated data at the statistical district for scientific research (Aerts et al., 2022; Trabelsi et al., 2019) and other report (Missinne et al., 2019). Analyses of these datasets reveal that Brussels exhibits pronounced health inequalities, with a clear social gradient in access to healthcare and in health outcomes. This pattern closely mirrors the spatial distribution of median income (Figure 1.14). Missinne et al. (2019) have produced an insightful report on social health disparities, featuring detailed maps and graphics. Chronic patient status, mental health disorders medication, and other medications for preventable diseases are more prevalent among lower-income populations, who also face greater difficulties in accessing preventive care. These disparities are further exacerbated by educational levels, employment status, and living conditions.

1.5.4. Association between Urban Liveability and Quality of Life in Brussels

The scientific literature on Brussels regarding the association between urban environment and health continues to expand each year. Several recent projects illustrate this growing research focus with some at the individual or aggregated level. One example is the "Green and Quiet" project funded by Innoviris, which investigates social inequalities in health-related outcomes linked to environmental characteristics in the Brussels-Capital Region (Noël et al., 2021; Rodriguez-Loureiro et al., 2021). Another contribution is the report on the state of knowledge regarding the links between environment and health in the Brussels-Capital Region (Andrieux et al., 2020).

Part of this thesis was linked to the Nature Impact on Mental Health Distribution (NAMED) project funded by Belspo, which aimed to provide a comprehensive understanding of the relationship between urban residential environments and mental health (Lauwers et al., 2020). Following a mixed-method approach, this project combined quantitative and qualitative research. The quantitative part aimed to examine the associations between long-term exposure to air pollution, noise, surrounding green spaces at different scales, and building morphology, with several dimensions of mental health in Brussels (Pelgrims et al., 2021). The qualitative part investigates neighbourhood factors and their interactions with mental well-being. This was explored through semi-structured walking interviews conducted with 28 adults living in the Brussels-Capital Region (Lauwers et al., 2021).

1.5.5. Fine spatial scale data in the Brussels-Capital Region

Rather than collecting new data across the entire region – which would have posed significant financial and time constraints – this thesis builds on the use of existing datasets from diverse sources, including institutional, modelled, and citizen-generated datasets. These datasets vary in accessibility – some are openly available, others require formal requests, and some are sensitive and necessitate the establishment of protocols to ensure privacy compliance.

INSTITUTIONAL SOURCES. Belgian institutions have responded significantly to the growing demand for open data. For example, **UrbIS vector** datasets integrate geographic and administrative data managed by the General Administration of Patrimonial Documentation, Statbel, Perspective, and Brussels Mobility. **Micro-data from Statbel** (individual-level data) and the **Belgian Health Interview Survey (BHIS)** require adherence to strict privacy standards, but there is a strong willingness to share these datasets for research projects. Additionally, the French and Flemish communities provide **school-level statistics**, some of which are open access, while more detailed data can be obtained upon request.

MODELLED SOURCES. **Vegetation coverage data** were derived from high-resolution remote sensing (Normalized Difference Vegetation Index with a threshold value of 0.275) provided by Brussels Environment, with a spatial resolution of 2.4 m (2008, computed by Van de Voorde *et al.*, 2010). To extend coverage to the entire country, we also utilized high-resolution land cover data (2015, 2m spatial resolution) (Radoux et al., 2023). **Air pollution data** were obtained from models combining regional pollution interpolation, a Gaussian dispersion model, and a street canyon model to account for varying scales and sources influencing urban air quality (Lefebvre et al., 2013). These models operate at a 10m resolution and provide annual averages. **Noise data** were also modelled by Brussels Environment (Gamblin et al., 2024).

CITIZEN-GENERATED SOURCES. We also incorporated data from **Fix My Street (FMS) Brussels**, a platform where residents report issues in public spaces, such as clogged sewer grids, malfunctioning streetlights, or instances of illegal dumping. This data source presented a particular challenge, as it was not created with the intent of providing an exhaustive inventory but rather as a tool for managing citizen complaints. Consequently, its use required careful consideration to extract meaningful insights while accounting for its inherent bias.

1.6. Objectives and outline of the thesis

The general objective of this thesis is to explore the association between urban environments and quality of life from a fine spatial scale perspective in the Brussels-Capital Region. The research emphasizes the urban social environment as a key confounder. The work presented here builds on the conceptual framework outlined earlier, with a specific focus on leveraging existing data to address the research question.

The main study area of the thesis is the Brussels-Capital Region, except in Chapter 5, which presents results at the national scale for Belgium. The broader analysis of Chapter 5 highlights the unique characteristics of Brussels within Belgium.

The contributions of this thesis are organized across seven chapters, including this introduction. Chapters 2 to 6 explore one or more parts of the conceptual framework (Figure 1.17), but from a distinct angle: using a specific research question, different datasets, varied indicators, and multiple spatial scales – from the individual to the neighbourhood. Table 1.1 offers a comparative overview of these chapters, highlighting the diversity approaches. It synthesizes the types of urban environments studied (physical and social), the indicators used, the unit and process of interest and the different scales.

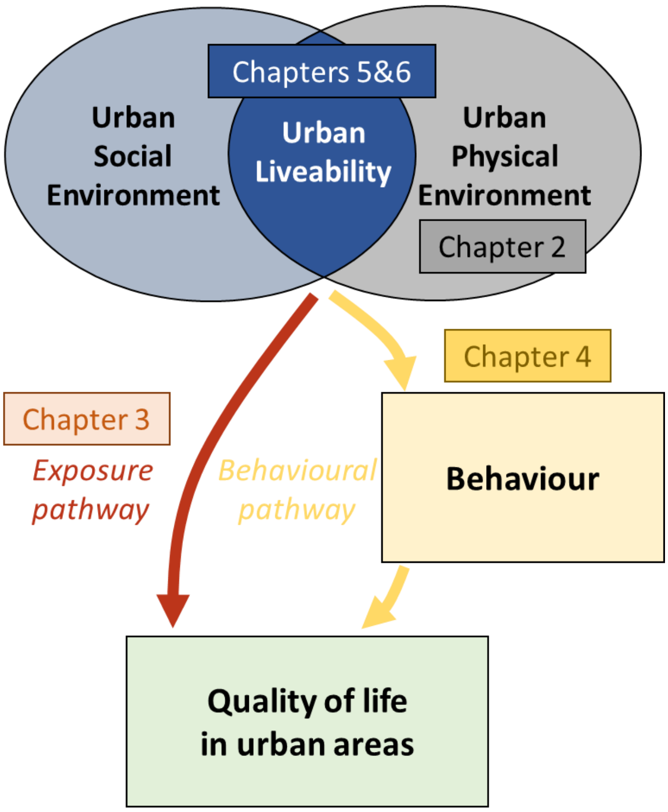


Figure 1.17. Connection between the different chapters of the thesis and the conceptual framework.

Chapter 2 focuses on how the urban physical environment can be characterized as a whole at the street-level, with a particular emphasis on the role of vegetation in modelling the "streetscape". To address this question, we utilized the Multiple Fabric Assessment (MFA) protocol, which identifies morphological clusters of urban fabric by incorporating a street-level perspective into a Naïve Bayesian clustering analysis. Furthermore, specific pedestrian and vegetation features of the urban form are specifically developed and introduced in the original MFA protocol.

Use of this procedure in the case study of the BCR allows us to observe the role played by vegetation in the identification of urban fabrics.

Chapter 3 explores the association between mental health and the urban physical environment, with a specific focus on the impact of partial non-response on the results. In the NAMED project, the quantitative analysis part examined the link between mental health and urban physical environments using individual data from the Belgian Health Interview Survey (2008 and 2013). The results could not demonstrate any association between urban environment (green surroundings, noise, building morphology) and mental health except for traffic-related air pollution exposure (black carbon, NO_2, PM_{10}) which was positively associated with higher odds of depressive disorders (Pelgrims et al., 2021). Several explanations have been proposed for the lack of associations, including the potential impact of partial non-response, which can introduce biases in survey estimates and statistical outcomes. This issue is explored in Chapter 3.

Chapter 4 examines the interaction between the behaviour, urban physical environment, and urban social environment, using illegal dumping sites as indicators of urban liveability deterioration. Illegal dumping is a significant nuisance, yet there are few quantitative studies on its drivers and none in Brussels. Citizen-generated administrative data, like Fix My Street, provide a valuable resource for studying such incivilities on a large scale. We tackle the methodological challenge of working with citizen-generated data to study whether urban and social environments are factors that influence the occurrence of illegal dumping. We also consider the socio-economic context and the tendency of illegal dumping sites to reoccur in previously identified locations, known as the “broken window theory” or disorder effect.

Chapter 5 analyses the environmental quality around schools in Belgium. Schools are a crucial component of children’s living environment, as they spend a significant portion of their day there. This chapter focuses on environmental justice, specifically the relationship between social environment and environmental quality. Using student mean socio-economic status (SES) data from the French- and Flemish-speaking communities in Belgium, along with environmental data on four air pollutants and green space coverage, we conducted analyses to examine the distribution of environmental quality around schools.

Chapter 6 aims to evaluate the association between the urban physical environment (built and vegetation) and population characteristics. While previous research has demonstrated that the uneven spatial distribution of urban physical environment quality contributes to patterns of segregation between poverty and affluence, no fine-scale studies have comprehensively linked the urban physical environment to multiple socio-demographic variables in Brussels. To fill this gap, we integrated the streetscape typology developed in Chapter 2 with socio-economic micro-data at the individual level.

Finally, in the concluding chapter (Chapter 7), we highlight the key messages of this thesis, structuring them into seven core contributions, both scientific and policy-oriented. Several of these contributions also reflect on the study's limitations and outline avenues for future research.

Table 1.1. Overview of focus, variables and spatial scales used in the thesis chapters. The colours refer to the conceptual framework.

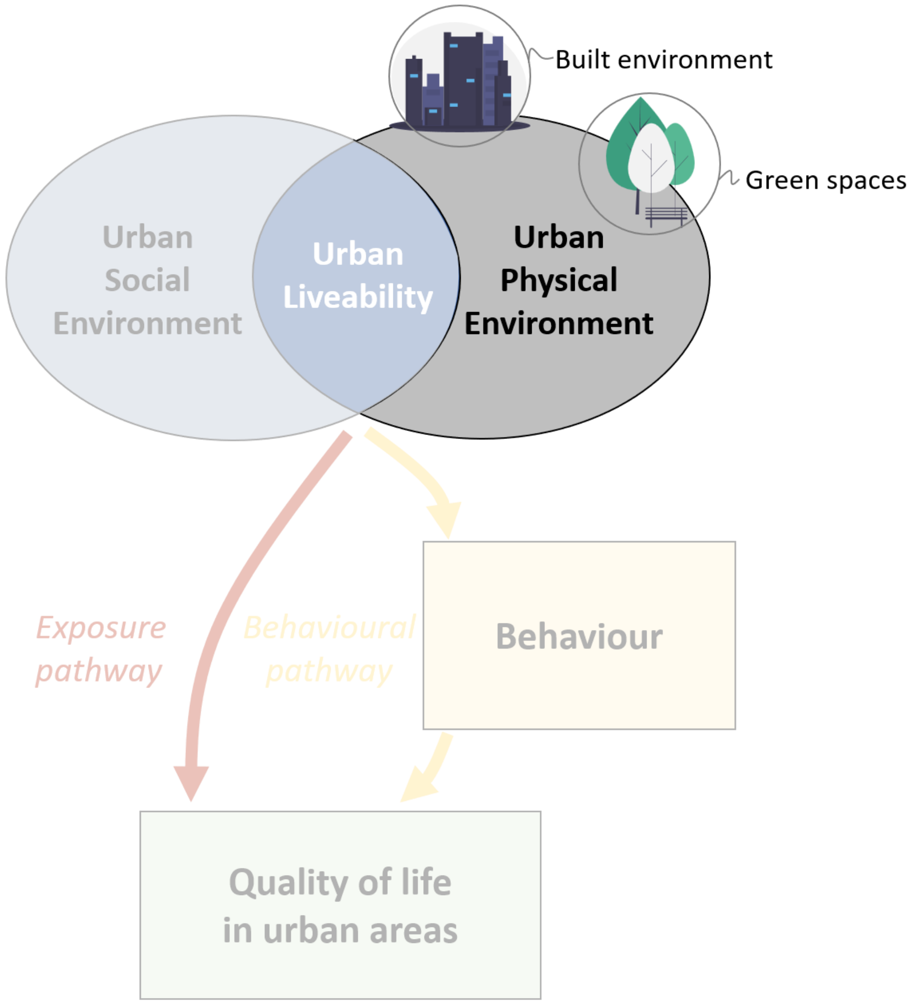
		**Chapter 2.** The urban form of Brussels from the street perspective	**Chapter 3.** Non-response bias in mental health studies	**Chapter 4.** A geographical analysis of illegal dumping by citizen sensor data	**Chapter 5.** Environmental inequalities at school	**Chapter 6.** A new approach to socio-spatial disparities in Brussels
Unit of interest		Street	Resident	Illegal dumping	School campuses	Resident
Processes of interest		Urban fabric	impact of non-response in the association between urban environment and mental health	association between anti-social behaviour and urban liveability	unequal distribution of environmental quality around schools	association between the urban environment and socio-spatial segregation
Urban physical environment			View of green	Road noise		
			Vegetation coverage (300m) Noise, Black carbon	Presence of tree, shop and recycling bank, vegetation cover	NO_2, $PM_{2.5}$, BC, PM_{10} and vegetation cover	
		17 indicators of the urban morphological characteristics of the streetscape 4 indicators related to vegetation	Linear tree density, Street visible vegetation coverage Street corridor effect and Street canyon effect.	Street and sidewalk width and building height		Urban fabric from Chapter 2
Urban social environment					Mean socio-economic index of school campus	
			Age and Gender			Origin, Age, Educational level
			Reported household income, Family composition and Highest educational level in the household			Household size and Income
				Household median income	Neighborhood household median income	

Spatial resolution: Individual level Household Event-level/Address level Ego-centred neighbourhoods (buffer) Street segment Statistical sector

2

The urban form of Brussels from the street perspective: the role of vegetation in the definition of the urban fabric

This chapter has been published here:
Guyot, M., Araldi, A., Fusco, G., & Thomas, I. (2021). The urban form of Brussels from the street perspective: The role of vegetation in the definition of the urban fabric. *Landscape and Urban Planning*, *205*, 103947. https://doi.org/10.1016/j.landurbplan.2020.103947



Abstract

In the context of rising interest in the impact of the urban environment on human well-being, appropriate modelling of the urban landscape needs to be developed. Traditional analyses from the aerial point of view are not suitable; it has become essential to consider the pedestrian perspective. The Multiple Fabric Assessment (MFA) is a recent protocol that provides morphological clusters of urban fabric by incorporating a street perspective into a Naïf Bayesian clustering analysis. We apply the protocol to all street segments in Brussels. We first investigate the role of vegetation and areas devoted to pedestrians in the identification of urban fabric. We show that incorporation of these measurements into the MFA allows of better definition of the urban fabric in suburban areas, demonstrating how vegetation has become fundamental to the description of residential neighbourhoods, while it has a less relevant role in defining the urban fabric in compact central areas. We then identify twelve meaningful clusters of urban fabric in Brussels and link them to the different urban development phases. Particular attention is paid to Brusselization in the city centre and garden districts in the suburbs. The results provide clear definition and clustering of streetscapes in an urban environment, a stepping stone via which future research could cross-analyse the relationships between well-being and built forms.

2.1. Introduction

Urban landscapes are the backdrop of life for 55% of the world's population, and this number is expected to increase (United Nations, 2019). Streets, squares, parks, and gardens are traditionally identified as public spaces where urban outdoor activities take place (Gehl, 1987). The surrounding urban landscape influences how city users perceive the urban space and, ultimately, their behaviour, activities, and well-being (Jacobs, 1961). Several features of urban morphology, such as building height, daylight, built-up density and presence of sidewalks, and their impacts on human behaviour, have been individually explored in the scientific literature (Evans, 2003; Rao et al., 2007; Sullivan and Chang, 2011). Likewise, more recent studies have investigated the beneficial effects of vegetation distribution and accessibility on psychological, emotional and mental health (Herzele and Vries, 2012; Beyer et al., 2014; Alcock et al., 2014). The link between urban environment and human well-being is a growing field of research, requiring the development of new tools, data and models.

Starting from the 1950s, urban geographers, morphologists and designers have produced a wide-ranging literature proposing different approaches to analysing the urban form and identifying typo-morphological urban regions (Vernez Moudon, 1997), and this activity has intensified over the last 30 years with the increasing use of Geographic Information Systems. Within this research domain, an increasing number of papers propose more or less sophisticated computer-aided procedures to enable the development of quantitative analytical approaches for the study of the urban form and its relationships with human-related phenomena (Berke and Vernez-Moudon, 2014; van Kamp et al., 2003). These approaches depend on the study context, the geographical scale, the indicator types (including objective or subjective measurements), and the time frame. More specifically to the urban form, the indicators depend on the register of the urban form concerned (Fusco, 2018; Levy, 2005), the metrics implemented (single or multiple), and the point of view from which the form of the physical city is observed (Araldi and Fusco, 2019).

When focusing on analysis of the urban form – the spatial organization of urban physical elements such as buildings, streets and parcels – several methods have been developed, such as: street-network configurational analyses (Hillier, 1996; Porta et al., 2006), fractal-based approaches (De Keersmaecker et al., 2003; Thomas et al., 2008), multivariate analysis of morphometric descriptors of built-up density (Berghauser Pont and Haupt, 2010), or a combination of geoprocessing and spatial statistic procedures (Caruso et al., 2017). Data can be very simple, such as the centroid of each building (Caruso et al., 2017; Thomas et al., 2008) or the building footprint (Hamaina et al., 2014), or include several morphological indicators (Araldi and Fusco, 2019; Gil et al., 2012; Vanderhaegen and Canters, 2017).

While these studies allow quantitative description of the urban form, two aspects are traditionally overlooked. Firstly, the pedestrian point of view: when analysing socio-economic phenomena occurring in the public space, the pedestrian perspective assumes crucial importance and should be preferred to the more aerial point of view traditionally favoured in urban studies (Araldi and Fusco, 2019). Secondly, public and private green spaces feature in the definition of urban morphology indicators and, consequently, in the urban fabric.

The importance of the urban form from the street perspective has already been recognized by several authors. From the urban design field of research, Purciel (2009), Vialard (2013) and Harvey et al. (2017) provide innovative protocols for quantitative analysis of the distribution of urban features along the edges of streets, i.e. the skeletal streetscape. Araldi & Fusco (2019) extended the analysis of the urban form of individual streetscapes to the analysis of urban fabrics and morphological regions using the Multiple Fabric Assessment (MFA) protocol. MFA allows both the characterization of individual morphometrics at street level and the identification of urban fabrics as perceived by pedestrians within large urban areas. This approach differs strongly from the aerial approach traditionally adopted by urban planners, geographers and morphologists: urban morphological features are described quantitatively from the pedestrian point of view and their spatial distribution is statistically evaluated in order to identify significant local patterns in the street-network layout. Lastly, patterns of morphological indicators are combined using Naïf Bayesian Classification approaches, allowing a probabilistic description of urban fabric profiles.

While the importance of vegetation distribution in urban public spaces has been widely investigated in quantitative analyses (e.g. Harvey et al., 2017; Li et al., 2015), urban form studies have focused on built-up rather than green spaces. There are some exceptions such as Hermosilla et al. (2014), who included vegetation cover data obtained from high-resolution satellite imagery and LiDAR to define urban typologies. Vegetation indicators such as these require specific data, either pre-processed or from high-resolution satellite imagery, in order to have a fine-grained definition of vegetation. There is also a rising interest among streetscape researchers in vegetation and built-up indicators based on street images (e.g. Google Street View), which provide realistic 3-D representations of urban streets from a pedestrian's perspective (Gong et al., 2018; Li et al., 2015; Richards and Edwards, 2017). The problem with all these vegetation data is that the choice of database significantly affects the modelling results (Le Texier et al., 2018; Trabelsi, 2020).

We focus here on the Brussels-Capital Region (BCR), Belgium. Modelling of intra-urban fabrics has already been carried out in relation to this study area (e.g. Vanderhaegen & Canters, 2017), but with different goals, data and tools. In this paper our goal consists in identifying urban morphological regions (defined in terms of a given urban fabric), as in the traditional urban typo-morphological approach. While Vanderhaegen and Canters (2017) analysed the urban form from the traditional planar point of view on the basis of an urban street-block partition, in this paper we will adopt the pedestrian perspective by our use of the MFA protocol. Furthermore, specific pedestrian and vegetation features of the urban form are specifically developed and introduced in the original MFA protocol. Use of this procedure in the case study of the BCR allows us to observe the role played by vegetation in the identification of urban fabrics.

The paper is organized as follows. After the study area description (Section 2.2), the main steps in the MFA protocol are presented, including the innovations in the context of the BCR in Section 2.3. A specific focus is then placed on the role of vegetation in the definition of the urban fabric: the MFA protocol is implemented both with and without vegetation indicators in order to identify the role of vegetation in defining the urban fabric. Our results are presented in Section 2.4, and Section 2.5 concludes the paper.

2.2. Study Area

Brussels is the capital of Belgium, centrally located in the country. The city extends into three administrative regions: the Brussels-Capital Region (BCR), Flanders and Wallonia. There is no official definition of the “urban agglomeration”; its delineation depends strongly on the indicators and methods used (Thomas et al., 2012). We focus here on the urban area encompassed within the administrative border of the Brussels-Capital Region (BCR). This choice limits problems arising from inter-regional data comparison by allowing the use of well-established and consistent databases: the Urbis open database (BRIC, 2017) and remotely sensed vegetation data (Van de Voorde et al., 2010) (Figure 2.1).

The BCR is divided into 19 municipalities. It covers 161.38 sq. km and has 1.2 million inhabitants (source: Statistics Belgium – 01/01/2018), which means an average density of 7,438 inhabitants per square kilometre. For the sake of simplicity, the BCR will henceforth be referred to in this paper as Brussels.

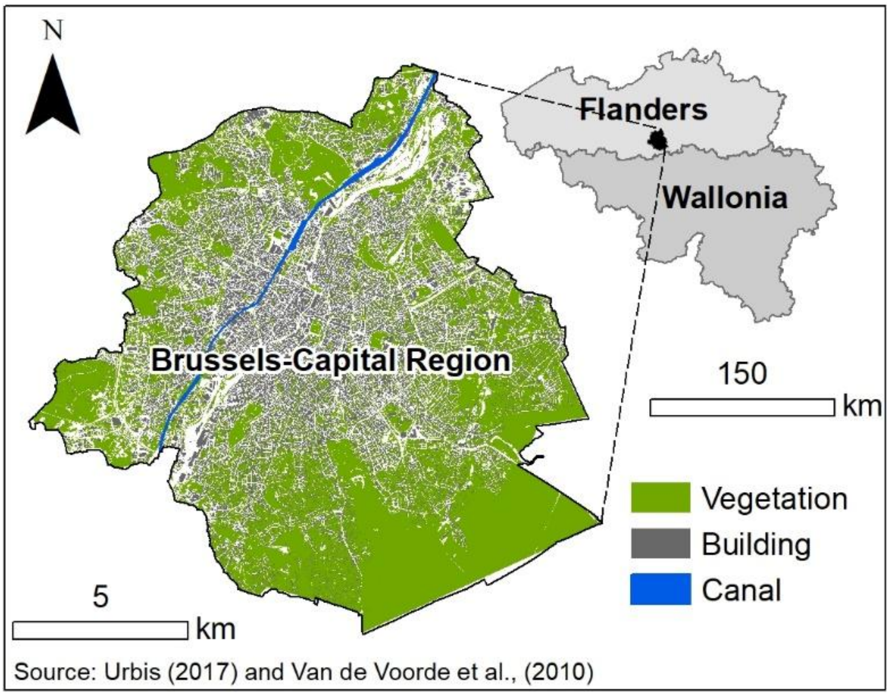


Figure 2.1. Brussels-Capital Region: relative location in Belgium and built-up composition

The current urban fabrics in Brussels and their spatial organization result from the long historical evolution of the city. The core of the city presents the oldest vestiges of the original settlement, enclosed within two successive ramparts (8th and 14th centuries) that can still be distinguished in the street pattern. Surrounding the historical centre, the first concentric expansion dates back to the 19th century and is characterized by the typical Brussels townhouses: contiguous bourgeois family houses. These are recognizable by their limited width (~6 m) and bel étage (piano nobile), which is generally raised by 1.80 m above the sidewalk level. This creates a distance from the public street and also provides lighting in semi-basement spaces (Ledent, 2017). This type of building is still a particular feature and a specific part of the identity of the Brussels urban landscape. At the beginning of the 20th century, the development of garden districts (inspired by the English garden cities) shaped some of the fabric of the suburbs. And since that same period, Brusselization has reshaped part of the central area as a result of the great increase in tertiary employment and the consequent new buildings and fabrics (De Beule and Dessouroux, 2011).

The vegetation in Brussels is not only a feature of the garden cities: it represents 54% of the BCR surface (Van de Voorde et al., 2010); this includes public parks and recreation areas and urban forests, as well as private gardens and estates.

Analysis of the urban morphological characteristics of Brussels has already been carried out by several authors. De Keersmaecker, Frankhauser and Thomas (2003) used fractal dimensions from a grid to highlight the spatial patterns of the multi-level building structure. More recently, Vanderhaegen and Canters (2017) computed urban metrics on city blocks to identify distinct types of urban form and function. In focusing on the spatial distribution of the Brussels green spaces, we might mention the studies of Stessens et al. (2017) and Van de Voorde (2017), in which several indicators of distribution, quality and accessibility to green spaces are suggested. Beyond these scientific studies, we might also consider the European project Urban Atlas, which is available for Brussels. Much more precise than CORINE land cover, it allows detailed and comparable classification of land use in European cities, but lacks the specifics of urban morphometrics.

As highlighted in the previous section, despite the great value of these studies in describing the urban form of Brussels using different approaches and emphases, they do not incorporate the pedestrian perspective into their analysis and they consider the distribution of vegetation and built form separately, without taking account of their combined effect on the definition of the urban fabric.

2.3. Method

Araldi and Fusco (2019) developed the Multiple Fabric Assessment (MFA) protocol for the identification and characterization of urban fabrics. This is a data-driven bottom-up procedure which could be summarized in four steps (Figure A.1, in the appendices). After definition of a street-based spatial unit partition – the Proximity Band (PB) (Section 2.3.1) –, urban form indicators are computed via geoprocessing protocols which capture different aspects of the skeletal streetscape (Section 2.3.2). Spatial patterns of morphological indicators are identified in a network-constrained environment (Section 2.3.3). Finally, local patterns are clustered using a Naïf Bayesian classification approach (Section 2.3.4). The MFA allows the urban landscape to be described at both the individual level (streetscape) and the meso-scale level (urban fabric).

This method has proved successful in the analysis of several case studies with different geographic extent and data sources: the French Riviera conurbation (Araldi and Fusco, 2019), the metropolitan region of Osaka-Kobe, Japan (Perez et al., 2019) and the Karşıyaka district, Turkey (Erim, Araldi, Fusco & Cubukcu, unpublished data). It is applied here to the intra-urban environment of Brussels.

2.3.1. Basic Spatial Unit: the Proximity Band

Finding the spatial unit of the right scale for analysing urban form has always been a challenge for geographers. Administrative divisions often do not match with urban landscapes: each spatial unit is hence heterogeneous in terms of built-up and non-built-up surfaces. The Proximity Band (PB) proposed in Araldi and Fusco (2019) provides a good means of analysing the urban form from the pedestrian point of view. It is a street-based partition that satisfies, on the one hand, the need to reduce the MAUP (modifiable areal unit problem) by minimizing spatial unit size variability (the size variability of PB partition is lower than that of the administrative unit), on the other, the need for a behaviourally based partition in which both the street point of view and street-network contiguity are incorporated. Finally, the street constitutes the bridging element that enables cross-analysis with different urban morphometric approaches or socio-economic events along the network (distribution of occurrences, movement, perception, etc.), thus avoiding possible spatial unit inconsistencies.

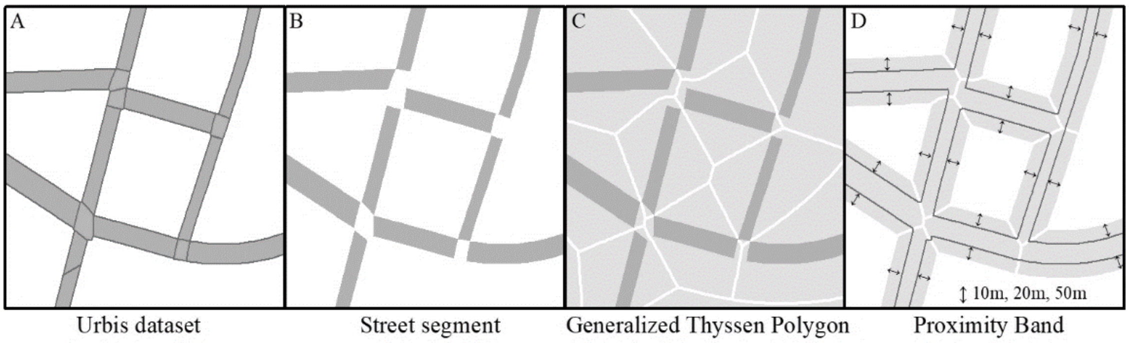


Figure 2.2. Computation of the basic spatial units: from the original data (A) to Proximity Band (D)

The implementation of the Proximity Band (PB) was adapted to the data available for Brussels (Urbis dataset) (Figure 2.2.A). Street surface data were simplified – notably by removing intersections – to give street segments (Figure 2.2.B). A street segment is the part of a street located between two intersections. Around each street segment, Generalized Thiessen Polygons were defined, allocating to each segment the nearest space (Figure 2.2.C). Then buffers (10 m, 20 m or 50 m) were computed from the street edges (Figure 2.2.D). Three different Proximity Band widths were used, depending on the indicator being considered. Thus 12,457 Proximity bands were identified for the BCR. The longest is 3 km, but 90% of the dataset lies between 20 m and 260 m.

2.3.2. Computation of urban form indicators using geoprocessing protocols

In the original implementation of MFA, twenty-one indicators were computed for each street segment, each of which described a different morphological aspect of the streetscape. As discussed in Araldi & Fusco (2019), MFA protocol is a flexible procedure which can be easily adapted to each case study by modifying and introducing specific morphometric indicators to capture particular features of the area being studied.

Of the indicators developed in the original MFA applied to the French Riviera, three were not included: (i) *Land ownership fragmentation along the street network* for its high similarity to *Building frequency*, (ii) *Surface slope* and (iii) *Street acclivity,* given the smoother site morphology in Brussels than in the original case study of the French Riviera.

The five indicators called *Prevalence of building types* are based on a classification of the surface of the building footprint adapted to the Brussels case study (Figure A.2, in the appendices). Starting from a threshold of 25 sq. m, which allows small structures such as separate garages and garden sheds to be overlooked, we are able to identify: (i) detached or small contiguous houses between 25 and 125 sq. m, mainly found in suburban residential areas and representing the most prevalent building type in Brussels (numerically); (ii) large villas and contiguous houses between 125 and 400 sq. m, encompassing the traditional “Brussels townhouses”; (iii) blocks of flats and offices between 400 and 2000 sq. m; (iv) large blocks of commercial, industrial or service buildings 2000–4000 sq. m; and (v) building footprints larger than 4000 sq. m corresponding to large buildings such as factories, railway stations, etc.

Further improvements pertain to the *Local connectivity* indicators, which have been replaced with a combination of two descriptors more suitable for describing the street network layout, while *Dead-end street* assigns a Boolean value to each PBs (similar to Node Degree 1), and a new indicator of *Regular street grid* is implemented as the average angular deviation from the regular street grid with the adjacent streets. This indicator takes the value of 0° if the street forms a right angle (90°) or a flat angle (180°) with all adjacent streets; it takes a value of between 0° and 45° in other cases (Figure 2.3).

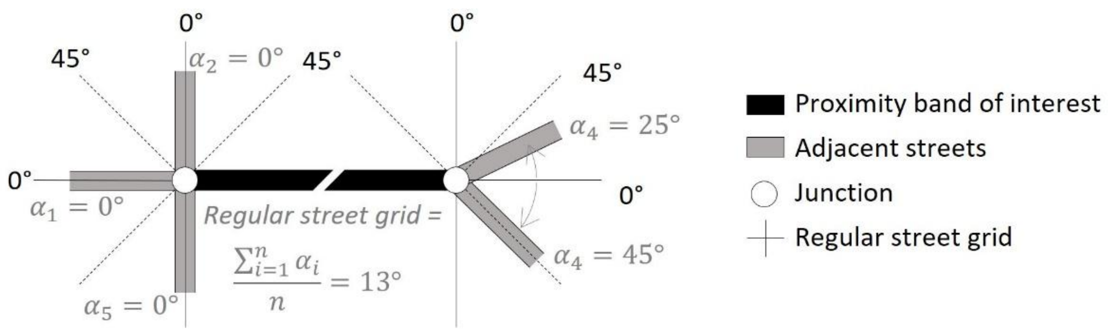


Figure 2.3. Regular street grid indicator: average angular deviation from the regular street grid with the adjacent streets

The other indicators were implemented as in the original version of MFA (see Araldi & Fusco, 2019 for further details). Each indicator relates to a specific PB depth (10, 20 or 50 metres from the street edge), specified in Table 2.1. We obtained an initial set of 17 indicators classified under three categories: **Street and Street Network Morphology**, **Built-up Morphology**, and **Network-Building Relationship**.

The 17 indicators described so far provide an overview of the urban morphological characteristics of the skeletal streetscape, taking into account only the spatial organization of streets and buildings. As highlighted in the introduction, in order to investigate the importance of vegetation and of available public space, four indicators were specifically designed for Brussels.

The distribution of vegetation in an urban space plays a part in the design and development of urban fabrics. In some urban fabrics, individual trees serve as landmarks or have been added a posteriori. In others, small green spaces have been incorporated into the planning of boulevards and urban fragments. More extensive green features might have been planned for specific urban development. Some neighbourhoods, such as garden districts, have fully integrated green space as a major component of their urban design. As we see from these examples, vegetation can take different forms and be located in different positions in relation to the other elements of the urban form. While green spaces are traditionally measured as urban facilities, in this study vegetation is treated as a constitutive element of the urban landscape at the same level as building, plot and street elements. For this purpose, we describe and summarize the various spatial configurations as a combination of three specific indicators, bearing in mind the pedestrian perspective (Figure 2.4). Both private and public green spaces are taken into consideration using the vegetation coverage data of Van de Voorde et al. (2010).

Visible street vegetation coverage quantifies the green spaces directly visible from the street. It can refer to green spaces in the public domain or private front gardens that can be seen by both passers-by and residents. It corresponds to the ratio of the green surface to the total surface of the 10m PBs. *Vegetation coverage* reflects the presence of large green spaces. In our case study, this indicator specifically allows a distinction to be made between the residential fabrics characterizing the eastern and the south-eastern areas of Brussels (as observed in Van de Voorde et al., 2010). Unlike the previous indicator, the vegetation coverage ratio is computed on the basis of the part of the PBs located at more than 10 metres from the street edge. As demonstrated by Asgarzadeh et al. (2012), the presence of trees along the street edge – especially those covering building façades – is an important aspect from the pedestrian's perspective, but not accounted for in the previous indicators. The *Linear density of urban trees* has hence been computed as the average number of trees per metre (point data from the Urbis database). These alignments of trees are not always green enough to be detected by remote sensing, but this indicator allows them to be taken into account.

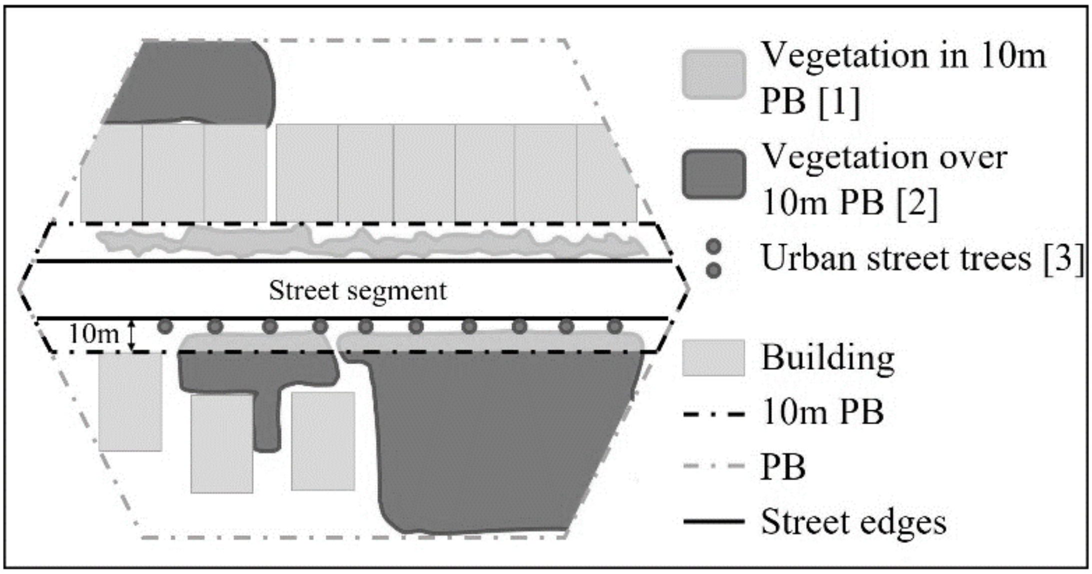


Figure 2.4. Vegetation elements considered for the computation of the three vegetation indicators: Visible street vegetation coverage [1], Vegetation coverage [2] and Linear density of urban trees [3]

Beyond the vegetation, a further aspect of the urban space considered here is the proportion of the street allocated to pedestrian use. The presence of space devoted to pedestrians is positively correlated with walking (Handy, 2004) and creates meeting places, which provide essential support for social interactions (Gehl, 1987). A *Pedestrian area* indicator is also included in the form of the ratio of pedestrian area to street surface (as in Gil et al., 2012).

In order to investigate the relative importance of these additional indicators of vegetation and pedestrian areas, the MFA procedure will be implemented twice: first we will consider only 17 indicators of built form and street network; the second implementation takes four additional indicators into account. Comparing the results of these two procedures will allow us to understand the relative importance of vegetation and pedestrian space in the definition and identification of the urban fabrics.

Table 2.1. Definition of the urban form indicators (*see Araldi and Fusco, 2019 for further details)

Urban fabric component	Name	$S_{ref.}$	Implementation	Output
Street and Street Network Morphology	Street length*	Street surface	Length of the street segment ($L_{str.}$) [m]	$L_{str.}$
	Windingness*		Ratio between Euclidean distance ($L_{eucl.}$) and street length	$1-\left(\frac{L_{eucl.}}{L_{str.}}\right)$
	Regular street grid		Average angular deviation from the regular street grid (α_i) with the adjacent streets (i) [0 to 45°]	$\frac{\sum_{i=1}^{n}\alpha_i}{n}\begin{cases}\alpha \le 45 \rightarrow \alpha_i = \alpha \\ 45 < \alpha \le 90 \rightarrow \alpha_i = 90-\alpha \\ 90 < \alpha \le 135 \rightarrow \alpha_i = \alpha - 90 \\ 135 < \alpha \le 180 \rightarrow \alpha_i = 180-\alpha\end{cases}$
	Dead-end street		Presence of dead-end street [0 or 1]	$\exists\ Deadend\ street$
	Pedestrian area		Ratio between pedestrian area ($S_{ped.}$) and street surf. ($S_{ref.}$)	$\frac{S_{ped.}}{S_{ref.}}$
Built-up Morphology	Prevalence of Building types	50m PB	Ratio between specific building surf. ($S_{\mathrm{x-x\,m^2\,b.}}$) and total built-up surf. (S_{build}) For: 25–125 sq. m, 125–400 sq. m, 400–2000 sq. m, 2000–4000 sq. m, >4000 sq. m.	$\frac{S_{\mathrm{x-x\,m^2\,b.}}}{S_{build}}$
	Proximity band coverage ratio*		Ratio between total built-up surf. and PB surf.	$\frac{S_{build}}{S_{ref.}}$
	Building Contiguity*		Weighted average of building fragmentation ($1/N_i$) on attached built-up units (i)	$\frac{\sum_{i=1}^{n}\left(\frac{1}{N_i}S_i\right)}{S_{build}}$
	Specialization of Building Types*		Ratio between specialized building footprint ($S_{\mathrm{sp.b.}}$) and total built-up surf. [%]	$\frac{S_{\mathrm{sp.b.}}}{S_{build}}$
Network-Building Relationship	Building frequency along the street network*	20m PB	Ratio between number of buildings ($N_{\mathrm{b.}}$) and street length [Building/m]	$\frac{N_{\mathrm{b.}}}{L_{str.}}$
	Proximity band building height*		Ratio between building vol. ($V_{b.}$) and PB surf. [m]	$\frac{V_{b.}}{S_{ref.}} = H$
	Open Space Width*		Ratio between open space (S_{nbuilt}) and street length [m]	$\frac{S_{\mathrm{nbuilt}}}{L_{str.}} = W$
	Height/Width Ratio*		Ratio between average building height and average open space width	$\frac{H}{W}$
	Street corridor effect*	10m PB	Ratio between parallel façades ($L_{f.}$) and street length [0–2]	$\frac{L_{f.}}{L_{str.}}$
Vegetation	Linear density of urban trees	10m PB	Ratio between number of trees (N_{tree}) and street length [tree/m]	$\frac{N_{\mathrm{tree}}}{L_{str.}}$
	Visible street vegetation coverage		Ratio between vegetation surface ($S_{\mathrm{veg.}}$) and PB surf.	$\frac{S_{\mathrm{veg.}}}{S_{ref.}}$
	Vegetation coverage	>10m PB		

2.3.3. Spatial patterns on a network-constrained space

Instead of studying and combining the raw indicators (as traditionally done in Berghauser Pont & Haupt, 2010; Gil et al., 2012; Harvey et al., 2017), the MFA procedure uses geostatistical analysis for the detection of significant spatial patterns for each streetscape morphological descriptor. The local Moran's I (Anselin, 1995) is computed on a network-constrained space (Yamada and Thill, 2010).

Thanks to these network-constrained geostatistical analyses, we pass from a collection of morphological values for each Proximity Band to morphological patterns that correspond to hot and cold spots of given morphological characteristics, using the usual categories of LISA analysis: High-High (HH), Low-Low (LL), and Non-Significant (NS). These geostatistical classifications are the result of analysis of the values of each PB, taking into consideration the local neighbourhood connected by the street network, with a topological depth of three units. For further details see Araldi and Fusco (2016), Fusco and Araldi (2017).

2.3.4. Bayesian clustering approach

The next step consists in studying the spatial co-occurrences of the 21 morphological patterns. The urban fabric seen from the pedestrian point of view is indeed the perception of persistent co-occurrences of given morphological characteristics when exploring urban space. A given urban fabric can be identified by the spatial co-occurrences of every morphological indicator, as well as by a few key characteristics. Clustering approaches aimed at achieving high intra-cluster homogeneity on the basis of variance minimization of the values of all the indicators (such as k-means, SOM and geo-SOM) are not well fitted for this task (Fusco and Perez, 2019). For this reason, Araldi and Fusco (2019) suggest the use of a Bayesian Network clustering of the results of geostatistical analysis to identify urban fabrics. Bayesian Network clustering does not impose cluster homogeneity on all variables (unlike more traditional k-means clustering), deals with categorical variables (such as the outcomes of geostatistical analysis) and allows probabilistic cluster assignment (Fusco and Perez, 2019). These features have proved particularly relevant in the identification of urban fabrics (Araldi and Fusco, 2019).

2.4. Results and discussion

2.4.1. The role of vegetation in the identification of the urban fabric

Two clusterings were carried out (Figure 2.5). Clustering 1 includes 17 indicators classified under three categories suggested by Araldi and Fusco (2019): **Street and Street Network Morphology** (except *Pedestrian area*), **Built-up Morphology** and **Network-Building Relationship**. Clustering 2 adds three **Vegetation** indicators and the *Pedestrian area* indicator to the previous set. The two clusterings were carried out using the Naïf Bayesian classifier method as presented by Araldi and Fusco (2019): using different random seeds, 1,000-step random walks explored the solution space to obtain optimal Bayesian clustering of spatial units. The search constraints were a minimum cluster content of 2% of the spatial units, a minimum average probability of assignment of units to each cluster of 0.9 and a maximum of 20 clusters. The optimal number of clusters was determined using a combined score of the log-likelihood of the clustering solution and of its parametric complexity (i.e. the number of clusters). For clustering 1, within eight random-walk searches, an optimum was always found for the 10-cluster solution. For clustering 2, 12 of the 14 random-walk searches showed an optimum for a 12-cluster solution. A successive refining phase of the cluster solution was carried out by imposing this fixed number of clusters on eight new random walk searches. Results were almost identical, the best one showing a contingency table fit score of 58.59% (clustering 1) and 53.41% (clustering 2). The two values are not directly comparable because the numbers of both indicators and clusters are unequal. Clusters are here designated as UFa, UFb,… and UFj in the case of clustering 1 and UF1, UF2,… and UF12 in the case of clustering 2.

The addition of vegetation and pedestrian area indicators (four variables) does not radically change the mutual information that indicators share with the clustering variable when considered individually [Table A.1, in the appendices]. **Network-Building relationship** indicators are the most correlated with the clustering variable, as well as *Building Contiguity*, *Proximity band coverage ratio* and *Prevalence of Building type 1 (25–125 sq. m).* Vegetation coverage indicators also have high mutual information with the clustering. The projection of the cluster variables in a space of mutual information shows a gradient of urban intensity (Figure A.3, in the appendices) that translates on the map as a centre-periphery gradient (Figure 2.5).

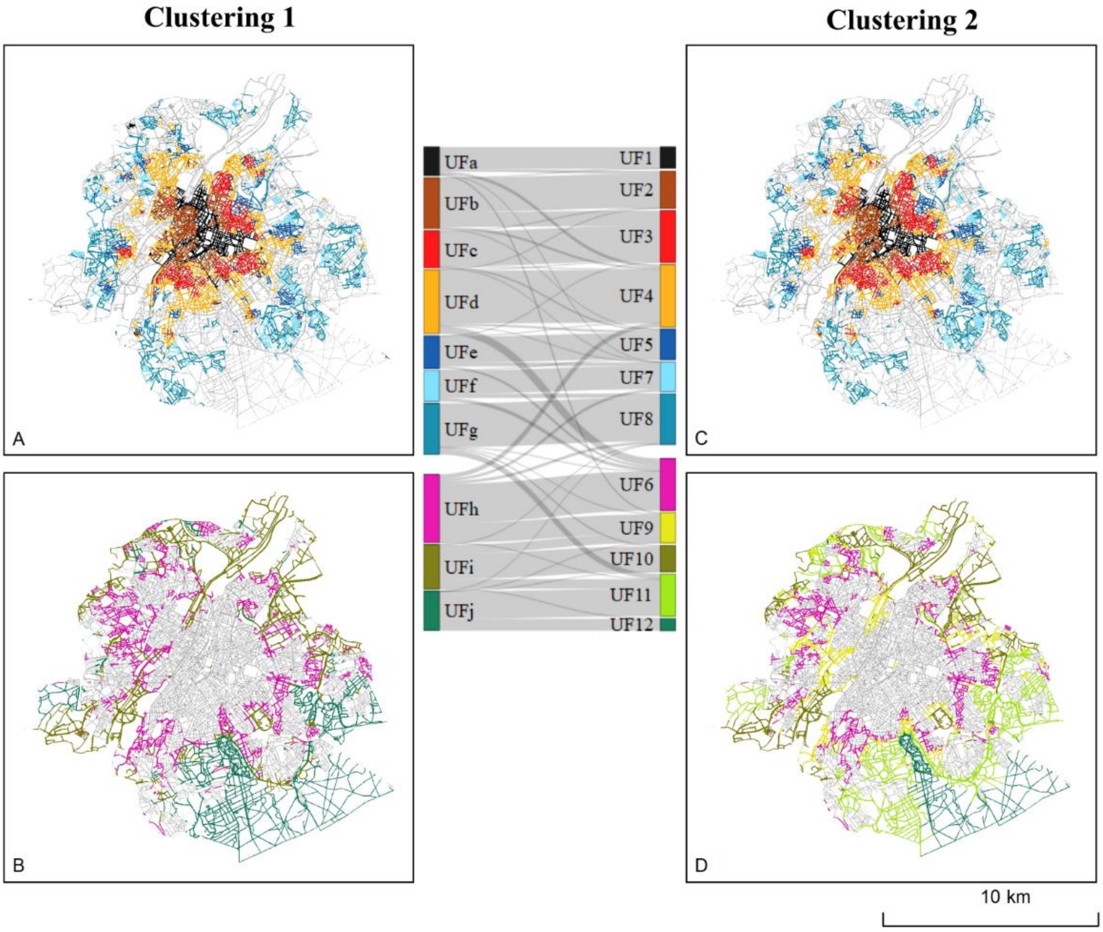


Figure 2.5. Clustering of urban fabrics without (A,B) and with (C,D) the three vegetation indicators and the pedestrian area indicator. The middle graph shows the differences between clusterings 1 and 2. The map splitting highlights the urban fabrics that remain almost unchanged (A to C) and those that change more significantly (B to D).

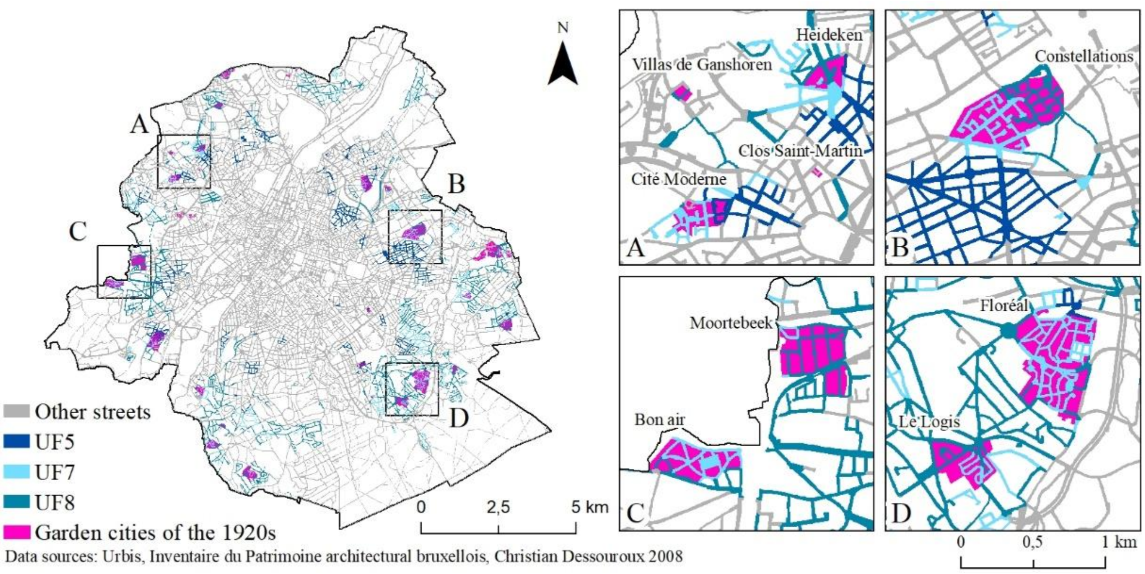


Figure 2.6. UF5, UF7 and UF8 urban fabrics and comparison with the extent of the 1920s garden cities

The delineation of the urban core as an entity distinct from more peripheral and suburban areas is constant in the two clustering outcomes. However, there is no clear cut-off between these two subspaces: not surprisingly, the urban core has a complex shape, with ramifications following main peripheral axes.

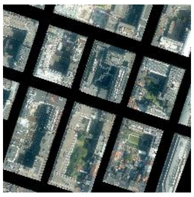
Adding vegetation and pedestrian area indicators allows delineation of meaningful new urban fabrics (UF) in the green suburban area of Brussels. Three clusters (h, i, and j) are redistributed among five new clusters (6, 9, 10, 11, and 12) characterized by a higher average class purity in terms of both the new urban fabrics and the entire clusterization outcomes (Figure 2.5.B/D). UFh – which becomes UF6 – fits better with reality, especially as a large cluster is subdivided into smaller ones. The specialized fabrics found in UFi (and some in UFh) in clustering 1 are split into two clusters in clustering 2: UF9, which takes over the specialized fabrics in a semi-continuous environment, and UF10 in an open environment. The classification of the vegetated suburbs is not accurate in clustering 1. Large green spaces such as forests or parks are not differentiated from green residential neighbourhoods. In clustering 2, UFj is divided into two clusters, making it possible to distinguish between natural spaces (UF12) and vegetated suburban spaces (UF11).

The impact of vegetation and pedestrian area indicators is limited as regards the delineation of the central fabrics and the most urbanized periphery. Seven clusters stay almost the same, with a few adjustments: only 17% of variation (Figure 2.5.A/C). They correspond to high density, well consolidated central areas and planned residential areas in the suburbs.

These observations are consistent with Hermosilla et al. (2014), who demonstrated that the vegetation distribution allows suburban fabrics to be distinguished from the other urban fabrics while, on the other hand, it becomes less efficient for the characterization of compact urban fabrics. In our study, not only do we confirm these results, but we also demonstrate with the implementation of a clustering procedure how the relative spatial configuration arrangement of vegetation and built forms might help characterize different types of suburban fabric.

However, one type of suburban fabric is excepted from this statement: the “garden districts”, which are planned residential fabrics typical of Brussels. Three clusters (UFe, UFf, and UFg, which become UF5, UF7, and UF8) are not significantly impacted by the addition of vegetation indicators despite the fact that vegetation abounds in this type of fabric. These fabrics are therefore already well determined by traditional urban form indicators given their specificities in terms of built form and street network.

Table 2.2. Characterization of urban fabrics in the BCR on the basis of probabilities of morphological patterns (only p(HH)>0,7 and p(LL)>0,7) and interpretation in terms of built-up functionalities. See Table A2 (in the appendices) for detailed results (Picture source: Urbis).

	**UF1. Continuous Modern Planned Non-Residential Fabric** - Low vegetation coverage - Large, tall buildings, absence of narrow buildings - 'Canyon' effect → European Quarter and CBD		**UF7. Semi-continuous Residential Fabric with small houses and small buildings** - Narrow buildings, absence of large buildings - Presence of vegetation → Garden neighbourhoods
	**UF2. Continuous Traditional Fabric** - Low vegetation coverage - High regular contiguous buildings - 'Corridor' and 'Canyon' effect, short, narrow streets - High building coverage → Historical center		**UF8. Semi-continuous Residential Fabric with houses and average buildings** - Low building coverage - Wide streets, absence of 'Canyon' effect - Low-rise isolated buildings → Garden neighbourhoods
	**UF3. Continuous, Dense Residential Fabric with regular small houses** - Regular and high contiguous buildings - 'Corridor' and 'Canyon' effect, narrow streets - Low vegetation coverage and high building coverage → Typical Brussels townhouses		**UF9. Semi-continuous Specialized Fabrics** - Absence of narrow buildings → Industrial zones
	**UF4. Continuous Residential Fabric with houses and small buildings** - Contiguous buildings - Low vegetation coverage - Absence of dead-end streets → Typical Brussels townhouses		**UF10. Open Specialized Fabrics** - Low building coverage - Long, wide streets, absence of 'Canyon'/'Corridor' effect - Isolated buildings, absence of narrow buildings → Industrial zones and business parks
	**UF5. Continuous Residential Fabric with regular small houses and wide streets** - Regular narrow adjoining building, no large buildings - 'Corridor' effect - Low vegetation coverage in the street → Garden neighbourhoods		**UF11. Open Suburban Residential Fabric** - High vegetation coverage - Long, wide streets, absence of 'Canyon'/'Corridor' effect - Low-rise isolated buildings, low building coverage → Villas
	**UF6. Semi-continuous Mixed Use/Form Fabric** - Mainly intermediate value (NS) of indicators → Intermediate space 200 m		**UF12. Open Natural and Artificial Non-Urbanized Areas** - Few buildings - High vegetation coverage - Presence of pedestrian areas → Natural spaces

In view of what has been discussed so far, we might infer the superiority of the second clustering in our case study. From now on we will focus only on clustering 2. There are three main categories of urban fabric: continuous, semi-continuous and open fabrics (Table 2.2). The sorting of UF clusters is supported by the statistically significant spatial patterns of each indicator for each cluster (see Table A.2, in the appendices). There is a clear vegetation gradient: low value for UF1 to UF4, high value for UF11 and UF12 and intermediate values in between. This gradient of urban intensity is also clearly apparent in the indicators in the category **Network-Building Relationship** and visible (to a lesser degree) in the case of the other two categories.

2.4.2. On the history of the Brussels urban fabric

Beyond the city's morphology, the resulting typology of urban fabric can be linked to several major developments in the history of urban planning in Brussels. UF2 refers to the medieval fabric, characterized by many small buildings and narrow, winding streets. UF3 and UF4 form the first ring of Brussels. These are dense fabrics characterized by the Brussels townhouses, typical 19^{th}-century bourgeois contiguous houses (Ledent, 2017). The second ring of Brussels is greener, characterized by what could be called "garden districts" (UF5, UF7, and UF8) and by UF11, fabrics made up of detached houses and villas. Fabrics with a more functional purpose are also highlighted: UF1 contains mainly offices, and the UF9 and UF10 fabrics are mainly industrial areas. See Table 2.2 for more details. In the next sections, two specific points in this history are explored in more detail: the construction of the garden districts (Section 4.2.1) and Brusselization (Section 4.2.2).

Garden Districts

In the inter-war period, the need for social housing became glaringly obvious. Inspired by the English garden cities, several social housing associations were formed to build what can be called "garden districts". In Brussels, rather than autonomous cities, it was districts, designed to expand, that were built. These "garden districts" were conceived by their designers as parts of the city in the countryside, with the underlying idea that the living environment influences the well-being of the inhabitants (Eggericx and Hanosset, 2003). After the Second World War, for financial reasons, the "garden district" model changed to blocks of flats freely integrated into a park. The aim was to provide modern, comfortable housing made accessible to middle-income households through maximum cost reduction (Leloutre, 2017), following the precepts of the modernist movement.

Many "garden districts" were built in Brussels. Some were developed with the idea of community in mind, constructed in a spirit of collective management. Other housing estates were inspired by garden cities, without directly appending that name to the urban planning operation or necessarily having any social idea behind them. One of the advantages of the method presented in this paper is that it makes it possible to identify both.

Three clusters of UFs are linked to the “garden district”: UF5, composed of row houses with gardens, UF7, composed mainly of small detached or semi-detached houses surrounded by vegetation, and UF8, composed of larger detached or semi-detached houses surrounded by vegetation. If we take the extent of the 1920s social garden cities (Dessouroux, 2008), 42% of the street segments are in UF7 and 30% in UF8 (Figure 2.6).

Brusselization

Brussels is mainly a tertiary city, with office activities expanded after the Second World War with relatively little regulation. The office towers have shaped Brussels. The financial benefit represented by offices has led to the transformation of some historical fabrics into business districts, to the detriment of residential areas, mixed neighbourhoods and the architectural heritage. This phenomenon has been described in the literature as “Brusselization” (De Beule and Dessouroux, 2011; Dessouroux, 2008).

UF1 includes street segments with high office density (Figure 2.7). These fabrics feature the major business districts of Brussels: the European Quarter, the eastern part of the Pentagon, and the North District.

The office development in the **eastern part of the Pentagon** (Figure 2.7) has historically been around the Cathedral of Saint Michael and St Gudula, Brussels Park, the small belt (second rampart layout), and the North-South junction. This railway junction shaped the fabric of Brussels because its redevelopment took the form of office buildings, contrasting with the historical fabric. The Leopold District was an upper-class residential district, which gradually became more and more service-oriented. Today, it is more commonly known as the **European Quarter**, because of the European institutions and associated entities (lobby firms, country representations, and embassies). The **North District** is a vast real-estate project that began in the 1960s. Unlike in the European Quarter, the land parcel and the road network have been modified to accommodate high office towers. Implementing this project meant displacing a large part of the neighbourhood’s population, with an outcome that fell far short of expectations. Following the failure of the North District, a different approach to urban planning was taken. It led in particular to the preservation of the Marolles neighbourhood in the face of a project to expand the Palais de Justice (law courts). A few years later, urban planning policy reverted to the earlier approach in the case of office development around the South Station (De Beule and Dessouroux, 2011).

While the method allows converted fabrics to be highlighted, it also identifies, as UF2, historical fabrics that have been preserved, such as the Marolles (Figure 2.7). The typology used sheds light on a heritage that is not always easy to identify – the urban fabric itself.

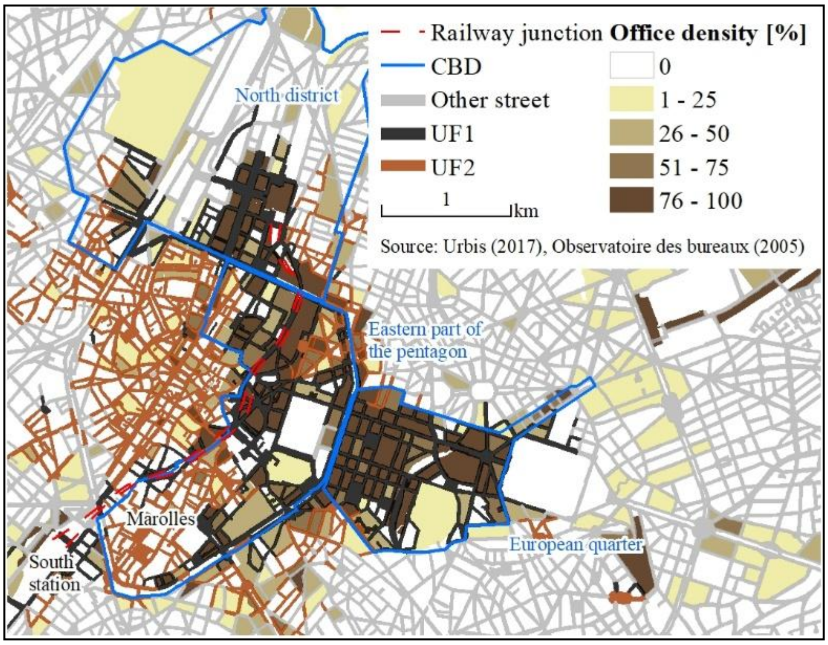


Figure 2.7. UF1 and UF2 urban fabrics and comparison with the extent of the business districts of Brussels (North District, European Quarter and eastern part of the Pentagon).

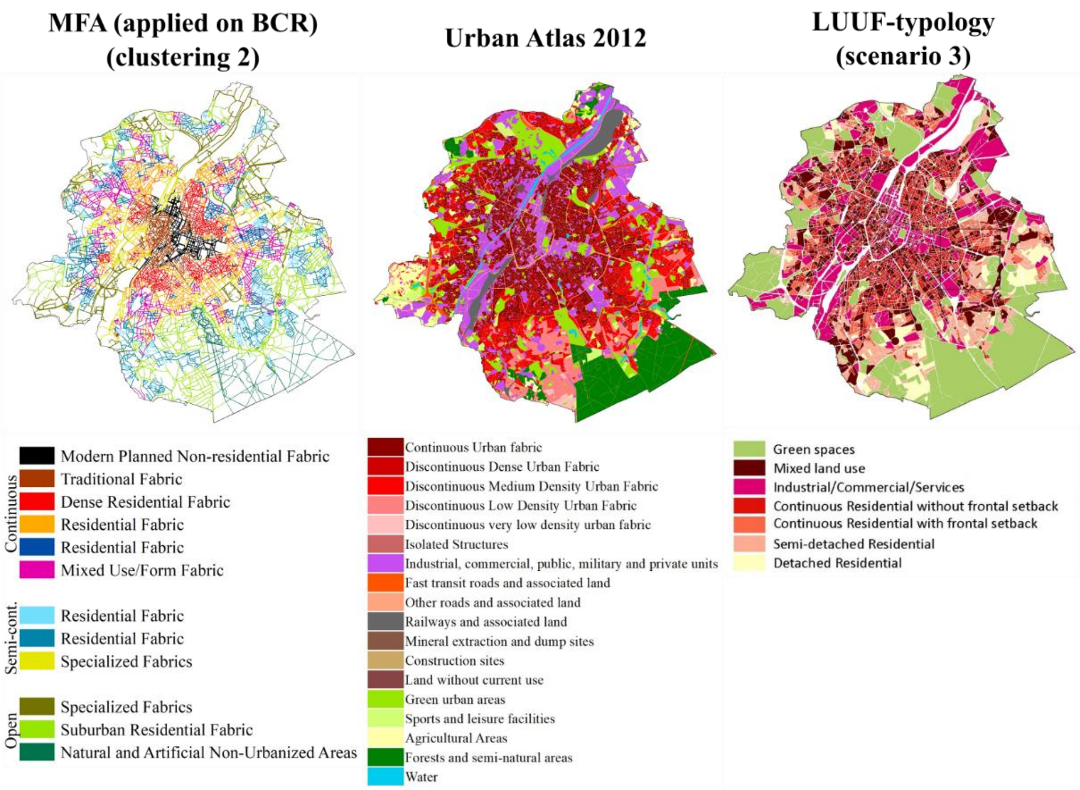


Figure 2.8. Spatial comparison of MFA and two other urban form classifications for the BCR

2.4.3. Advantages and limitations

Here we aim to compare our results (clustering 2) with the European Urban Atlas (UA) (European Environment Agency, 2012) and with the land use/urban form (LUUF) typology (scenario 3) developed by Vanderhaegen and Canters (2017) (Table 2.3). This comparison will focus in particular on three aspects: the use of expert knowledge, the objective and the spatial result.

Table 2.3. Methodological comparison between MFA and two other classifications of urban forms in the BCR.

	MFA	Urban Atlas 2012	LUUF-typology
Source	This paper – clustering 2	European Environment Agency (2012)	Vanderhaegen and Canters (2017) – scenario 3
Objectives	Providing a typology of urban street landscapes in Brussels with the further goal of studying human behaviour and well-being	Pan-European comparable land use and land cover data for Functional Urban Areas	Mapping types of urban forms and functions for land use mapping (applicable to other cities with similar urban structure)
Basic spatial unit	Proximity Band around street segments	~ Urban block	Urban block
Urban form indicators	• Network and Street Morphology • Built-up Morphology • Network-Building Relationship • Vegetation	• Land uses and percentage of block footprint coverage	• Patch-based: landscape ecological metrics • Profile-based: radial and contour-based profile metrics • Building based: internal structure of the built-up area
Definition of classes	With a neutral prior on classes of urban fabric	18 classes for BCR	Six urban forms defined on the basis of theoretical models
Classification methods	1. Characterization of each indicator in terms of spatial association: clusters of high value, of low value and of non-significant elements 2. Clustering of local patterns using Bayesian approach	Interpretation of high-resolution satellite imagery and use of national in situ data	Classification tree, with tree bagging
Final classification	12 classes	18 classes	6 classes

The UA is essentially based on expert knowledge with little use of automatic workflows. The classes were pre-defined, identical for all Functional Urban Areas. The classification method is also based essentially on expert interpretation of high-resolution satellite imagery and use of national in situ data. Vanderhaegen and Canters (2017) defined, on the basis of the literature, the indicators used to classify the urban blocks. The clustering methodology is a classification tree, with tree bagging of six urban form classes defined on the basis of theoretical models of urban residential morphology. As in the aforementioned work, the indicators used in the MFA method were inspired by the literature. The difference in design is that Bayesian clustering uses a neutral prior for the number and profile of the urban fabric classes (with a maximum of 20 classes). A shared feature of the LUUF and the MFA method is the treatment of uncertainties, also commented on from the perspective of the urban continuum by Vanderhaegen and Canters (2017). Both methods compute to each element a probability of association with the assigned typology. The uncertainties are not addressed in this paper but were discussed in Araldi and Fusco (2019).

The objectives of each typology of urban form of Brussels are also different. The advantage of the UA is that it is a comparable database covering 693 Functional Urban Areas in Europe, which means that the database is not specific to Brussels. The LUUF-typology, even though it applies more specifically to Brussels, has been found to be "rather generic […], to be easily applicable to other cities with similar urban structure" (Vanderhaegen & Canters, 2017, p. 407). The aforementioned authors tested different metrics for the characterization of urban form, and voiced criticisms of the intensive use of landscape ecology metrics. They concluded that specific metrics should be used which describe more explicitly the morphological characteristics of the urban fabric. Their conclusions are consistent with the MFA method. One of the contributions of this paper is to add, and evaluate the advantages of adding, vegetation as an indicator of urban form. The resulting typology of urban street landscapes is specific to Brussels. It provides a detailed overview of the intra-urban fabric of Brussels, and is hence not intended for comparison purposes.

The maps show major differences (Figure 2.8). The UA and LUUF-typology classify each urban block according to its intrinsic characteristics, while the MFA method uses local patterns of street-based urban form indicators. This gives two different results. On the one hand, each urban block is classified while, on the other, the street-based urban fabric is highlighted. So the MFA method does not highlight specific characteristics of each element, but instead provides an overview of the context in which it is found. The choice of method will therefore depend on the objective of the modelling.

In the context of well-being research, the MFA method seems the most appropriate. First, the choice of indicators was made on the basis of the pedestrian's perception of the urban environment, and is consequently human-based. Second, the method highlights urban fabrics (especially through local patterns in the street network) that more closely resemble a pedestrian's experience when walking in the city. Indeed, “it is by moving from one street to another that pedestrians can experience the spatial variability or homogeneity of urban fabric characteristics” (Araldi & Fusco, 2019, p. 1247).

2.5. Conclusions

This paper set out to identify the urban fabrics of Brussel in the same way as the traditional urban typo-morphological approach, but using state-of-the-art geoprocessing protocols. We have chosen two guiding principles: taking a human-perspective approach and adding vegetation to the traditional indicators. In order to achieve this goal, the MFA procedure was adapted and implemented in the specific case study of the BCR. Two classifications were tested. Clustering 1 reflects more closely the original method carried out by Araldi and Fusco (2019). Clustering 2 includes the same indicators, but with the addition of three vegetation-related indicators and one pedestrian-area indicator. The results show that the added indicators allow of a better definition of greener peripheral areas, but that their impact is limited as regards the definition of central fabrics and the planned suburban residential fabric (the “garden districts”). The additional indicators allow of a more detailed classification of the urban fabric. Twelve clusters of urban fabrics were identified, divided into three main groups: continuous, semi-continuous and open fabrics. This provides a new way of dividing up Brussels that can be linked to several chapters in the history of Brussels, such as the construction of “garden districts” and Brusselization. The method proved to be successful in identifying Brussels urban fabrics and their spatial arrangements. The typologies identified are consistent with the outcomes of previous studies on the morphological characteristics of the BCR, while developing a more finely grained analysis able to detect urban fabrics from the pedestrian’s point of view. The addition of vegetation indicators has demonstrated the relevance of vegetation in defining the urban fabric, suggesting that it could be usefully included in further studies of the urban form. Vegetation is here seen as an integral part of the urban landscape and measured in terms of its spatial distribution within the streetscape and the urban fabric environment. This protocol differs strongly from the mainstream approach, where vegetation is considered and measured as a distance-based service with accessibility measures.

The resulting typology can be used in various ways in further work as a contextual factor highlighting the variety of urban fabrics in Brussels. Research on human behaviour and well-being in the city could benefit from a knowledge of urban forms as perceived by the pedestrian in the street. Discontinuities in the urban fabric could be identified by planners with a view to creating a more cohesive urban street landscape. An objective representation of the urban fabric at any given time could also serve as a reference for future interventions on the form of the physical city. The MFA protocol could even be used to assess the potential impact of specific projects on the urban form.

From the methodological point of view, several aspects could be explored further. For example, a sensitivity assessment of statistical and clustering parameter choices would enable the stability of the MFA protocol to be assessed. Outcomes might also vary depending on the underlying street-network impedances and contiguity modelling approaches that reveal how the urban fabric might be perceived differently, in terms of its walkability properties. Finally, the development of an MFA tool for GIS platforms would also allow the study of the urban fabric to be extended to large synchronic and diachronic comparative studies.

3

Non-response bias in the analysis of the association between mental health and the urban environment: a cross-sectional study in Brussels, Belgium

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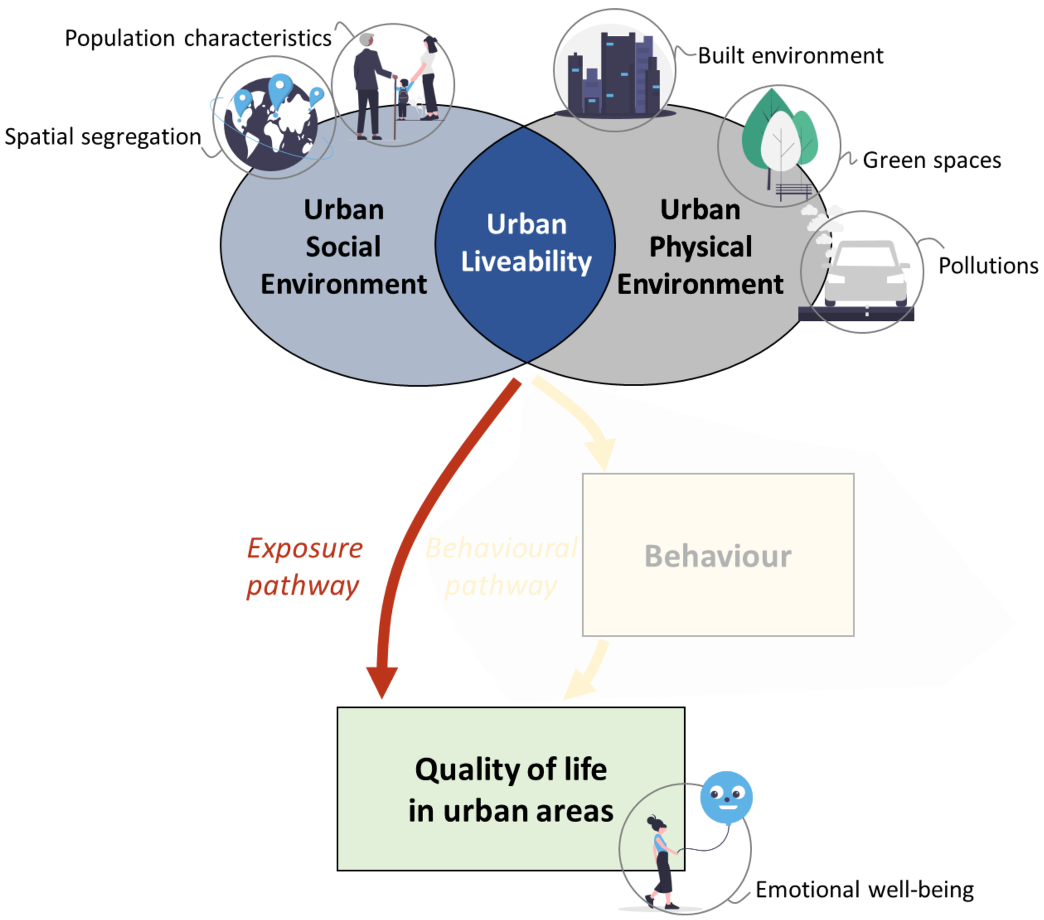


Abstract

This paper aims at analysing the impact of partial non-response in the association between urban environment and mental health in Brussels. The potential threats of the partial non-response are biases in survey estimates and statistics. The effect of non-response on statistical associations is often overlooked, and evidence in the research literature is lacking. Data from the Belgian Health Interview Survey 2008 and 2013 were used. The association between non-response and potential determinants was explored through logistic regressions. Participants with low income, low educational levels, lower or higher age or in households with children were less likely to respond. When adjusting for socio-economic variables, non-response was higher in areas which are less vegetated, more polluted or more urbanized. Because the determinants of non-response and depressive disorders were similar, it is reasonable to assume that there will be more people with mental health problems among the non-respondents. And because more non-responses were found in low vegetation areas, the protective association between green spaces and mental health may be underestimated. Our capacity to measure the association between the urban environment and health is affected by non-response in surveys. The non-random spatial and socio-economic distribution of this bias affects the research findings.

3.1. Background

The issue of non-response and incomplete data, that often confronts population studies such as health surveys, is a well-known challenge in epidemiology (Johnson and Wislar, 2012; Peytchev, 2013) that has already been extensively studied (Berete et al., 2019; Boshuizen et al., 2006; Burzykowski et al., 1999; Ekholm et al., 2010; Jaehn et al., 2020; Korkeila et al., 2001; Volken, 2013). Non-response can occur at different stages of the survey and varies from the refusal to participate (initial non-response) to a non-response to one of the questions (partial non-response). While the determinants of initial non-response are difficult to study (via auxiliary data as in Ekholm et al., 2010 or via non-responder questionnaire as in Jaehn et al., 2020), partial non-response has the advantage that it can be studied on the basis of participants' partial responses (Berete et al., 2019; Boshuizen et al., 2006; Volken, 2013).

Personal characteristics, such as economic status, are important in the variation of non-response (Burzykowski et al., 1999; Ekholm et al., 2010; Jaehn et al., 2020; Korkeila et al., 2001). In the case of the Belgian Health Interview Survey (BHIS), determinants of partial non-response have already been evaluated by Berete et al (2019): non-response is more frequent among youngsters, non-Belgians, low educational levels, lower income, residents of Brussels and Wallonia, and people with poor perceived health. Partial non-response is also strongly associated with the interviewer: it explains almost half (46.6%) of the variability in partial non-response. Other studies (Boshuizen et al., 2006; Volken, 2013) on partial non-response have additionally shown that non-response is greater for men and for unskilled workers. The potential threats of this partial non-response are biases in survey estimates and statistics. The effect of non-response on statistical associations is often overlooked and evidence in the research literature is lacking (Peytchev, 2013).

Understanding the association between the urban environment and mental health is a challenging exercise. Cities are complex systems, with urban mental health outcomes affected by many interactions (Evans, 2003). This topic has been attracting a lot of interest and the literature has grown substantially over the past few years (Chi et al., 2022; Gong et al., 2016; Gruebner et al., 2017; Hankey and Marshall, 2017; Okkels et al., 2018; Rautio et al., 2017; Ventriglio et al., 2021; Wal et al., 2021). A study conducted in Brussels concluded that exposure to traffic-related air pollution (black carbon, NO2, PM10) was positively associated with higher odds of depressive disorders but no association between mental health and green surroundings, noise, or building morphology could be demonstrated

(Pelgrims et al., 2021). Concerning vegetation, these results differ from many studies that describe how higher levels of exposure to greenness can reduce levels of depressive symptoms (Fong et al., 2018). This raises the question of why there is no association in the case of Brussels.

Personal characteristics, such as economic status, are also important in mental health while the urban environment appears to be a less important determinant (Kabisch, 2019). Moreover, in Brussels, as in other cities, socio-spatial inequalities complicate matters: environmental factors are strongly correlated with socio-economic ones (Stessens et al., 2017). It is therefore difficult to disentangle the variance due to socio-economic status from the variance due to the urban environment.

If personal characteristics play an important role in explaining non-response and mental health status, we can question the magnitude of bias generated by non-response in the analysis of the association between urban environment and mental health. This paper therefore aims at analysing, characterizing and discussing the impacts of non-responses in this association with the example of Brussels.

3.2. Methods

3.2.1. Study area

Brussels is the capital of Belgium, centrally located in the country. The city extends into three administrative regions: the Brussels-Capital Region (BCR), Flanders and Wallonia (Thomas et al., 2012). We focus here on the urban area encompassed within the administrative border of the Brussels-Capital Region (BCR) because the Region was more intensively sampled compared to the rest of Belgium and because of data consistency issues for the urban environment indicators. The BCR is divided into 19 municipalities. It covers 161.38 km² and has 1.2 million inhabitants (source: Statistics Belgium – 01/01/2018), which means an average density of 7438 inhabitants per square kilometre.

3.2.2. Study design

The study presented here consists of a secondary analysis of a population-based, cross-sectional study of the association between urban environment and mental health in Brussels, Belgium. Results from the original research could not demonstrate any association between urban environment (green surroundings, noise, building morphology) and mental health except for traffic-related air pollution (black carbon, NO2, PM10) exposure which was positively associated with higher odds of depressive disorders (Pelgrims et al., 2021).

3.2.3. Study population and data

The Belgian Health Interview Surveys (BHIS) of 2008 and 2013 were used. We kept participants aged over 15 (minimum age to fill the self-administered questionnaire) and living at the place of residence for at least one year (n = 4,355).

In the BHIS, three types of non-response can be highlighted: (i) Initial non-response: refusal to participate in the survey (Van der Heyden et al., 2014), not addressed in this paper; (ii) Self-administered questionnaire (SAQ) non-response: for those over 15 years of age, the survey consists in two parts: a face-to-face (F2F) interview and a SAQ, the latter of which is not filled out; and (iii) Item non-response: at various points of the survey some questions were not answered by the participants. These last two types can be designated as partial non-response. Questions related to mental health are particularly sensitive. They are generally not asked in a F2F interview to avoid desirability bias and are included in a SAQ, as is the case for the BHIS.

3.2.4. Mental health and non-response definition

The response to six indicators related to mental health was extracted from the BHIS (Gisle, 2014): *Energy level (SF-36 "vitality scale")* [based on 4 items in SAQ] (Ware and Sherbourne, 1992), *General Health Questionnaire (GHQ-12)* [based on 13 items in SAQ] (Goldberg and Williams, 1988), *Self-reported depression* during the last year [based on 1 item in F2F interview], *Depressive disorder* [based on 13 items in SAQ], *Anxiety disorder* [based on 10 items in SAQ] and *Sleeping disorder* [based on 3 items in SAQ] (SCL-90-R subscales) (Derogatis, 1994).

Non-response to a mental health indicator means that there are not enough items answered to compute the indicator. The reason may be either that the SAQ was not completed or that some or all of the items related to an indicator were not answered. If at least 75% of the items related to an indicator have valid responses, the missing item(s) are substituted by the mean value of the valid responses. For example, if 1 to 3 items out of the 12 items of the GHQ scale have missing values, the GHQ is still computed; whereas if more than 3 items are missing, the indicator score is considered missing (Scientific Institute of Public Health, 2013).

3.2.5. Urban environment

The urban environment was measured by eight indicators computed at the residence address of the BHIS participants. Urban greenness was assessed at three different geographical levels (residence, street, neighbourhood). At residence level, v*iew of green* was determined by the ratio of the total green area from Google

Street View panorama (~picture 360°) to the total area of the panorama. At street level, *Linear tree density* was defined as the ratio between the number of trees (point data from Urbis) (BRIC, 2017) and the street length and *Street visible vegetation coverage* is the vegetation coverage (from Brussels Environment) (Van de Voorde et al., 2010) on the street, and 10 m on either side. At neighbourhood level, *Vegetation coverage* was defined as the ratio of vegetation coverage (from Brussels Environment) in a 1000m circle around the respondent's residence. The built-up environment was assessed by two indicators at the street level: the *Street canyon effect* which is the ratio between average building height and average open space width and the *Street corridor effect* which is the ratio between parallel facades length and street length. *Noise* was extracted from noise from multiple sources map (day – evening – night noise level, Lden) from Bruxelles Environnement for the years 2006 and 2011 at residence level. *Black carbon* exposition was defined as the annual average in the year of BHIS participation at residence level (Janssen et al., 2008; Lefebvre et al., 2013; Lefebvre and Vranckx, 2013). See Pelgrims *et al.* (2021) for more detailed descriptions of the indicators. These indicators were missing when the health survey could not be coupled with the participant's address (in Brussels). To address this, a "no data" category was added to each indicator with missing value.

3.2.6. Socio-economic status

Five socio-economic indicators were used: *Reported household income*, *Age*, *Gender*, *Family composition* and *Highest educational level in the household*. These indicators were extracted from the BHIS. Non-responses were observed if the item has not been answered. To address this, a "no answer" category was added to each indicator with non-responses.

3.2.7. Statistical analyses

The frequency of non-response was summarized for each mental health and socio-economic indicator. Descriptive statistics were calculated to account for the sampling strategy. "The weight for each sampled individual in the BHIS is the product of the reciprocal of the selection probability within a household and of a post stratification factor for each province according to age, gender, household size and quarter of the year in which the interview was done" (Scientific Institute of Public Health, 2013).

In order to assess the association of socio-economic and urban environmental with non-response, logistic regressions with the non-response as dependent variable were computed: no missing data (0) vs. at least one non-response among six mental health indicators (1). Taking non-response to at least one mental health outcome as a proxy for non-response is a somewhat crude generalization. However, it reflects a practice: if we want to analyse a complete case, i.e. take only those individuals who responded to all the questions we are interested in, we will then remove all individuals who did not respond to at least one question. Our purpose here was first to identify the characteristics of those excluded from the complete case by running models for socio-economic indicators. Secondly, we aimed at analysing whether these individuals were concentrated in specific environments by running single-exposure models for urban environment indicators (models A) and adjusted models (with gender, age, reported household income and year of the BHIS) for urban environment indicators (models B).

In order to assess the differences and similarities between the socio-economic characteristics of non-respondents and participants with depressive disorders, two groups of logistic regressions were performed for socio-economic variables: (i) with depressive disorders as dependent variable (models C) and (ii) with the non-response to depressive disorders related questions as dependent variable (models D). Correct estimates and valid inferences of odds ratio (OR) were obtained by taking into account the survey weights, strata and clusters relative to the sample design. All analyses were performed using the statistical software R (R Core Team, 2020) using the survey package (Lumley, 2004).

3.3. Results

3.3.1. Data description

A total of 4355 residents of the BCR were included in the study population. Table 3.1 describes all considered variables.

Overview of non-responses among the study population is displayed in Table 3.2. The number of individuals refers to the number of respondents in the sample while the percentage is weighted to represent the study population. In our sample of 4,355 individuals, the SAQ was not available for 1,602 participants (35.48% of the population). For 18.97%, SAQ was required but not available and for 16.51%, SAQ was not required and not available (when the interview is done by a proxy such as a parent). Non-response to mental health items (excluding SAQ non-response) ranged from 1.03% (Self-reported depression) to 7.33% (Energy level). In the subset of participants for whom the SAQ was available and who answered all mental health and socio-economic items, data was available for 1,929 individuals (45.92% of the initial population).

Table 3.1. Characteristics of the study population (weighted percentages and weighted mean).

Socio-economic status	
Reported household income %/N	
Quartile 1 (low)	20.66%/893
Quartile 2	18.53%/866
Quartile 3	21.64%/926
Quartile 4 (high)	22.24%/904
No answer	16.93%/766
Reported household income [€] mean [IQR]	1525.03 [1473.46-1576.61]
Age %/N	
15–24	13.81%/536
25–44	37.39%/1439
45–64	30.06%/1317
65+	18.74%/1063
Age median [IQR]	46.08 [45.35-46.81]
Gender %/N	
M	48.19%/1986
F	51.81%/2369
Year of the BHIS %/N	
2008	45.26%/2203
2013	54.74%/2152
Family composition %/N	
Single	28.79%/1176
Couple with child (ren)	33.81%/1469
Couple without child (ren)	17.20%/809
One parent with child (ren)	11.25%/502
Other/unknown	8.95%/399
Highest educational level in the household %/N	
Higher	45.49%/1882
Higher secondary	26.13%/1142
Lower secondary	13.68%/631
No diploma or primary education	11.87%/556
No answer	2.84%/144
Environmental factors	
Street canyon effect mean [IQR]	0.67 [0.65-0.69]
Street corridor effect [0–2] mean [IQR]	1.66 [1.64-1.69]
Street corridor effect %/N	
<median	23.87%/668
>=median	24.90%/652
maximum	50.14%/1209
No data	1.09%/33
Linear tree density mean [IQR]	0.09 [0.08-0.09]
Linear tree density %/N	
No tree	27.21%/669
<median	35.62%/932
>=median	36.08%/928
No data	1.09%/33
Vegetation coverage (1 km buffer) mean [IQR]	0.38 [0.37-0.39]
Street visible vegetation coverage (within 10m) mean [IQR]	0.17 [0.16-0.19]
View of green mean [IQR]	14.52 [13.98-15.07]
Noise from multiple sources Lden [dB] mean [IQR]	51.29 [51.04-51.55]
Black carbon mean [IQR]	2.30 [2.27-2.33]

Table 3.2. Non-response in the study population. No answer (NA) is due to an item non-response or to the self-administered questionnaire (SAQ) not filled out (rows in grey). Complete cases are individuals with all socio-economic (SE) and/or mental health (MH) indicators answered. * whole study population; ° participants with SAQ available. Weighted percentages.

	Initial sample*		SAQ subset°	
	Obs	%	Obs	%
Initial sample	4355	100.00%		
NA Reported household income (SE)	766	16.93%		
NA Age (SE)	0	0.00%		
NA Gender (SE)	0	0.00%		
NA Family composition (SE)	399	8.95%		
NA Highest educational level in the household (SE)	144	2.84%		
NA Self-reported depression (MH)	44	1.03%		
SAQ required but not available	842	18.97%		
SAQ not required and not available	760	16.51%		
SAQ not required but available	110	2.50%		
SAQ required and available	2643	62.02%		
SAQ available		64.52%	2753	100.00%
NA General Health Questionnaire (GHQ-12) (MH)	1723	38.17%	121	2.70%
NA Energy level (SF-36 “vitality scale”) (MH)	1918	42.80%	316	7.33%
NA Depressive disorder (MH)	1793	39.51%	191	4.04%
NA Anxiety disorder (MH)	1801	39.75%	199	4.27%
NA Sleeping disorder (MH)	1811	39.91%	209	4.44%
Complete case for mental health	2285	53.93%		
Complete case for mental health and socio-economic	1929	45.92%		

3.3.2. Determinants of partial non-response

Figure 3.1 shows the association between socio-economic variables and non-responses through univariate models and fully adjusted model. These models are also displayed in Additional File 1. Considering that the coefficients between the univariate models and the fully adjusted model are very similar, only the coefficients of the univariate models will be discussed below. Participants in the lower socio-economic quartiles (Quartile 1 and Quartile 2) were less likely to respond than those in the higher quartile (Quartile 4) ($p < 0.001$, OR = 2.19, 95% CI = 1.66–2.90 and $p < 0.001$, OR = 2.15, 95% CI = 1.63–2.82 respectively). Compared to 25–44 yr, older (65 + yr) and younger (15–24 yr) participants were less likely to respond ($p < 0.001$, OR = 1.66, 95% CI = 1.36–2.02 and $p < 0.001$, OR = 1.9, 95% CI = 1.47–2.46 respectively). Compared to single participants, couples with child (ren) and one parent with child (ren) were less likely to respond ($p < 0.001$, OR = 1.61, 95% CI = 1.3–2 and p = 0.008, OR = 1.45, 95%CI = 1.1–1.91 respectively). Finally, participants from households with a lower educational level (higher secondary, lower secondary and no diploma or primary education) were less likely to respond than those with a higher education (after secondary) and the effect size increases as the level of education decrease (p = 0,004, OR = 1.36, 95%

CI = 1.1–1.69 and p <0.001, OR = 1.85, 95% CI = 1.43–2.39 and p <0,001, OR = 3.6, 95% CI = 2.7–4.79 respectively).

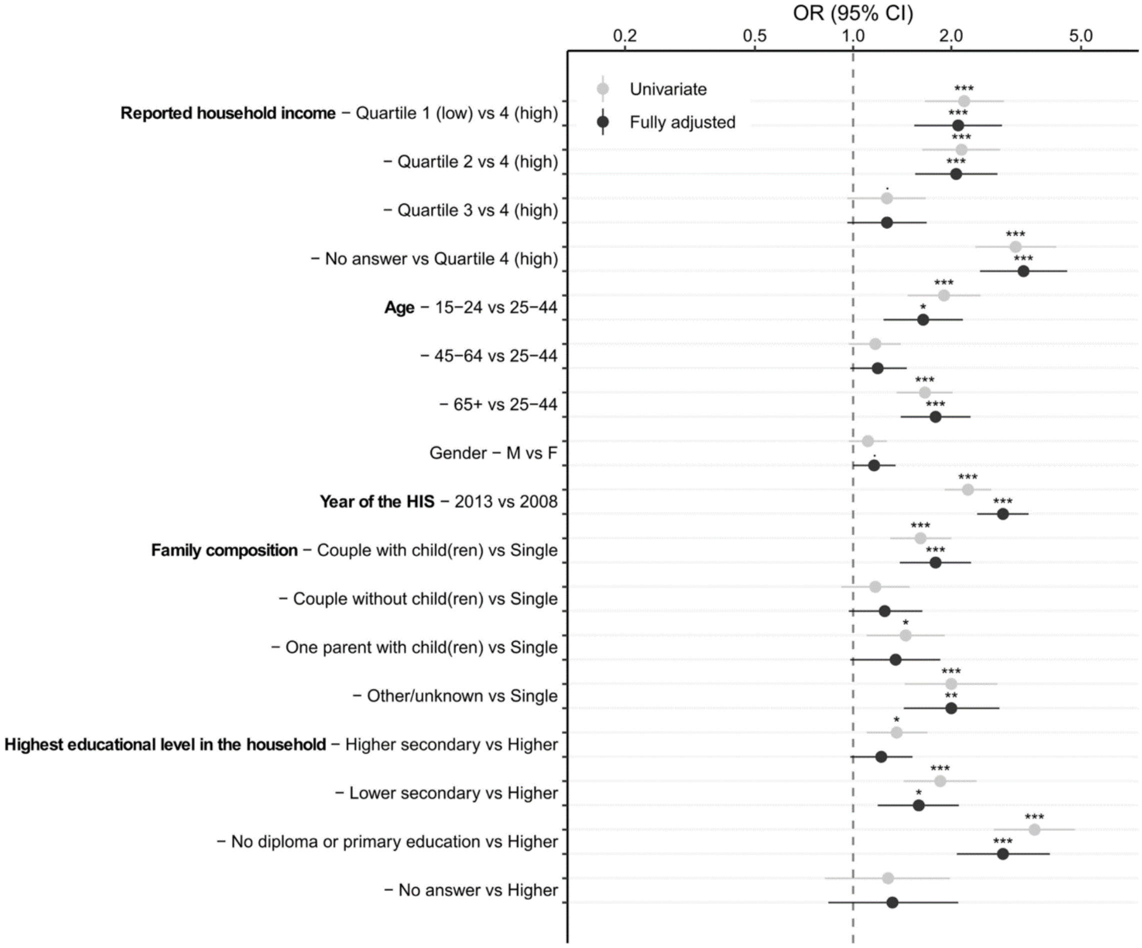


Figure 3.1. Association between non-response and socio-economic indicators (univariate regression models and fully adjusted regression model). Levels of significance: "***" = p <0.0001, "**" = p <0.001, "*" = p <0.01, "·" = p <0.05

Figure 3.2 shows the association between urban environment indicators and non-response through univariate models (Models A) and adjusted models (Models B) for gender, age, reported household income and year of the BHIS. These models are also displayed in Additional File 2. When adjusted for socio-economic variables, non-response was higher in areas with lower amounts of vegetation cover (vegetation at 1 km buffer, p = 0.001, OR = 1.44, 95% CI = 1.16–1.78 and street visible vegetation, p = 0.022, OR = 1.29, 95% CI = 1.04–1.59), lower in less polluted areas (black carbon, p = 0.003, OR = 0.71, 95% CI = 0.56–0.89) and in less urbanized areas (street canyon, p = 0.04, OR = 0.8, 95% CI = 0.65–0.99 and street corridor effect, p = 0.044, OR = 0.8, 95% CI = 0.65–0.99).

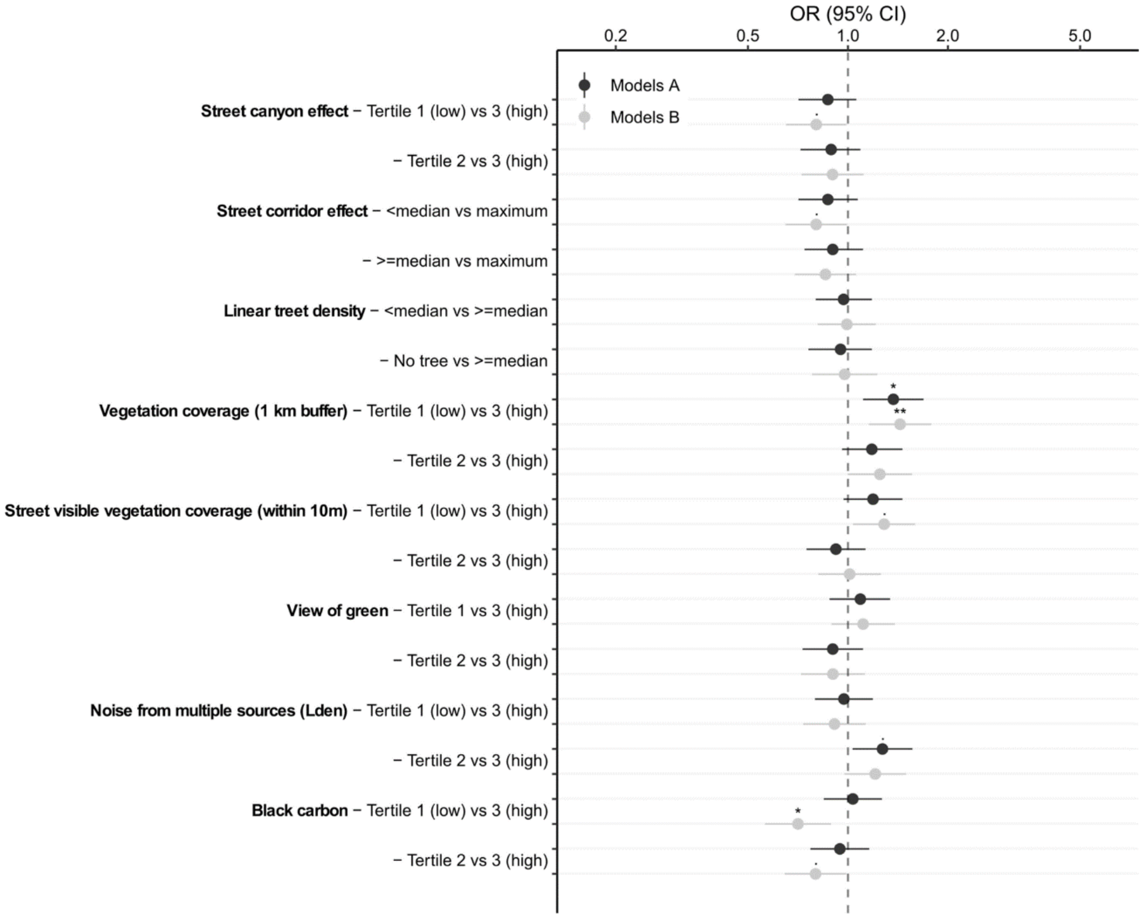


Figure 3.2. Association between non-response and urban environment indicators. Models A are univariate regression models. Models B are adjusted regression models for gender, age, reported household income and year of the BHIS. Levels of significance: "***" = p <0.0001, "**" = p <0.001, "*" = p <0.01, "·" = p <0.05

3.3.3. Comparison of partial non-response determinant and depressive disorders determinants

Figure 3.3 shows the associations between socio-economic variables and non-response to depressive disorders related questions (univariate regression models C and fully adjusted regression model E) and the associations between socio-economic variables and depressive disorders (univariate regression models D and fully adjusted regression model F). These models are also displayed in Additional File 3 and 4. It should be noted that the two populations studied are different: population of models D and F is limited to the respondents to depressive disorders related questions only. The comparison of the two types of models nevertheless allows us to have an overview of the similarities and differences even if it cannot be compared on a more formal basis. The determinants of non-response are quite similar to the determinants of depressive disorders. Odds ratios are similar for household income, age (except for 15–24 y) and education level, while there are substantial differences for family composition and gender.

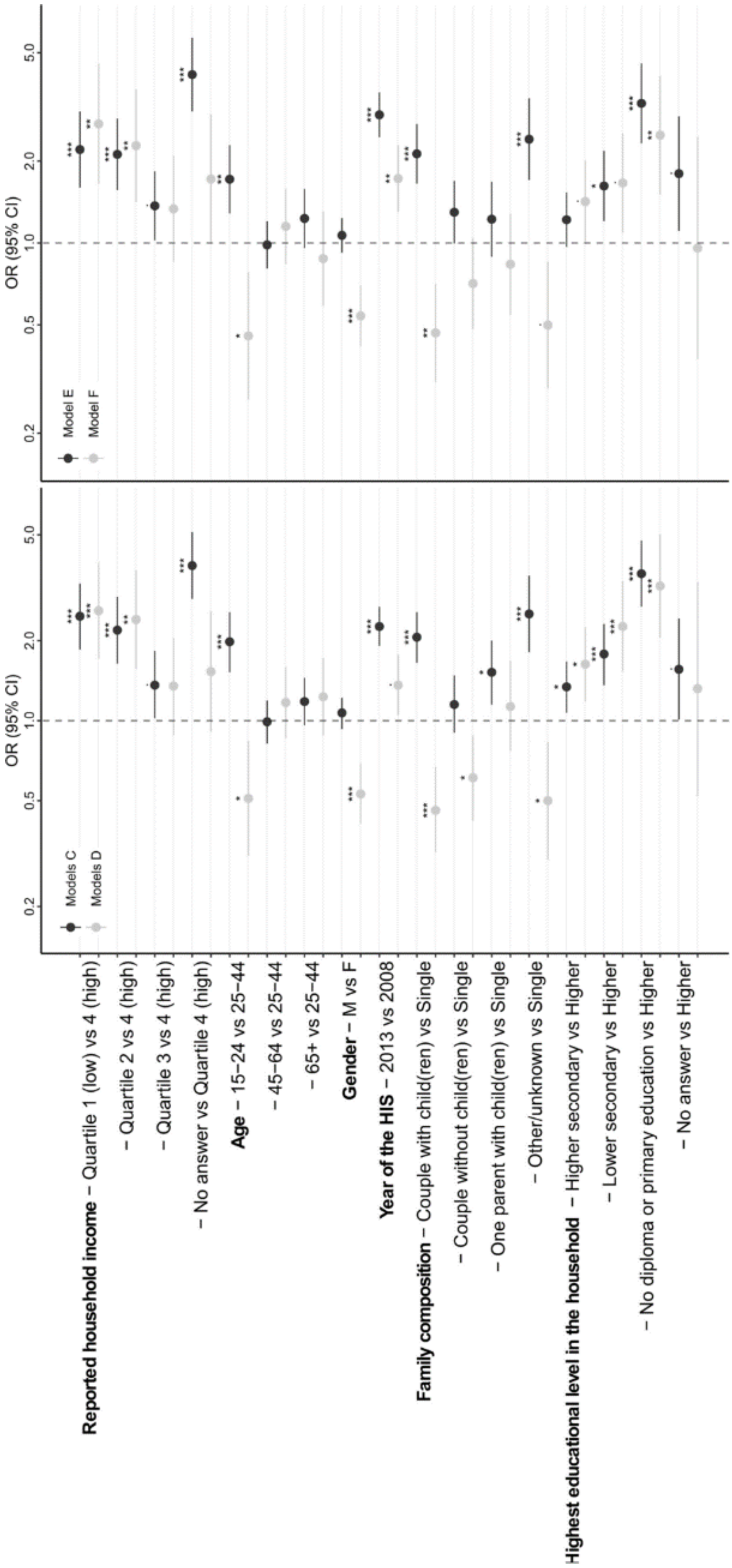


Figure 3.3. Association between non-response to depressive disorders related questions and socio-economic indicators (univariate regression models C and fully adjusted regression model E) and between depressive disorders and socio-economic indicators (univariate regression models D and fully adjusted regression model F). Levels of significance: '***' = p < 0.0001, '**' = p < 0.001, '*' = p < 0.01, '.' = p < 0.05

3.4. Discussion

Our results confirm that personal characteristics play a major role in explaining both non-response and mental health status. The socio-economic variables associated with non-response found in this paper (Figure 3.1) are similar to those found in the literature: non-response is more frequent among young (Berete et al., 2019; Ekholm et al., 2010), low educated (Berete et al., 2019; Boshuizen et al., 2006; Jaehn et al., 2020; Volken, 2013) and low income (Berete et al., 2019) inhabitants. Family composition or type of household is not a common studied factor in the literature; Ekholm et al. (2010) and Jaehn et al. (2020) found that married people are more likely to respond to the survey than unmarried people but it is difficult to link this finding to our results because marital status has not been taken into account as such and being in a couple is mixed with having children. A higher non-response rate for men than for women is often found in the literature (Boshuizen et al., 2006; Ekholm et al., 2010; Volken, 2013) but was not found in our study.

Based on the comparison between the personal characteristics associated with non-response and depressive disorders in the results (Figure 3.3), it is reasonable to assume that there will be more people with mental health problems within the group of non-respondents compared to the group of respondents. This is coherent with the literature that examined poor subjective health (Jaehn et al., 2020; Volken, 2013), chronic condition (Berete et al., 2019) or long-term health condition (Boshuizen et al., 2006) as a determinant for non-response.

With these results, we can extrapolate the effect of non-response to the association between mental health and the urban environment. Considering the association between vegetation and mental health, several studies on the topic have shown that vegetation is a protective factor for mental health (Gascon et al., 2018; Lee and Maheswaran, 2011). However, in a previous study using the same data as this paper (Pelgrims et al., 2021), no association was found. With our results, it can be assumed that there would be proportionally higher number of respondents with mental disorders and low vegetation cover (A_{true}) than actually observed due to non-responses ($A_{observed}$) because both low vegetation cover and mental health problems are associated with a higher probability for non-responses. Indeed, results show that the personal characteristics associated with mental health have strong similarities with those of non-response and significantly more non-responses are found in places with lower vegetation cover.

Considering the equation of an odds ratio (OR) with A as the number of respondents with mental disorder (MD +) and exposed to low green space cover (LGS +), B as the number of respondents with no mental disorder (MD-) and exposed to low vegetation cover (LGS +), C as the number of respondents with mental disorder (MD +) and high vegetation cover (LGS-) and D as the number of respondents with no mental disorder (MD-) and high vegetation cover (LGS-) (Table 3.3):

Table 3.3. Contingency table of disease vs. exposure to calculate the odds ratio.

		Disease or condition	
		Mental disorder (MD+)	No mental disorder (MD-)
Exposure of factor	Low green space cover (LGS+) = exposed	A	B
	High green space cover (LGS-) = control	C	D

$$OR = \frac{A * D}{B * C}$$

When this OR is greater than 1, it indicates that the odds of exposure (to low green space) among case-patients (mental disorder, MD +) are greater than the odds of exposure among controls. The exposure (to low green space cover) is interpreted as a risk factor for the disease or condition (mental disorder).

If $A_{true} > A_{observed}$ we may conclude that $OR_{true} > OR_{observed}$. Therefore, the risk of having a mental disorder associated with exposure to low green space cover is underestimated ($OR_{observed} < OR_{true}$), i.e. the odds ratio observed is smaller than the true odds ratio.

Despite the strength of the arguments presented and the valuable insights gained from this study, we have to acknowledge missing data cannot be recovered. Without complete data on all individuals, it is challenging to ascertain associations and their implications accurately. Future prospective studies can provide a more comprehensive understanding of the relationship between personal characteristics, non-response, mental health, and the urban environment.

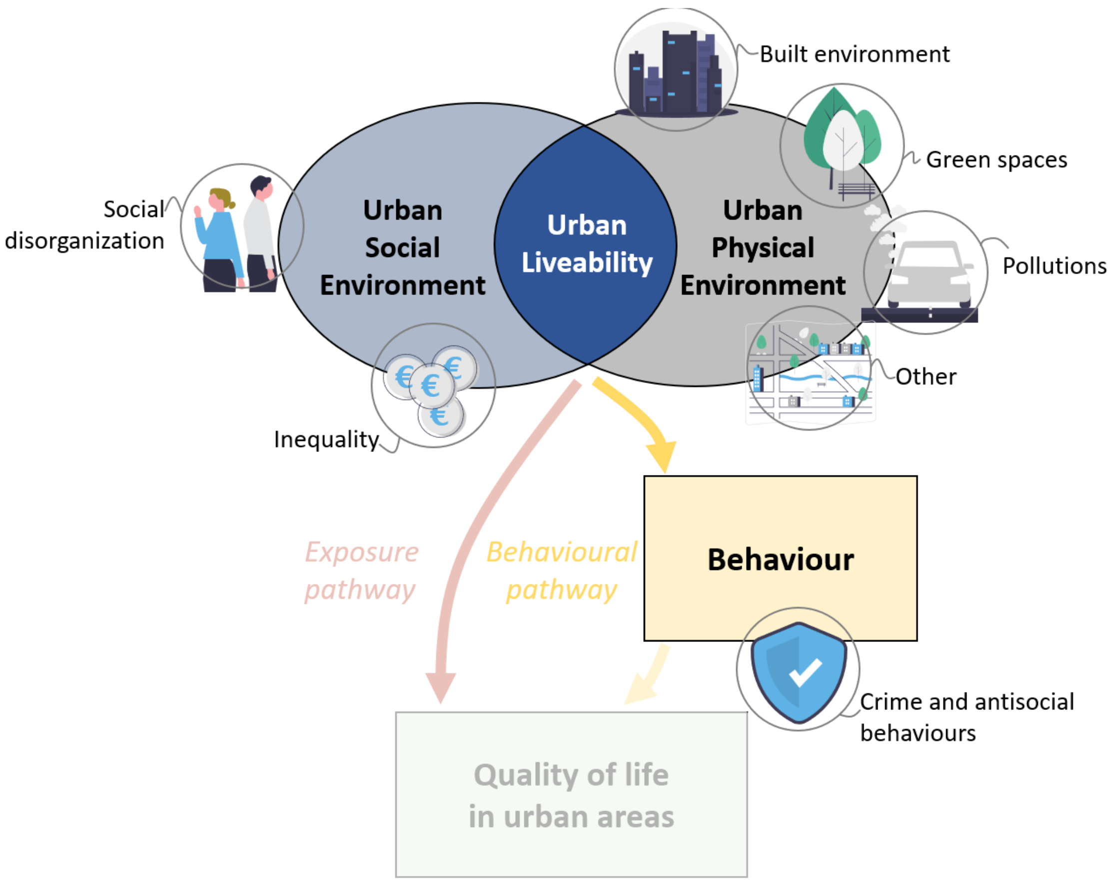
3.5. Conclusions

In conclusion, we here show that the risk of low green space cover (or, conversely, the protective effect of high green space cover) is underestimated using the BHIS data. Indeed, the capacity to measure the association between urban environment and health is affected by non-response in surveys. The non-random spatial and socio-economic distribution of this bias affects the parameter estimates in the statistical models. In a sense, non-responses may be seen as a cause of a loss of statistical power, leading to a lower probability to statistically detect differences if such differences existed. This may explain why when studying environment and human health, results are sometimes inconclusive or inconsistent with the literature. The environment and human health association is particularly challenging to study as we are dealing with multifactorial elements. More attention should be given to understand the biases that can be encountered due to non-responses and to the non-random character of this bias. A combination of methods or a mixed-method approach (quantitative and qualitative) can help to obtain a comprehensive understanding of these highly complex topics.

4

From complaints to insights: A geographical analysis of illegal dumping by citizen sensor data.

This chapter has been published here: Guyot, M., Thomas, I., & Vanwambeke, S. O. (2025). From Complaints to Insights: A Geographical Analysis of Illegal Dumping by Citizen Sensor Data. *Cities* (in the second tour of reviews). http://dx.doi.org/10.2139/ssrn.4793143
An extension of this work can be found here: Guyot M, Thomas I, Vanwambeke S, 2021, “Is illegal dumping associated with some urban designs? Evidence from Fix My Street data, Brussels”, in *ISUF Annual Conference Proceedings* (University of Strathclyde Publishing), https://strathprints.strath.ac.uk/80414/



Abstract

As urban areas expand, urban environmental quality assessment becomes increasingly crucial. We investigate the interaction between human experience and the urban environment at the street scale, using illegal dumping sites as indicators of urban liveability deterioration. We tackle the methodological challenge of working with citizen-generated data from Fix My Street (FMS) Brussels to study whether urban and social environments influence illegal dumping occurrence. FMS is a platform where individuals can complain about incidents in public spaces, such as clogged sewer grids, malfunctioning public lamps, or instances of illegal dumping. To mitigate selection bias in FMS, we compare 45,569 illegal dumping incidents with 53,516 "control" incidents. Our results suggest that illegal dumping typically takes place in a narrow, quiet, low-income, residential street and often under a tree. Emphasizing the need to account for local specificities, we use a geographically weighted regression to observe spatial contrasts. Our study underscores the significance of informal social control, social deprivation, and the disorder effect (illegal dumping more likely to recur in previously affected areas) in addressing urban liveability deterioration. Future research should explore innovative ways to measure informal social control and the disorder effect.

4.1. Introduction

As cities continue to expand, assessing and improving urban environmental quality become increasingly crucial. Urban liveability, a multifaceted and dynamic concept, represents an evolving paradigm at the complex interplay between urban environmental quality and quality of life (van Kamp et al., 2003; Pacione, 1990). It is a concept that has gained substantial public traction and now occupies a central position in research agendas (Du et al., 2021) and policymaking (i.e. Bruxelles-Propreté, 2022). The street scale is interesting for studying interactions between human experience and urban design (Harvey and Aultman-Hall, 2016): streetscape – the physical characteristic of the street – forms the background of citizen experience and facilitates or discourages certain behaviours (Jacobs, 1961; Jeffery, 1971). Incivilities, such as illegal dumping, can be used to assess the quality of human experience and the quality of the urban environment. Here we focused on illegal dumping, a behaviour regulated against in many cities due to its negative perception.

Cities face increasing challenges in managing society's problems such as noise, air pollution, or uncleanliness. Among these issues, illegal dumping stands out as a prevalent nuisance, particularly magnified within urban settings due to the concentrated nature of the problem and its visually disruptive impact (Hodsman and Williams, 2011; Webb et al., 2006). Illegal dumping involves disposing of waste without adhering to legal provisions (DECC, 2008; US EPA, 1998). Uncleanliness generates numerous negative impacts: environmental, social and financial (Du et al., 2021). It is a major nuisance for residents, degrading their environment and impacting their well-being: locations that are regularly unclean and appear abandoned negatively affect community spirit and well-being, including mental health (Bruxelles-Propreté, 2022; Lauwers et al., 2021), and can lead to a feeling of insecurity (Innes, 2004). The financial costs include costs for removal and proper disposal, lower property prices for owners (DECC, 2008), and damages to the brand image of businesses/activities (Bruxelles-Propreté, 2022). Therefore, urban illegal dumping is a valuable mean to understand what urban features attract this and potentially other types of incivilities, providing insights beyond reducing the nuisance itself.

Quantitative studies on urban illegal dumping are relatively scarce, but some have provided insights into socio-environmental correlates (Du et al., 2021). In Australia, population mobility and lower education were associated with higher levels of illegal dumping (Wright et al., 2018) and, in Japan, unemployment rates were positively associated to the occurrence of illegal dumping (Matsumoto and Takeuchi, 2011). In England, illegal dumping was more frequent in densely populated areas, especially in those regions facing multiple forms of deprivation, including overcrowding, poverty, unemployment, and a high proportion of rented accommodation (Hodsman and Williams, 2011; Webb et al., 2006). In China, residential areas, high population mobility and low mean income were the three most important driving factors (Xiong et al., 2022). In Malawi, homeownership has been associated with reducing inappropriate waste disposal choices (Kalonde et al., 2023). Past incidents of illegal dumping, and other disorders in the urban environment, increased the likelihood of occurrence (Kelling and Wilson, 1982; O'Brien et al., 2015). In Korea, the presence of urban green spaces has been found to decrease the occurrence of illegal dumping (Joo and Kwon, 2015) while, in Australia, park collection bins attracted it (Wright et al., 2018). Principally (but not only) for Global South cities, waste disposal choices were driven by the accessibility of disposal options (Niyobuhungiro and Schenck, 2022; Sotamenou et al., 2019). In Cameroon, proximity to dumpsites encouraged illegal dumping (Sotamenou et al., 2019), while in Malawi, it discouraged it (Kalonde et al., 2023). While illegal dumping is a global issue, this paper, with a focus on Brussels, holds particular relevance for northern countries where most residential areas have waste collection services. To date, no similar studies have been conducted on Brussels.

The scarcity of studies on this question is partly due to the challenge of addressing incivilities on a large scale. There are three main options for conducting such studies: audits, administrative databases (e.g. police records), and citizen-generated databases. Audits can be expensive, time-limited, and unable to cover a large territory, but they offer the advantage of rigorous measurement using a pre-established methodology. For example, in Wallonia (the southern region of Belgium, in charge of environmental matters) (Service Public de Wallonie, 2016) and in France (Jacob, 2013), initiatives exist that aim to monitor the cleanliness of municipalities. Unfortunately, the results of these audits are rarely publicly available. Police databases also exist, but they only report illegal dumping incidents resulting in fines. For instance, in 2021, in the Brussels-Capital Region, only 275 fines were issued for illegal dumping and 822 for being caught littering (Bruxelles-Propreté, 2021). Alternative sources of data are required to address this challenge comprehensively, and enlisting citizen contribution to report on various issues on the street is one such source.

To facilitate the reporting of street deteriorations by citizens, mobile applications have been developed, such as Fix My Street, which was launched in Brussels in 2013 (BRIC, 2020). It was inspired by MySociety's FixMyStreet, launched in England in 2007 (mySociety, 2023). Using the app, citizens can report incidents such as broken street lamps or blocked sewers. In 2017, an "Illegal dump" category was added and it has since become the most reported incident. These citizen-generated administrative data offer extensive and continuous information over time. However, a challenge arises in avoiding selection bias, as the reporting may not be uniformly distributed across the entire territory (O'Brien et al., 2015; Pak et al., 2017; Rae and Nyanzu, 2021). To shed light on this issue, Rae and Nyanzu (2021) found that significantly fewer reports are submitted from the most deprived neighbourhoods in Fix My Street England. In Brussels, Pak, Chua and Vande Moere (2017) noted that Fix My Street is less used by low-income and ethnically diverse communities. To our knowledge, large citizen-generated databases, like Fix My Street, have never been used to investigate the risk factors of illegal dumping.

In this paper, we examine the interaction between human experience and the urban environment at the street scale, using illegal dumping as reported by citizens as indicators of urban liveability deterioration. Illegal dumping is a significant nuisance, yet there are few quantitative studies on its drivers and none in Brussels. Citizen-generated administrative data, like Fix My Street, provide a valuable resource for studying such incivilities on a large scale. We tackle the methodological challenge of working with citizen-generated data to study whether urban and social environments are factors that influence the occurrence of illegal dumping. We will also consider the socio-economic context and the tendency of illegal dumping sites to reoccur in previously identified locations, known as the "broken window theory" or disorder effect. We also compute a geographically weighted regression (GWR) to examine the spatial variation and explore the localized impacts of the different variables.

4.2. Data and method

4.2.1. Study area

Brussels is a capital city, an administrative region but also an agglomeration that extends into three administrative regions: Brussels-Capital Region (BCR), Flanders and Wallonia (Adam et al., 2017; Montero et al., 2021). We here concentrated on the urban area defined by the administrative borders of the BCR. It is divided into 19 municipalities, each holding the authority to manage public cleanliness within its territory, excluding regional streets, managed at the regional level.

Brussels is a densely populated yet green city, characterized by significant spatial inequality. Covering an area of 161.38 km², the BCR has a population of 1.24 million inhabitants (source: Statistics Belgium, 1/1/23), i.e. an average population density of 7691 inhabitants/km². Approximately 54% of the BCR is covered with vegetation, with most green spaces near the city's periphery (Van de Voorde et al., 2010). This vegetation includes public parks, recreational areas, urban forests, as well as private gardens and estates. From a socio-economic perspective, a clear contrast emerges between densely populated, economically disadvantaged areas in the city centre and more affluent zones on the outskirts (Dujardin et al., 2008; Haandrikman et al., 2023).

4.2.2. Fix My Street

Fix My Street Brussels is a web and mobile platform (Figure 4.1) available to the public and the administrations (e.g. municipal or police officers) to report incidents that occur in the public space in the Brussels-Capital Region. Incidents are categorized by type – such as roads, public cleanliness, vegetation, signage, public lighting, public furniture, monuments and abandoned vehicles – each with additional subcategories (BRIC, 2020). The subcategory "Illegal dump" records the highest number of incidents. In Belgium, any abandonment of waste or bulky items on the street outside of collection periods without following regulations is considered illegal dumping and is subject to fines. Recycling parks and home collection services are provided to dispose of bulky items properly (Bruxelles-Propreté, 2021). Figure 4.2 provides an overview of what has been reported in the "Illegal dump" subcategory in the app. The dumps are generally relatively small, with very few large-scale illegal dumps.

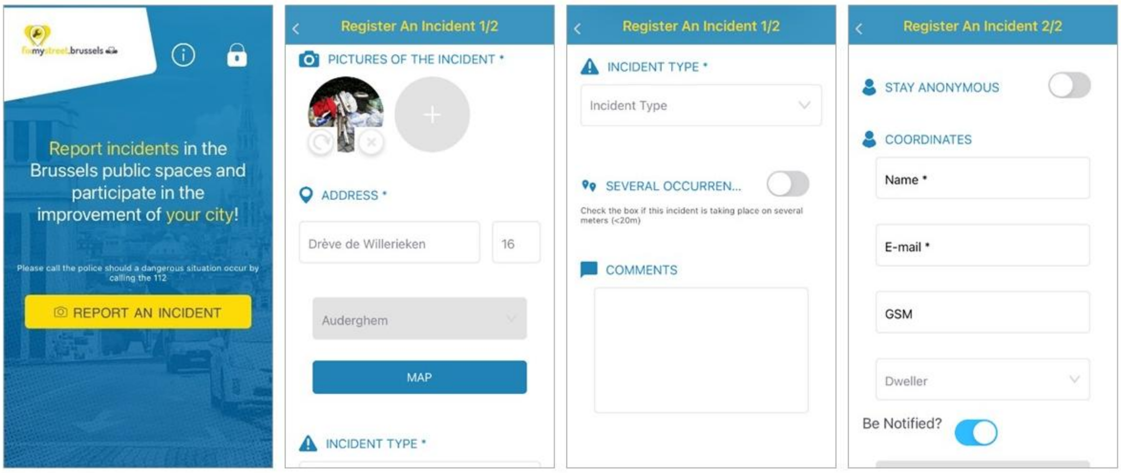


Figure 4.1. Smartphone interface of the Fix My Street Brussels app (Source: Fix My Street, Brussels).

Between 2013 and February 2020, 203,539 incidents were reported in Fix My Street Brussels, with globally slightly over half reported by professionals ($n = 104{,}751$). The incidents used in this paper were reported between July 2017 and February 2020 ($n = 122{,}701$) and were made available by the Brussels Regional Informatics Centre (BRIC, 2020).

The use of the Fix My Street App is not uniform across the Brussels-Capital Region: it differs from one municipality to the other and some areas have no reports at all. It was therefore impossible to consider the reported illegal dumps as an exhaustive inventory. To avoid this selection bias, we compared the illegal dump incidents ($n = 45{,}569$) with "control" incidents ($n = 53{,}516$) that are neither dumps nor incivilities. These "control" incidents included for example sewer grid clogged or public lighting turned off. A complete inventory of the types of incidents considered is available in the appendices (Table B.1). We assumed that users report illegal dumps and control incidents evenly. Based on this, we established the variable *Illegal Dump*, which was coded as follows: 1 if it is an illegal dump incident and 0 if it is a "control" incident. 23,616 incidents were omitted from our database: those that could be classified as incivility but are not illegal dumping (e.g. vandalized fountains, damage to lighting) or those linked to uncleanliness, but perhaps not illegal dumping (e.g. broken bin bags, bin bags not collected, bin bags taken out on the wrong day).

Figure 4.2. Examples of illegal dumping reported in Fix My Street (Source: Fix My Street, Brussels)

4.2.3. Urban environment and "broken window" indicators

We computed a selection of urban environment indicators (Table 4.1) based on general assumptions and the literature. Our main hypotheses were based on Crime Prevention through Environmental Design (CPTED) (Jeffery, 1971) and informal social control (Jacobs, 1961). We limited ourselves to officially available databases.

We selected the presence of a *Tree* (see appendices, Figure B.1.B) or a *Recycling bank* (Figure B.1.D) as they provide space for illegal dumping. The assumption that tree presence is correlated with illegal dumping was made qualitatively based on photos of illegal dumping from the Fix My Street Brussels database. Illegal dumping at the foot of recycling banks was discussed in Wright et al. (2018). We computed presence or absence of a tree or a recycling bank based on geographic proximity to an incident: within 10 metres of a tree (point data from Urbis: BRIC, 2017) and within 20 metres of a recycling bank (point data from Bruxelles-Propreté, 2020 for glass banks; Ressources, 2020 for clothing banks). We allowed some margin to account for geolocation inaccuracies of FMS incidents and the distance from the banks, as dumps are not always made at the foot.

Informal social control ("eyes on the street") plays a role in the development of antisocial behaviour (e.g. Jacobs, 1961). Informal social control is "the spectrum of actions taken by citizens to signal unacceptable behaviour" (Groff, 2015, p. 90). While there is no clear-cut indicator for informal social control, we tried to bring together a series of assumed proxies. The presence of *Shops* (Figure B.1.C) induces a degree of informal social control through the comings and goings they generate. We computed the presence or absence of shops based on geographic proximity: within 20 metres of a shop (point data from Atrium.Brussels, 2017). *Road noise* (Figure B.1.H) and *Speed limit* are proxies of traffic patterns. However, predicting traffic effects on antisocial activities is challenging; while traffic can hinder residents' activities in the streets, thereby reducing informal social control (Groff, 2015), drivers themselves are actors of informal social control. *Road noise* was extracted from a mean annual road noise levels model (Bruxelles Environnement, 2016) and categorized in tertiles. The *Speed limit* is the maximum speed allowed on the street of the incident (Bruxelles Mobilité, 2020). We selected *Land cover* types (Figure B.1.I), which encompass residential, green space, office and industrial areas, as we assumed they are associated with informal social control. Predominantly, residential areas foster a sense of community and informal social control that deters antisocial activities, while industrial and office areas with few residents, mostly no presence outside of office hours, and less social cohesion, may facilitate antisocial behaviours (Groff, 2015). But industrial and office areas may experience higher daytime activity, ensuring informal social control if some residents are also present (Jacobs, 1961). To define the land cover type of each incident, we simplified the Urban Atlas database (European Environment Agency, 2020) into three categories (residential, green space and industrial areas) and we added an office class from the Office Observatory data (De Beule and Dessouroux, 2011). It should be noted that in the land-use data, the "industrial" class includes a diverse range of areas, including university campuses, which are associated to different activity profiles and patterns.

The association between antisocial behaviour and vegetation is ambiguous in cities like Brussels. Vegetation is often perceived negatively as it obstructs visibility, providing potential hiding spots, but may also increase surveillance as it encourages people to go out (Kuo and Sullivan, 2001). The ratio of *Vegetation cover* (Figure B.1.A) was computed based on high-resolution remote sensing data (Normalized Difference Vegetation Index [NDVI], spatial resolution of 2.4 m from Van de Voorde et al., 2010). NDVI was transformed into a binary variable (presence/absence of vegetation with a threshold value of 0.275). The ratio of vegetation was then computed within a 100 m buffer. For *Vegetation cover*, incidents without vegetation were considered in one category with the rest categorized in tertiles.

The street configuration also plays a role in shaping antisocial behaviour (Cozens and Love, 2015; Jacobs, 1961): tall buildings create a sense of anonymity and lack of surveillance, while lower buildings promote social interactions that contribute to a safer street environment (Jacobs, 1961). Wide and well-maintained sidewalks provide space for pedestrians, encouraging social interactions (Jacobs, 1961). We selected *Building height* (Figure B.1.E), *Street width* (Figure B.1.F) *and Sidewalk width* (Figure B.1.G) as representative of street configuration. The computation methods are detailed in Table 4.1. These indicators were categorized in tertiles. Street lighting would have been an interesting indicator (Welsh and Farrington, 2008) but no comprehensive database was available for Brussels.

We also considered the “broken window” or disorder effect (Kelling and Wilson, 1982; O’Brien et al., 2015) which assumes illegal dumping to be more likely where it has occurred before. To quantify this, we developed an indicator: *Recurrence* (Table 4.1). *Recurrence* was determined as the number of incidents of the same type (illegal dumping or “control” incidents) that have occurred previously at the location (within a 10-meter radius to account for location inaccuracies). Two groups were categorized: “no or one other event” (prior or subsequent) or “more than one event”.

4.2.4. Socio-economic indicators

Socially disorganized neighbourhoods typically exhibit low economic levels and high residential mobility and often coincide with areas characterized by deteriorated infrastructure and higher levels of physical disorder (Groff, 2015). Hodsman and Williams (2011) indicated that illegal dumping is a significant issue, particularly in areas with high deprivation, high population density, and most rented dwellings. Three indicators allow us to capture the concept of social disorganization (Sampson and Groves, 1989) or social deprivation: *Household median income* (Figure B.1.J), *Tenant ratio*, and *Population density* (Table 4.1). The computation methods are detailed in Table 4.1. These indicators were categorized in tertiles.

We included the municipality where the incident occurred (Figure B.1.K) as a control variable to account for potential differences in app use between municipalities. Only some municipalities use the app as part of their strategies for recording and processing illegal dumping (i.e. Etterbeek propreté, 2021). *Municipality* was solely a control variable and will not be presented in the results.

Table 4.1. Computation and sources of used indicators.

Class	Name	Computation	Data source
Urban environment	Tree	Nearest tree closer than 10 m (Yes/No).	Urbis (BRIC, 2017)
	Recycling bank	Nearest glass or clothes bank closer than 20 m (Yes/No).	Bruxelles-Propreté (2020); Ressources (2020)
	Shop	Nearest shop closer than 20 m (Yes/No).	Atrium. Brussels (2017)
	Road noise	Mean annual road noise levels (dB).	Bruxelles Environnement (2016)
	Speed limit	Speed limit of the street.	Bruxelles Mobilité (2020)
	Land cover	Land cover type at the location of the incident. Simplification of the Urban Atlas categories into three categories + addition of the office class from the Office Observatory (Brussels) data (Residential, Green, Industrial and Office).	Urban Atlas (European Environment Agency, 2020) Office Observatory (De Beule and Dessouroux, 2011)
	Vegetation cover	Ratio of vegetation cover within 100 m (%).	Bruxelles Environnement (Van de Voorde et al., 2010)
	Street width	Width of the street at the point of the incident (m).	Urbis (BRIC, 2017)
	Sidewalk width	Sidewalk width at the level of the incident (m).	Urbis (BRIC, 2017)
	Building height	Average height of buildings in the street section (between two junctions) in which the incident is (m).	Urbis 3D (BRIC, 2017)
Broken window	Recurrence	Number of incidents of the same group within 10 m (0 or 1/More than one).	Fix My Street (BRIC, 2020)
Socio-economic	Household median income	Value of the statistical sector[1] (€).	Statistics Belgium (2017a)
	Tenant ratio	Value of the statistical sector[1] (%).	Census (Statistics Belgium, 2011)
	Population density	Value of the statistical sector[1] (hab/km²)	Statistics Belgium (2017b)

[1]If no data for the statistical sector = value of the nearest statistical sector with data

4.2.5. Statistical methods

Among all the potential explanatory variables presented in Table 4.1, we opted to select only a subset to maintain model simplicity. The selection was made based on the highest correlations between ordinal variables (i.e. excluding Land Cover) and *Illegal Dump*, using Spearman's rho. Given the strong hypotheses regarding the connection between socio-economic factors and the likelihood of illegal dumping, we retained one variable. However, since the literature currently has few firmly established hypotheses concerning the urban environment, and since each variable represents a different aspect of this environment, we retained all. The only exception was *Road noise* and *Speed limit*, which were both chosen as proxies for traffic, with one of them being retained.

We then computed binomial logistic regression between urban and socio-economic environments and the dependent variable *Illegal dump*. Analyses were performed using the statistical software R (R Core Team, 2020) using the stats package, glm function. All incidents described in section 4.2.2 ($n = 99{,}085$) were considered. Two outputs of the logistic regressions were extracted: the odds ratios (OR) and the associated *p*-values (considered significant below 0.05). We computed three types of global models. First, we considered the effect of each variable on its own (**univariate models**). Second, we incorporated the *Household median income* and *Municipality* variables into each univariate model to account for their potential influence on the outcome (**adjusted models**). Finally, we computed a **multiple model** to identify the residual effects of each variable once the other explanatory variables were included. This allowed us to gain a more comprehensive understanding of the individual and collective impacts of the variables on the outcome.

We computed two supplementary analyses to assess the robustness of our multiple model. Firstly, we divided the dataset into two parts with an equal number of incidents based on the incident date: from July 2017 to mid-February 2019 and from mid-February 2019 to March 2020. Secondly, we ran the model separately for the four municipalities where the highest number of incidents were reported. These analyses assess model stability, temporal consistency, and spatial variation.

To further extend the study of spatial variation and explore the local effects of different variables, we applied a geographically weighted regression (GWR) (Brunsdon et al., 1996; Fotheringham et al., 2002) to calibrate a **spatial model**. GWR allows the exploration of spatial heterogeneity of the outcomes with a high level of precision. It is a technique that estimates a regression model for each statistical individual, allowing coefficients to vary across space. We used the R library GWmodel (Gollini et al., 2015). GWR is computationally intensive for large data sets as it computes one weighted regression model by point location. To limit computation time, we here limited the dataset to the period from April 2019 to March 2020 ($n = 43{,}640$).

The results of GWR are relatively insensitive to the choice of weighting function but are sensitive to the bandwidth of the weighting function chosen (Fotheringham et al., 2002). However, determining the optimal bandwidth involves costly calibrations. Considering the confirmatory role of our GWR, we opted to explore a solution without fully calibrating the bandwidth. We used a fixed spatial kernel with a Gaussian function and a 1000 m bandwidth, representing easy walking distance.

4.3. Results

We retained *Household median income* of our set of socio-economic variables as it had the strongest correlation with illegal dumping incidents (Spearman's rho =-0.32). Among traffic-related factors, we kept *Road noise* (Spearman's rho = 0.32). Spearman correlations provide additional insights (Figure 4.3). High vegetation cover is typically found around incidents in high-income neighbourhoods, as indicated by the positive correlation between *Vegetation cover* and *Household median income* (Spearman's rho = 0.41). Conversely, low vegetation cover is found around incidents in commercial areas (Spearman's rho = -0.32) and high-rise buildings (Spearman's rho = -0.45). Shops are more frequent in areas with high-rise buildings (Spearman's rho = -0.31). Finally, wider streets tend to have wider sidewalks (Spearman's rho = 0.32) and experience greater traffic volumes, as reflected by their positive correlation with *Road noise* (Spearman's rho = 0.31).

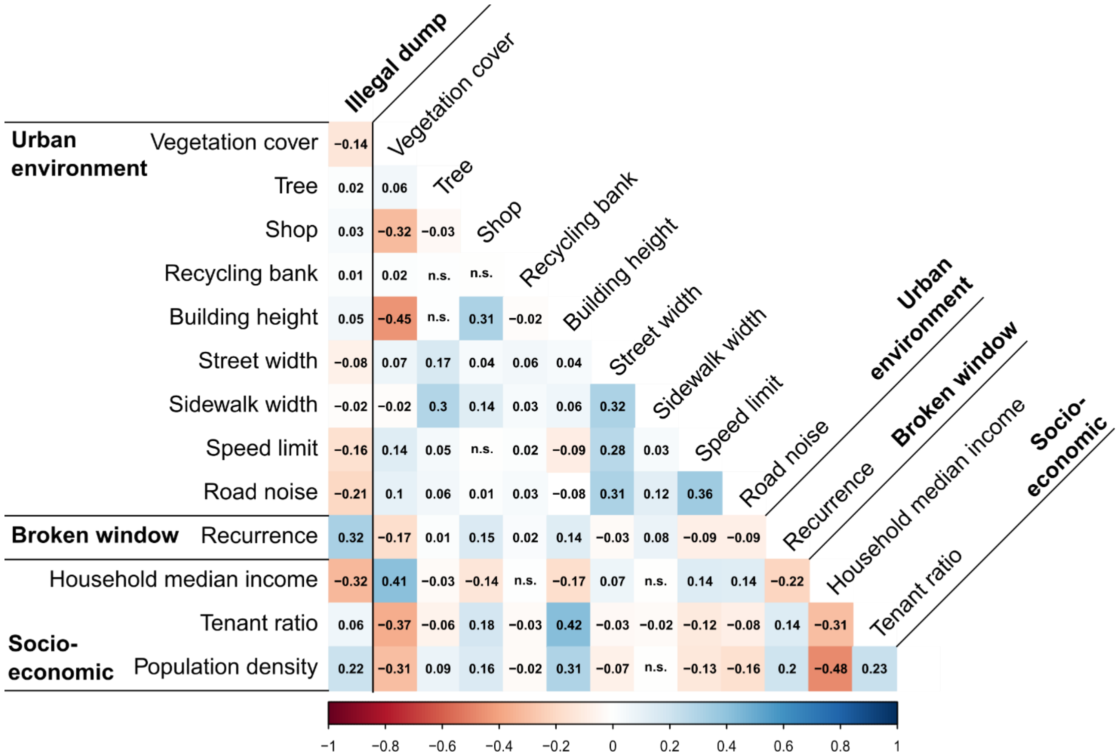


Figure 4.3: Spearman's correlation matrix between ordinal variables, n.s. = non-significant correlation (Bonferroni adjusted p-value).

Table 4.2 presents the outcomes of the **univariate**, **adjusted**, and **multiple models**. The outcomes of multiple models are also provided based on subdivided datasets in the appendices within Table B.2 (data split in two based on the date) and Table B.3 (data from the four municipalities with the highest number of incidents).

Table 4.2. Result of the logistic regressions. Significant OR (p <0.5) are coloured in a gradient of blue (protective factor, OR <1) or red (risk factor, OR>1). The darker the colour, the larger the effect size.

Variables	Models	Univariate	Adjusted[1]	Multiple[2]	*n*
Vegetation cover	No (0%)	Reference	Reference	Reference	10,785
	Low (<14%)	1.69 (1.62-1.77)***	1.8 (1.71-1.89)***	1.88 (1.78-1.99)***	29,420
	Medium (14–30%)	1.16 (1.11-1.21)***	1.96 (1.86-2.07)***	2.14 (2.02-2.27)***	29,450
	High (>30%)	0.67 (0.64-0.70)***	1.56 (1.47-1.65)***	1.80 (1.68-1.92)***	29,430
Tree	No	Reference	Reference	Reference	62,418
	Yes (Under a tree)	1.08 (1.05-1.11)***	1.15 (1.12-1.19)***	1.27 (1.22-1.31)***	36,667
Shop	No	Reference	Reference	Reference	63,559
	Yes	1.14 (1.11-1.17)***	0.97 (0.94-1)	0.91 (0.88-0.94)***	35,526
Recycling bank	No	Reference	Reference	Reference	96,856
	Yes	1.19 (1.09-1.30)***	1.15 (1.05-1.27)**	1.22 (1.10-1.36)***	2,229
Building height	Low (<8m)	Reference	Reference	Reference	33,015
	Medium (8–12 m)	1.53 (1.48-1.58)***	1.39 (1.33-1.44)***	1.20 (1.15-1.25)***	33,042
	High (>12m)	1.29 (1.25-1.33)***	1.12 (1.08-1.17)***	1.09 (1.04-1.14)**	33,028
Street width	Low (<14m)	Reference	Reference	Reference	33,022
	Medium (14–19 m)	0.91 (0.88-0.94)***	0.9 (0.87-0.93)***	0.99 (0.95-1.03)	33,028
	High (>19m)	0.69 (0.66-0.71)***	0.63 (0.61-0.66)***	0.82 (0.79-0.86)***	33,035
Sidewalk width	Low (<2.5m)	Reference	Reference	Reference	33,025
	Medium (2.5-4m)	1.02 (0.99-1.05)	1.09 (1.06-1.13)***	1.01 (0.97-1.05)	33,027
	High (>4m)	0.92 (0.90-0.95)***	0.81 (0.78-0.84)***	0.75 (0.72-0.78)***	33,033
Road noise	Low (<49dB)	Reference	Reference	Reference	33,032
	Medium (49–66 dB)	0.67 (0.65-0.70)***	0.74 (0.72-0.77)***	0.79 (0.76-0.82)***	33,016
	High (>66dB)	0.35 (0.34-0.36)***	0.43 (0.41-0.44)***	0.48 (0.46-0.50)***	33,037
Land cover	Residential	Reference	Reference	Reference	81,417
	Green	0.61 (0.57-0.66)***	0.62 (0.58-0.68)***	0.92 (0.84-1.00)*	3,611
	Industrial	0.76 (0.73-0.79)***	0.57 (0.55-0.6)***	0.72 (0.69-0.75)***	12,522
	Office	0.45 (0.41-0.51)***	0.42 (0.37-0.47)***	0.48 (0.42-0.55)***	1,535
Recurrence	No (0 or 1)	Reference	Reference	Reference	52,854
	Yes (More than 1)	3.83 (3.73-3.93)***	3.05 (2.96-3.14)***	3.12 (3.02-3.22)***	46,231
Household median income	Low	5.55 (5.37-5.74)***	-	2.72 (2.60-2.85)***	32,506
	Medium	3.47 (3.35-3.59)***	-	1.80 (1.73-1.88)***	33,534
	High	Reference	-	Reference	33,045

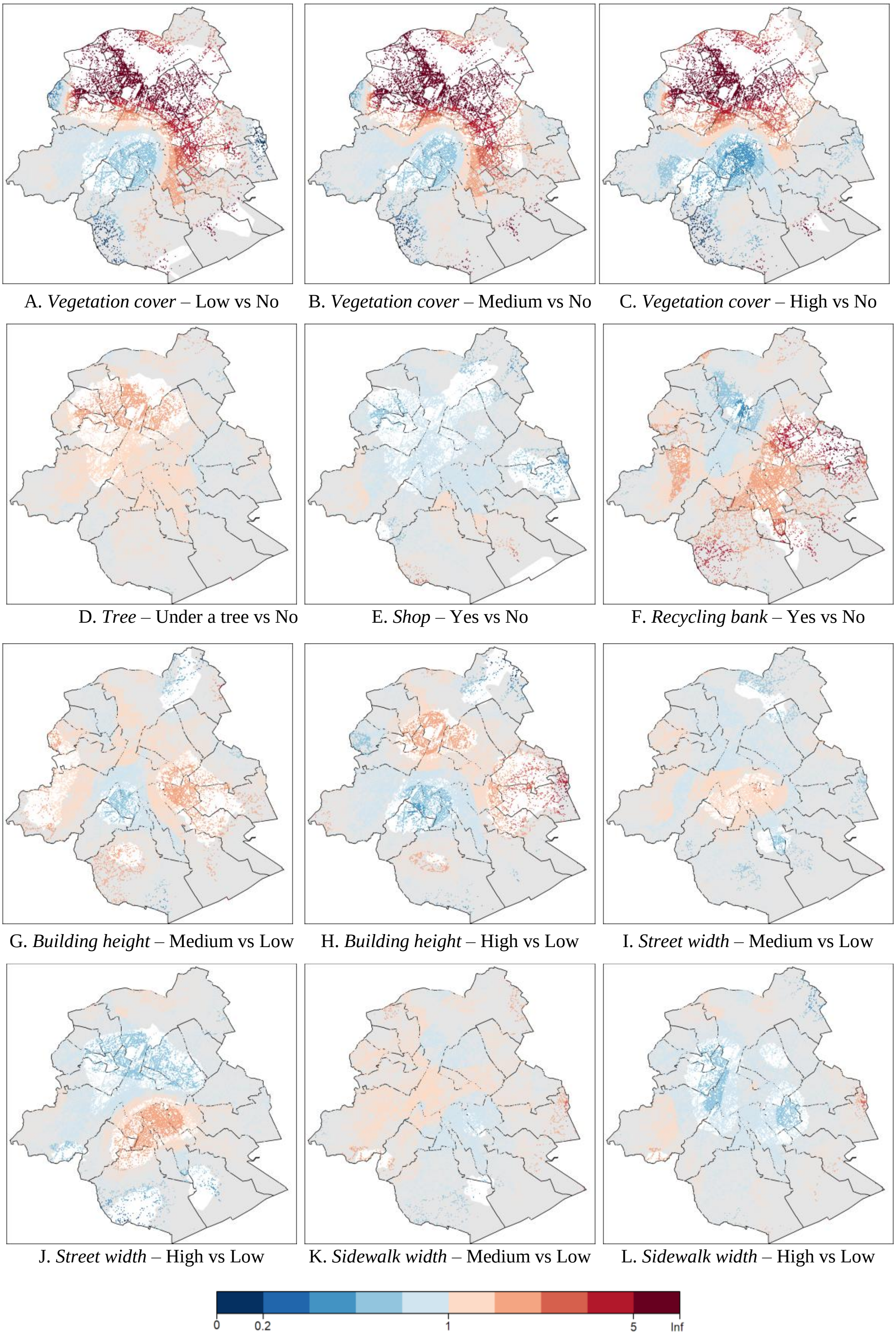
Signif. codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 [1]With Household median income and Municipality [2]With Municipality

The association between the independent variables and *Illegal dumping* remains consistent across the global models present in Table 4.2, except for the *Shop* and *Vegetation coverage>30%* indicators which change signs between the univariate and the multiple model. *Recurrence* consistently shows a strong positive correlation with *Illegal dumping*, indicating that illegal dumps are more likely in places that have already had dumps. Similarly, *Household median income* reveals that neighbourhoods with low incomes experience more illegal dumping. *Road noise* has an important size effect, with illegal dumps more likely to occur in quiet areas with little traffic. Additionally, office areas are less likely to experience illegal dumping in contrast to residential areas. Additional factors also have a significant impact, albeit with smaller effect sizes, on the occurrence of illegal dumping. Areas categorized as green or industrial, in contrast to residential areas, tend to have less illegal dumping. Furthermore, areas with wider sidewalks also have less illegal dumping. Areas with more vegetation coverage, more urban trees, hosted more glass/clothing collection points, or had taller buildings, tend to attract more illegal dumping.

The results are stable over time (Table B.2): if the database is divided into two parts based on the date of occurrence, similar results are found. This result confirms the relevance of having used only a subset of the database to run the spatial model. Also, the results are not stable across space (Table B.3). An analysis of the four municipalities with the largest number of incidents shows significant variation in the coefficients. Only some variables consistently have similar coefficients: the presence of a tree as a risk factor, while wider streets and sidewalks are protective factors. Similarly, higher levels of traffic noise also act as a protective factor consistently over time. We analysed these variations further with the spatial model.

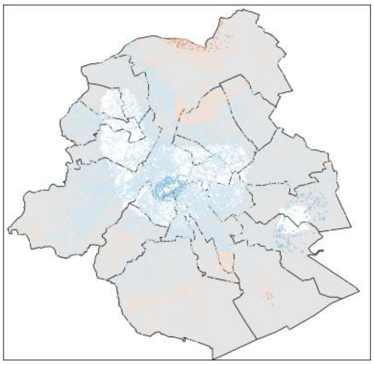
The outcomes of the **spatial model** are mapped in Figure 4.4. Table 4.3 provides the percentage of incidents where illegal dumping is positively, negatively or non-significantly associated with each independent variable derived from this spatial model. Some coefficients exhibit minimal spatial variation. High-level road noise (*Road noise – High vs Low*, Figure 4.4.N) acts as a protective factor across the majority of the BCR, with 91.8% of incidents exhibiting a positive association (Table 4.3). Medium income neighbourhoods (*Household median income – Medium vs High*, Figure 4.4.T) tend to attract higher levels of illegal dumping as 72.29% of incidents display a negative association. The widespread presence of the broken window effect (*Recurrence – Yes vs No*, Figure 4.4.R) is evident, with 89.65% of incidents presenting a negative association.

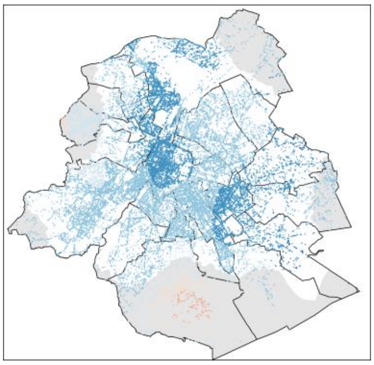
Other coefficients exhibit only small spatial variability. The presence of a shop (*Shop – Yes vs No*, Figure 4.4.E) is positively associated with illegal dumping for 43.76% of incidents. Wide sidewalks (*Sidewalk width – high vs low*, Figure 4.4.L) exhibit a positive association in 43.56% of cases. The presence of a tree (*Tree – yes vs no*, Figure 4.4.D) reveals a negative association in 40.17% of incidents. Office area (*Land cover – office vs residential*, Figure 4.4.Q) is linked to a positive association in 45.71% of incidents, and industrial areas (*Land cover – industrial vs residential*, Figure 4.4.P) results in a positive association in 46.17% of cases.

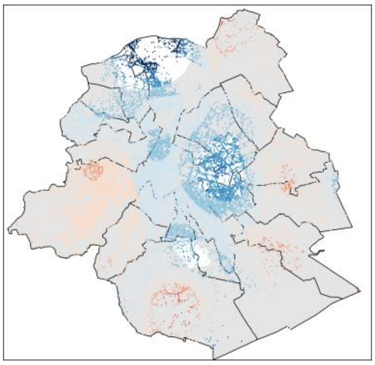


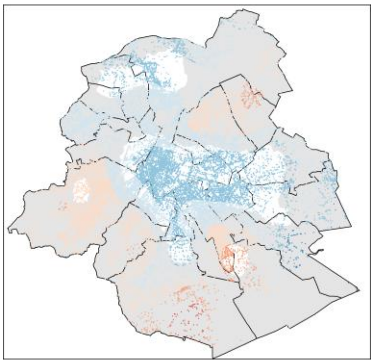
A. *Vegetation cover* – Low vs No
B. *Vegetation cover* – Medium vs No
C. *Vegetation cover* – High vs No
D. *Tree* – Under a tree vs No
E. *Shop* – Yes vs No
F. *Recycling bank* – Yes vs No
G. *Building height* – Medium vs Low
H. *Building height* – High vs Low
I. *Street width* – Medium vs Low
J. *Street width* – High vs Low
K. *Sidewalk width* – Medium vs Low
L. *Sidewalk width* – High vs Low

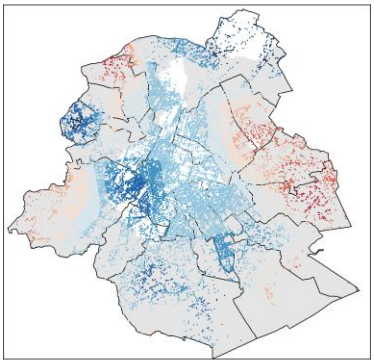
Figure 4.4. Maps of GWR odd ratios. Red colour indicates risk factors, blue indicates protective ones.

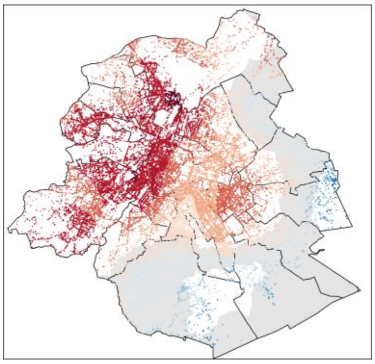

M. *Road noise* – Medium vs Low

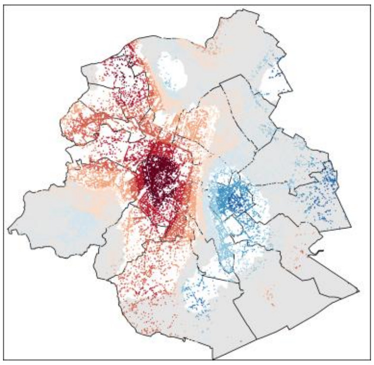

N. *Road noise* – High vs Low

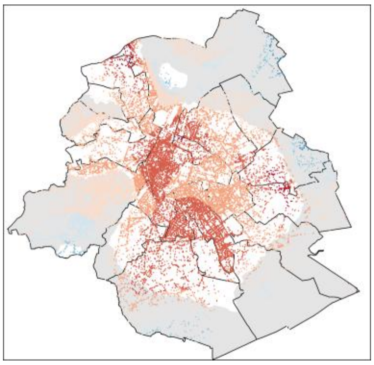

O. *Land cover* – Green vs Residential


P. *Land cover* – Industrial vs Residential


Q. *Land cover* – Office vs Residential


R. *Recurrence* – Yes vs No


S. *Household median income* – Low vs High


T. *Household median income* – Medium vs High

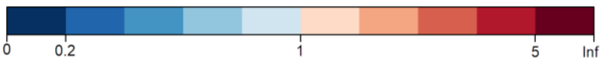


Figure 4.4 (continued). Maps of GWR odd ratios. Red colour indicates risk factors, blue indicates protective ones

Several variables have coefficients that exhibit higher spatial variation: *Recycling bank*, *Building height*, *Street width and Vegetation cover*. The case of *Vegetation cover* is noteworthy. It predominantly demonstrates a negative association with illegal dumping in the global models. However, a significant positive association is found in the “high vs low” category in the univariate model and the region encompassing the municipality of Saint-Gilles (Figure B.1.K) and its surroundings in the spatial model (Figure 4.4.C). Furthermore, in all models this association is nonlinear, as the effect size does not increase linearly between the different classes.

Table 4.3. Percentage of incidents according to the odd ratio obtained for the geographically weighted regression

Variable		Not significantly associated (OR ≈ 1) [%]	Positively associated (OR <1) [%]	Negatively associated (OR>1) [%]
Tree	Yes vs No	59.83	0	40.17
Vegetation	Low vs No	40.34	20.64	39.02
	Medium vs No	46.45	13.21	40.34
	High vs No	46.94	16.96	36.10
Shop	Yes vs No	56.24	43.76	0.01
Recycling bank	Yes vs No	74.49	4.41	21.10
Buildings height	Medium vs Low	72.53	9.84	17.63
	High vs Low	61.79	18.66	19.56
Street width	Medium vs Low	85.06	2.17	12.77
	High vs Low	48.58	29.76	21.67
Sidewalk width	Medium vs Low	94.96	4.78	0.25
	High vs Low	56.15	43.56	0.29
Road noise	Medium vs Low	54.95	45.05	0
	High vs Low	8.2	91.8	0
Land cover	Green vs Residential	87.73	12.27	0
	Industrial vs Residential	52.33	46.17	1.50
	Office vs Residential	54.22	45.71	0.07
Recurrence	Yes vs No	8.89	1.46	89.65
Household median income	Low vs High	27.81	13.23	58.96
	Medium vs High	27.36	0.34	72.29

4.4. Discussion

This paper offers a twofold contribution. Firstly, we identified both global and local associations between the urban and social environment and illegal dumping as a manifestation of urban liveability. Our results suggest that the archetypal street where a dump has taken place can be described as a narrow, quiet, low income, residential street and often found under a tree. The analyses consistently show strong associations with road noise, household median income, and recurrence (broken windows effect). Other associations, with land cover, the presence of a tree or a wide sidewalk are often significant. Secondly, we addressed a challenge inherent to working with citizen-generated data. To mitigate selection bias associated with varying Fix My Street Brussels app usage, we compared 46,681 incidents of illegal dumping with 56,069 "control" incidents not involving incivilities.

These results align with previous studies and the experience of the Brussels administration (Bruxelles-Propreté, 2012, 2021). The description of the archetypal street where a dump takes place suggests that offenders seek hidden and secluded areas, thus avoiding the informal social control. It is surprising that more isolated locations, such as industrial areas, do not exhibit a significant dumping pattern. The limited number of observations in these areas may result in a somewhat “blind” understanding of the phenomenon. Indeed, a close examination of the spatial variation of the association between industrial areas and illegal dumping (Figure 4.4.P), compared with the map of industrial zones (Figure B.1.E), shows that the association is not significant in areas with large industrial zones, such as along the canal or within the business park. Instead, the association appears to be driven by small industrial spaces within the city. An alternative interpretation is that residents often play a role in illegal dumping, as some offenders are residents trying to give a second life to their unwanted items (Bruxelles-Propreté, 2021; Comerford et al., 2018), and that industrial zones are simply too distant from residential sources. The strong association between illegal dumping and household median income reaffirms that social deprivation constitutes a risk factor for illegal dumping, as proposed by Bruxelles-Propreté (2012) and widely discussed in the literature (Hodsman and Williams, 2011; Sampson and Groves, 1989). The robust association between illegal dumping and recurrence aligns with the “broken windows” or disorder effect literature (Kelling and Wilson, 1982; O’Brien et al., 2015), a phenomenon that some residents are well acquainted with due to the recurrence of illegal dumping plaguing their streets (Lauwers et al., 2021). Like other studies before (Joo and Kwon, 2015; Kuo and Sullivan, 2001; Wright et al., 2018), the analysis revealed an ambiguous relationship between the antisocial behaviour at hand and vegetation: the direction of the association between vegetation and illegal dumping varies across different models and exhibits spatial variability.

Spatial inequalities in Brussels are pronounced, marked by strong associations between poor-quality environments, limited access to green spaces, dense urban development, and low socio-economic status (Dujardin et al., 2008; Haandrikman et al., 2023; Van de Voorde et al., 2010). This pattern is also evident in our data. This was addressed using geographically weighted regression to complement traditional modelling approaches. The presence or absence of spatial variation in the coefficients highlighted robust indicators of illegal dumping (*Road noise*, *Recurrence* and *Household median income*), for which minimal spatial variation was observed.

Working at the city-wide scale allowed to examine more diverse situations but is constrained by available data, in particular at fine resolution. On the one hand, field collection is not possible for such a wide area, and on the other hand, existing, management-focused datasets may be patchy or incompatible across municipalities. In our study, indicators such as street lighting have not been consolidated at this point and were not usable yet despite the relevance to the issue.

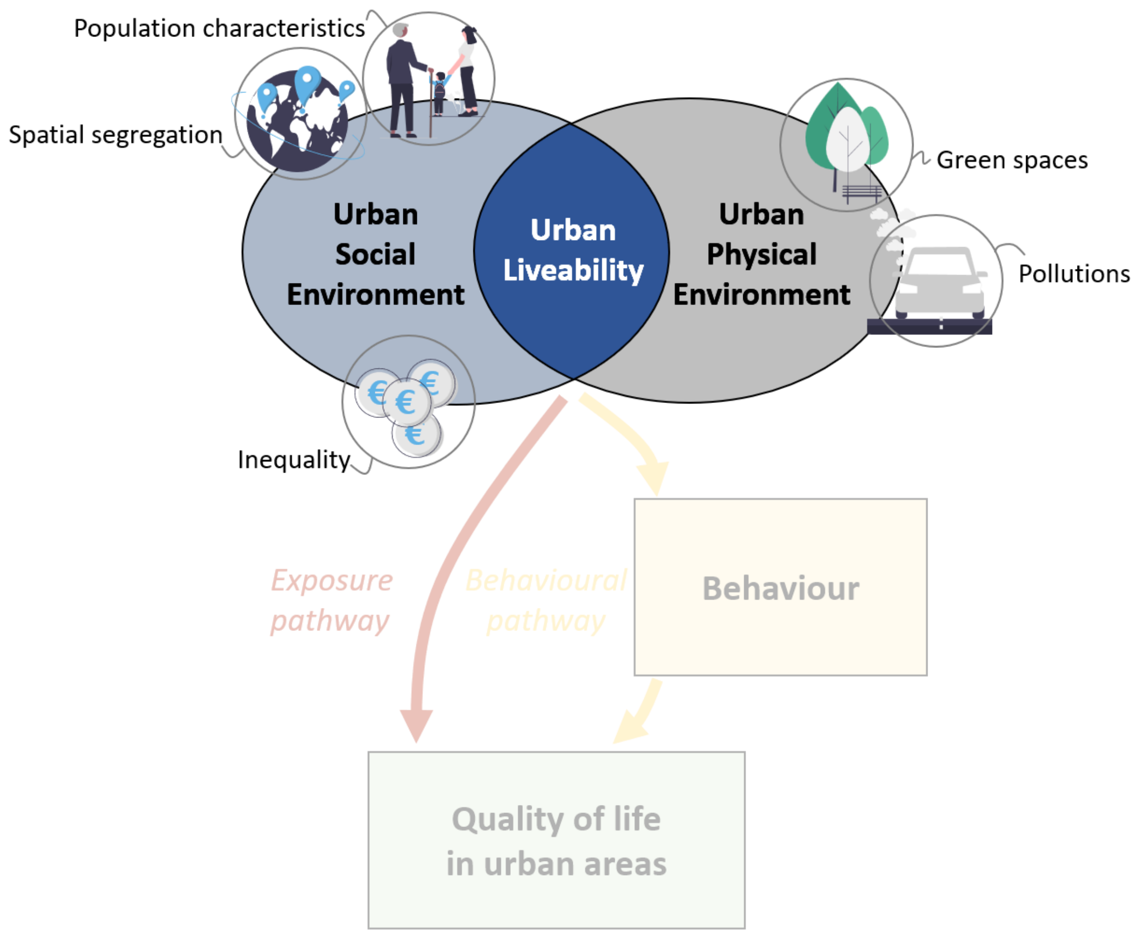
Data from Fix My Street prove valuable for measuring the phenomenon of illegal dumping. One of its key advantages lies in its cost-effectiveness and the widespread availability of spatial and temporal data, as well as precise location information (xy coordinates). However, Fix My Street app usage exhibits disparities, resulting in data scarcity in certain areas, which limits our insights. However, our approach allowed us to circumvent potential biases by comparing illegal dumping incidents with control incidents. The stability of our results over time attests to the reliability of the associations uncovered, making this method suitable for various applications. For instance, policymakers can employ it to monitor the efficacy of initiatives aimed at enhancing public spaces by conducting before-and-after comparisons.

In conclusion, our study highlights the importance of three key concepts in addressing the deterioration of urban liveability: informal social control, social deprivation and the disorder effect. Firstly, while informal social control, through informal gathering places like shops or passage of people, plays a crucial role in combating incivility, its direct measurement remains a challenge. In our study, factors such as road noise and the presence of shops consistently emerge as influential contributors. Road noise may be indicative of the flow of people, with drivers acting as passive observers of the street life, while shops act as meeting points, generating regular pedestrian flow during business hours. Office areas may also play a role in this dynamic. Future analyses should explore innovative ways to measure informal social control, such as pedestrian flow. Secondly, our research underscores the role of social deprivation, through the household median income indicator. Our results suggest that improving living standards can reduce incivility. Finally, the disorder effect is a central theme in this paper, as evident from the recurrence indicator. Future investigations will benefit from the incorporation of more disorder effect indicators, such as the occurrence of other types of offences or the condition of urban structures. Moreover, this FMS dataset, in a separate study, could serve as an indicator of the disorder itself. As cities continue to evolve, understanding urban liveability and the factors influencing the prevalence of incivilities is crucial for effective policy and intervention strategies. Our findings contribute to this understanding, shedding light on the multifaceted of the urban environment and its impact on residents' well-being.

5

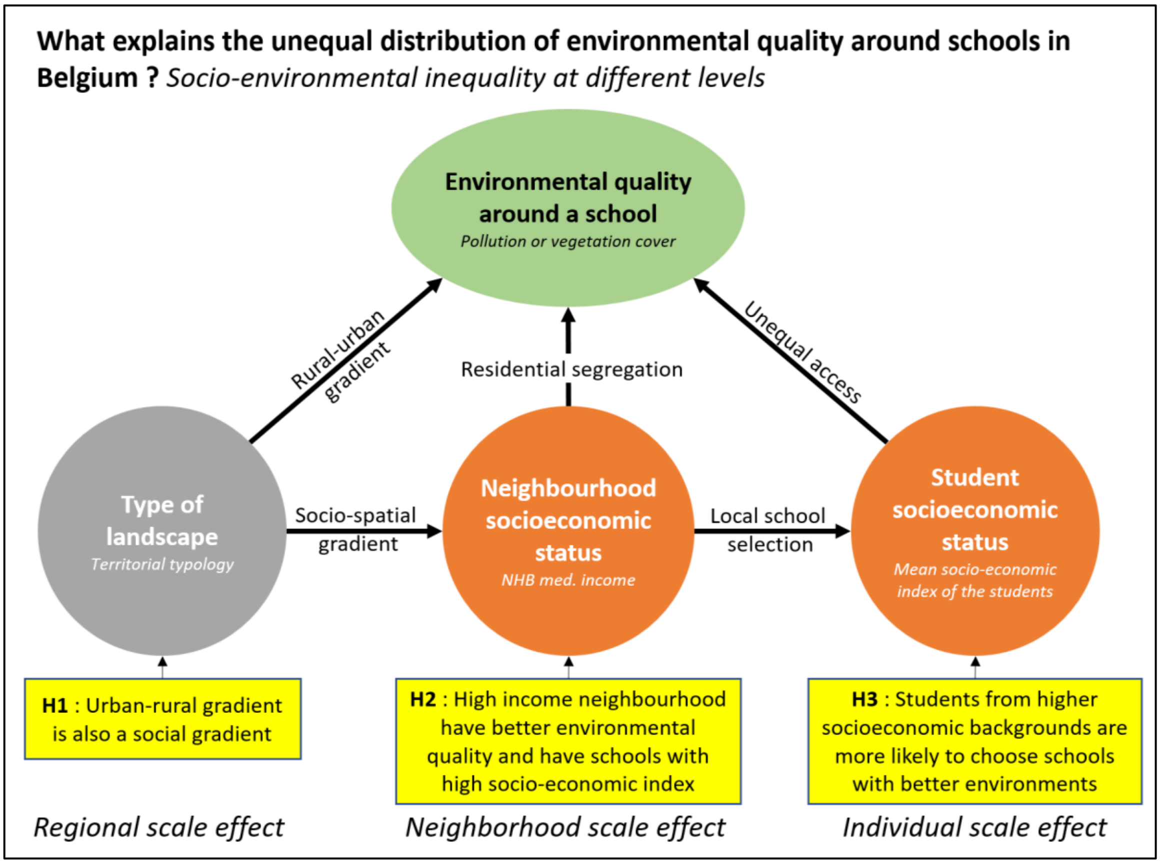
Who has a greener and cleaner environment at school? Multi-scale environmental inequalities in Belgium

This chapter is currently in preparation for publication. It is co-authored by Hans Van Calster, Harmony Brulein, Antoine Lecat, Hans Keune, Raf Aerts And Sophie O. Vanwambeke. It's a side project from the B@SEBALL (Biodiversity at School Environments Benefits for ALL) project funded by Belspo (BRAIN – be 2.0).



Abstract

The living environment is a crucial determinant of well-being, especially in childhood, making the environmental quality in and around schools – where children spend much of their time – essential. This environmental quality is usually unequally distributed. Using student mean socio-economic status (SES) data from the French- and Flemish-speaking communities in Belgium and environmental data from models of four air pollutants and green cover, we analysed the (unequal) distribution of environmental quality around schools. Our results show that lower SES schools are often located in areas with higher air pollution levels and reduced green space. This finding is especially stark in urban centres like Brussels and Antwerp. This may be explained by socio-environmental inequalities at multiple scales. At the regional scale, the urban-rural gradient mirrors a social gradient, as rural areas tend to feature more green spaces and lower levels of air pollution related to traffic and residential heating, along with higher SES, the latter being particularly evident in areas close to large urban agglomerations (H1). At the neighbourhood level, residential segregation exacerbates environmental disparities, with schools reflecting the socio-economic and environmental characteristics of their surroundings (H2). Additionally, our analysis suggests that school segregation amplifies these inequalities, driven by a “quasi-market in education” and the tendency of high-SES families to select schools with similar peers (H3). This dynamic may reinforce environmental inequalities originating at broader geographic levels. Improving environmental quality around low-SES schools is urgent, not only to reduce environmental inequalities but also because good air quality and green spaces have been shown to disproportionately benefit disadvantaged communities. Yet, low-SES schools often face additional challenges in mobilizing resources to improve their environments, underscoring the need for targeted support and intervention.



Graphical abstract

5.1. Introduction

The living environment plays a critical role in overall well-being. The positive impact of green spaces on health has been widely demonstrated (Lee and Maheswaran, 2011; Tzoulas et al., 2007) as well as the detrimental effects of air pollution (Landrigan et al., 2018). Moreover, children are identified as an at-risk group. Compelling evidence indicates that exposure to nature during childhood improves cognitive development and mental health (Amicone et al., 2018; Engemann et al., 2019; Vanaken and Danckaerts, 2018). Children are also highly susceptible to pollution-related diseases. Moreover, increasing evidence indicates that air pollution negatively impacts cognitive development in children and may contribute to the development of chronic diseases in adulthood (Landrigan et al., 2018; WHO, 2017).

At the same time, socio-environmental inequalities present significant challenges within our societies. The most vulnerable population groups are often exposed to environments with limited green spaces (Schüle et al., 2019) and higher air pollution levels (Fairburn et al., 2019). Furthermore, the cumulative environmental burdens that children from low socio-economic backgrounds experience at home are also present in schools (Bolte et al., 2010; Carrier et al., 2014). These inequalities can be examined through the theoretical frameworks of spatial justice (Harvey, 1996) and geographies of environmental justice (Walker and Bulkeley, 2006). The spatial dimension of environmental justice is a field of study gradually gaining traction in Europe. It is crucial not only to explore the distribution of environmental inequalities but also to analyse the processes that produce and reinforce these disparities.

Children today are increasingly less exposed to nature, reflecting a decline in outdoor time in developed countries, largely driven by changing lifestyles. Factors such as heavier road traffic, excessive screen time, and heightened societal safety concerns (Jidovtseff et al., 2022) contribute to this trend. Belgium is no exception (Jidovtseff et al., 2020). Yet, research shows that time spent outdoors directly impacts physical activity levels, promotes better health, and offers children extensive opportunities for development and learning (Gray et al., 2015). Moreover, this issue also carries an environmental justice dimension: not all children grow up in environments conducive to outdoor activities (Lee et al., 2021). For instance, in the Brussels-Capital Region, areas within the "poor crescent" not only have the highest concentration of children but also the lowest access to public or private green spaces (Humblet et al., 2015).

Environmental justice in schools is a critical issue, as children spend a significant portion of their time at school (OECD, 2019). As green spaces become increasingly scarce due to urbanization, school grounds have the potential to serve as vital recreational areas for students (Akoumianaki-Ioannidou et al., 2016). By introducing greenery (Ray et al., 2016) and reducing air pollution (Rawat and Kumar, 2023) in and around schools, we can help address inequalities in children's exposure to a healthy environment (Osborne et al., 2021). This approach not only benefits students but also positively impacts the surrounding community.

Socio-environmental inequalities in school settings remain an underexplored topic, with most research focusing on exposure to greenery from residential locations. To date, only a few studies address the uneven distribution of environmental quality around schools, with the majority concentrating on access and exposure to green spaces (Baró et al., 2021; Fernández et al., 2022; Gallez, Fraile Mujica, et al., 2024; Requia et al., 2022; Shoari et al., 2021; van Velzen and Helbich, 2023; Zhang et al., 2022; Zhao et al., 2019), and just one study examining air quality around schools (Carrier et al., 2014). Many of these studies do not directly incorporate the socio-economic status (SES) of the school population, often relying on proxies like neighbourhood SES. Furthermore, no research has yet been conducted on this issue at the national level in Belgium; existing work has been limited to the Brussels region (Gallez, Fraile Mujica, et al., 2024).

In this study, we explore the association between the socio-economic status of the pupils and the school environment in Belgium. We specifically investigate the levels of greenness and air pollution around the school campuses. Our main hypothesis was that children from low socio-economic backgrounds are more likely to attend schools located in environments with low levels of greenness and high levels of air pollution.

To investigate the unequal distribution of environmental quality around schools, we analyse several underlying factors by studying socio-environmental inequalities at multiple levels: regional, neighbourhood, and individual school levels. First, we hypothesize that the urban-rural divide reflects a social gradient, which is mirrored in schools (H1). Second, we propose that the social composition of the neighbourhood where the school is located influences both the school's social composition and its environmental quality (H2). In other words, socio-economic residential segregation is reflected in the neighbourhood's environment and, by extension, that of the school. Third, we hypothesize that schools populated by students with a higher SES tend to benefit from better environmental conditions regardless of neighbourhood and regional contexts (H3). Additionally, we investigate potential variations in this relationship across the educational levels (primary and secondary).

5.2. Data and methods

5.2.1. A nationwide systematic study

In the federal state of Belgium, education is overseen by language-based Communities. Belgium has three language-based Communities: the Flemish (Dutch-speaking), the French (French-speaking, also known as *Fédération Wallonie-Bruxelles*) and the German-speaking Community. Both the French and Flemish Communities are present in the Brussels-Capital Region (BCR) (Figure 5.1). We did not include the German-speaking community given its smaller size and the complexity of combining different data sources. Mandatory schooling begins at the age of 6 (5 as of September 2020) and ends at 18. Students can attend part-time education from the age of 15. In 2019, compulsory primary education will amount to 821 hours in the Flemish Community and 826 hours in the French Community, and 949 hours and 885 hours respectively in secondary education (OECD, 2019).

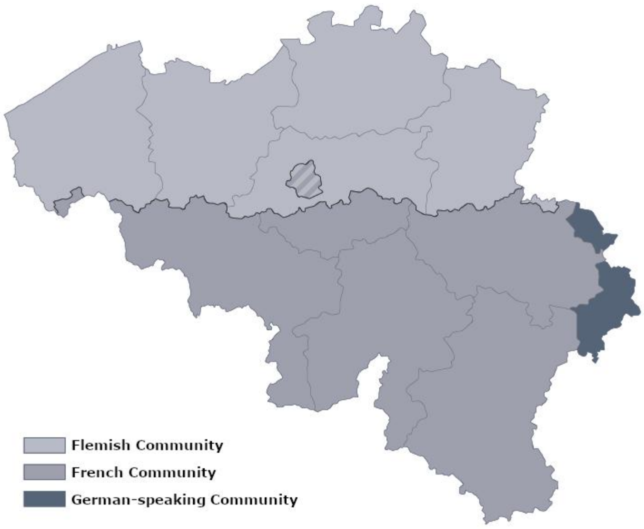


Figure 5.1. Belgium has three Communities, based on the “language”: the Flemish (Dutch-speaking), the French (French-speaking) and the German-speaking Community. French and Flemish Communities are both present in Brussels.

School choice is free and not officially bound by place of residence. However, in the French Community, enrolment in the first year of secondary school is subjected to an official application procedure accounting for eight coefficients weighing priorities for school to enrol, two coefficients out of which account for the distance between home and school (primary and secondary), and one coefficient considers the distance between primary and secondary schools (this coefficient was suppressed by 2023) (Fédération Wallonie-Bruxelles, 2019a). Nevertheless, at the primary level, school-to-home distances are mostly short. In 2001, in the Flemish Region, 76.2% of primary or kindergarten students lived within 0.5 km of their school, compared to 77.2% in the BCR and 66.6% in the Walloon Region. For secondary education, these percentages decrease to 34.4%, 54.5%, and 31.0% respectively (Verhetsel et al., 2009). An update has been made in Flanders, for primary schools in the year 2012, the median distance travelled from home to school was 1346 m (Boussauw et al., 2014).

Usually, “schools” refers to educational institutions led by a principal, which may operate across multiple geographic locations, referred to here as campuses. Each campus operates under the umbrella of the school, sharing administrative oversight, educational policies, and often a common identity. However, multiple schools may be located at the same address, each with its distinct principal. Schools are governed by an organizing body, referred to as organizing power, which can be either public or private. Public organizing bodies include entities such as communities, provinces or municipality, while private ones are typically associations, both religious and non-religious. Although the organizing bodies of part of the schools are private, nearly all Belgian schools, including those in this study, receive public funding (Fédération Wallonie-Bruxelles, 2019a).

5.2.2. School data

Socio-economic and geographical data were obtained from the French and Flemish Communities for the academic year 2018–2019. Both communities compute socio-economic indexes aimed at allocating additional funding and teaching resources to schools with lower index values.

The French Community has slightly fewer than 2,700 schools (divided into ~4,200 school campuses) serving over 900,000 students across kindergarten, primary, and secondary education, encompassing both regular and specialized programs (Fédération Wallonie-Bruxelles, 2020). About a fifth of school campuses provide secondary education ($n = 795$). Secondary schools are thus larger, and are more often located in urban areas. Specialized schools were not included in the study and only school campuses with more than 10 students were selected. A total of 3,823 school campuses were included in the study.

The French Community calculates a socio-economic index (SEI) for each school campus. This composite index classifies school campus based on indicators measuring the socio-economic status of their population. For each student, the index takes into account seven household variables related to socio-economic status, including income, education level, employment, unemployment, occupation rates, and social assistance recipient status. Variables are aggregated at the school level and a Principal Component Analysis (PCA) is applied. Finally, the SEI is computed based on the PCA coefficients of the first principal component which is rescaled to have standard deviation equal to 1. A (more) negative value of the index indicates less privileged socio-economic status (FW-B, 2021).

The Flemish Community reported lightly fewer than 3,400 schools (divided into ~5,000 school campuses) serving about 1,145,000 students across kindergarten, primary, and secondary education, excluding specialized programs. Over a quarter of these campuses provide secondary education ($n = 1{,}377$). Specialized schools were not included in the study and only school campuses with more than 10 students were selected. A total of 4,898 school campuses were included in the study.

The Flemish Community publicly provides access to four indicators of equal opportunity at the school campus level, detailing the proportion of pupils who speak a family language different from the language of instruction, whose mothers have not completed upper secondary education, who receive school allowances, and who reside in neighbourhoods with high levels of educational underachievement

(Vlaamse Overheid, 2024). Due to privacy reasons, data was not provided when the proportion of an indicator exceeded 95% of the total school enrolment. In such cases, the value of 0.95 was used. To create a single SEI for each school campus as in the French community, all variables were first standardized. Variables, being proportions, were logit-transformed (with an added value of 0.001 to avoid issues with zeros) before standardization. We then performed a PCA and extracted the first principal component, which after rescaling to unit standard deviation, was used as the SEI. We aimed to use two comparable methodologies for calculating the SEI, but the indicators differ slightly, making a strict comparison of the results between the French and Flemish communities inappropriate.

A series of variables were calculated for each school (Table 5.1). In addition to SEI, data on each school's educational level (kindergarten, primary, and secondary), and student enrolment numbers are also available. Additionally, the median neighbourhood income for statistical sectors (Statbel, 2018), was included (Figure C.1.A, in the appendices).

Table 5.1. Description of variables

Indicator name	***Description***	***Year***	***Data source***
SEI	Mean socio-economic index	2018–	French and Flemish
Number of students	Number of students	2019	Communities
NBH med. income	Median income of the statistical sector of the school campus	2018	Statbel
NO_2	Annual mean of NO_2 (µg/m^3), in 100m buffer around the school address	2018	IRCELINE
$PM_{2.5}$	Annual mean of $PM_{2.5}$ (µg/m^3), in 100m buffer around the school address	2018	IRCELINE
BC	Annual mean of back carbon (µg/m^3), in 100m buffer around the school address	2018	IRCELINE
PM_{10}	Annual mean of PM_{10} (µg/m^3), in 100m buffer around the school address	2018	IRCELINE
Vegetation *x* m	Vegetation coverage ratio in *x* m buffer around the school address	2015	Lifewatch
Territorial typologies	Belonging to rural, urban or high density cluster	2018	Eurostat

5.2.3. Environmental variables

Environmental variables were also derived based on school address locations (Table 5.1 and Figure 5.2). We used the address point due to the lack of reliable data to accurately assign each school campus to the correct buildings and parcels. To approximate exposure to nature in our study, we assessed vegetation cover at multiple buffer sizes, considering both the immediate surroundings of the school (100 m and 300 m) and the broader neighbourhood context (500 m, 1000 m, and 2000 m). High-resolution land cover data (2015, 2m spatial resolution, Figure C.1.B, in the appendices) (Radoux et al., 2023) was employed to ascertain the percentage of greenness (%), considering trees, shrubs, open vegetation of biological interest, and grasslands, while excluding arable land. To quantify the greenness within each school's environment, we computed buffer zones of 100 m, 300 m, 500 m, 1000 m, and 2000m around the school's address point.

To evaluate exposure, we relied on high-resolution models of air pollution levels focusing on four pollutants: NO_2, $PM_{2.5}$, PM_{10}, and black carbon (BC) (Figure C.1, in the appendices). These models combine an interpolation model for regional pollution levels with a Gaussian dispersion model and a street canyon model to capture the different scales and sources influencing urban air quality (Lefebvre et al., 2013). These models operate at a 10m resolution and provide annual average values. We calculated the 100m annual mean around the school's address to gauge air pollution levels. The selection of these four pollutants was not solely guided by their varying health impacts but also by the distinct sources they represent, offering a nuanced understanding of air pollution's origins and distribution patterns.

Fine particles (PM_{10} and $PM_{2.5}$) encompass all solid and liquid particles suspended in the atmosphere. PM_{10} refers to particles with a diameter of less than 10 µm, while $PM_{2.5}$ refers to those with a diameter of less than 2.5 µm. The primary sources of PM_{10} emissions are industry (34% in 2018), residential heating (29%), road transport (15%), and agriculture (10%). For $PM_{2.5}$, the main sources are residential heating (47%), industry (20%), and road transport (17%) (IRCELINE, 2022).

Black carbon (BC) is a subset of fine particles (entirely within the $PM_{2.5}$ fraction). As the name suggests, black carbon includes all carbon-based particles that are black, meaning they absorb light, with diameters ranging from 10 to 500 nm. BC is strongly associated with combustion processes and is often identified as "soot." The major sources of BC are road transport (42%), residential heating (37%), and, to a lesser extent, industry (7%) (IRCELINE, 2022).

Nitrogen oxides (including NO_2) are produced during all combustion processes in the atmosphere. The main sources of nitrogen oxides are road transport (particularly diesel engines) (42%), industry (24%), agriculture (10%), and residential heating (6%) (IRCELINE, 2022).

Following the approach of prior research (Briggs et al., 2008) and because of the significant socio-economic disparities between rural and urban areas in Belgium (Costa and de Valk, 2018; Grimmeau et al., 2012; Vanderstraeten and Van Hecke, 2019), we accounted for the urban-rural typology. We adopted the typology of Eurostat of 2018 (Angelova-Tosheva and Müller, 2019) (Figure 5.3). The typology classifies 1 km² grid cells into three types based on population density in individual grid cells and the cumulative population of clusters, where clusters comprise contiguous cells. Urban centres (high density clusters) are defined as areas with the density of at least 1,500 inhabitants per km² and a minimum cluster population of 50,000. Urban clusters are characterized by the density of at least 300 inhabitants per km² and a minimum cluster population of 5,000. Rural grid cells encompass those outside high-density and urban clusters.

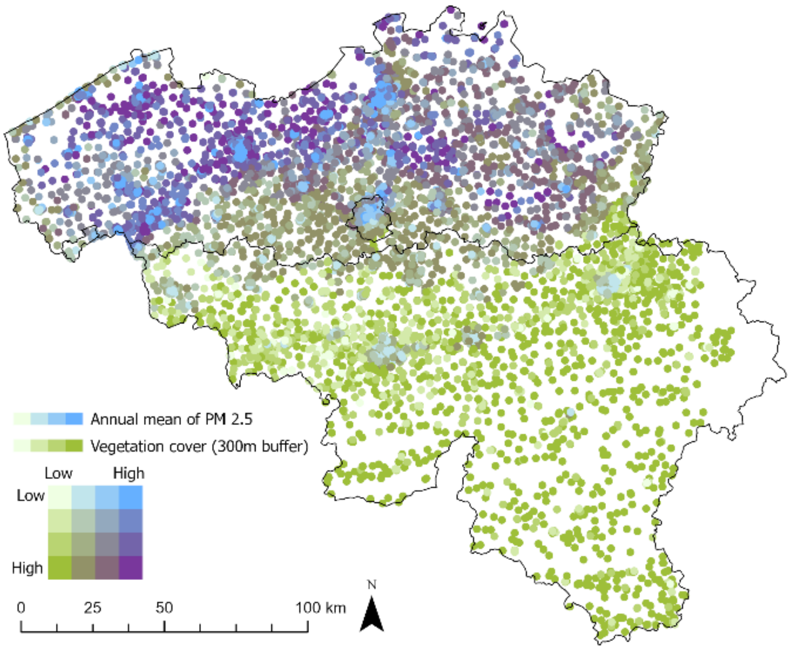


Figure 5.2. School outdoor environment of all the schools considered in the study. The colour gradient combines annual mean of PM 2.5 in 100 m buffer and vegetation cover in 300 m buffer around campus addresses.

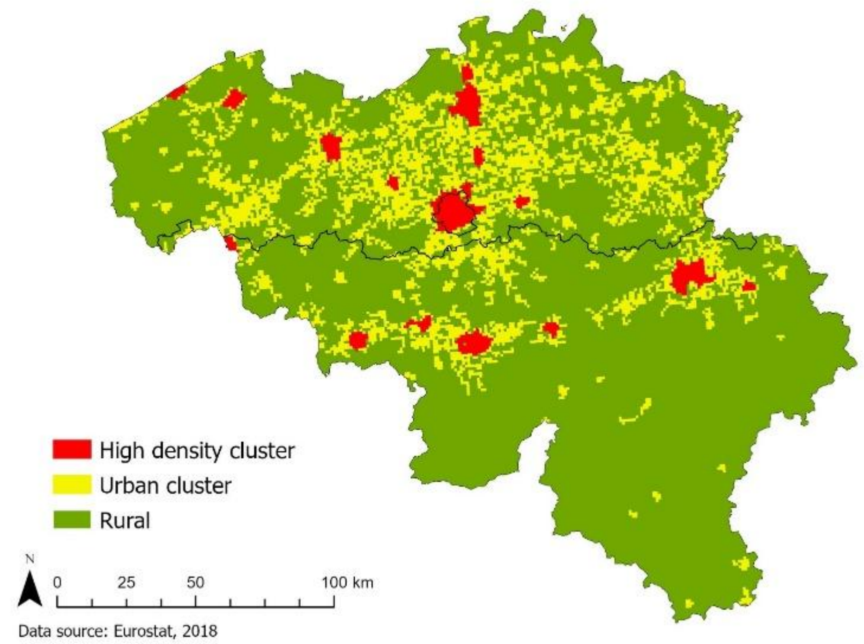


Figure 5.3. Territorial typology across Belgium

5.2.4. Statistical methods

To investigate the unequal distribution of environmental quality around schools, we conducted univariate, bivariate, and multivariate statistical analyses. Descriptive statistics – including means, standard deviations, and percentages – provided a comprehensive summary of the data.

Following other studies on Belgian schools, we assessed whether green cover (Gallez, Fraile Mujica, et al., 2024) and air pollution levels (Greenpeace Belgium, 2018; Leemans, 2024) around schools aligned with recommended standards. Specifically, we applied the World Health Organization's air quality guidelines (WHO, 2021), and adapted Konijnendijk's "3–30 – 300 rule" (2023) to evaluate access to greenery. This guideline suggests that all residences, schools, and workplaces should have at least three visible trees, neighbourhoods should maintain 30% tree canopy, and green spaces should be within 300 m. We took significant interpretative liberties with the 30% tree canopy guideline by broadening the definition of green spaces. Instead of focusing strictly on tree cover, we included greenness in a larger definition (see above). Using this adapted approach, we measured whether vegetation cover within a 300 m radius around each school reached a minimum of 30%. To examine differences in socio-economic index (SEI) between schools meeting these guidelines and those falling short, we used boxplots to display median values and interquartile ranges of SEI.

To visualize socio-economic and environmental disparities, we used boxplots to display median values and interquartile ranges of SEI and environmental indicators, categorized by territorial typology or educational level.

To further examine inequality, we calculated the Gini index, typically illustrated by a Lorenz curve (Figure 5.4). Lorenz curves were originally developed in economics as graphical tools to illustrate the cumulative distribution of wealth or income across a population (Lorenz, 1905). However, they have broad applicability and can be used to depict cumulative distributions for any quantifiable variable, including environmental and social measures. In our study, the Lorenz curve represents the rank-ordered cumulative value of socio-economic capital; specifically, we used the SEI (socio-economic index) adjusted with an offset to ensure positive values. The x-axis shows the cumulative percentage of schools, while the y-axis displays the cumulative percentage of socio-economic capital based on a rank-ordering from low to high SEI values. The greater the deviation of the curve from the diagonal line (representing perfect equality), the higher the level of inequality.

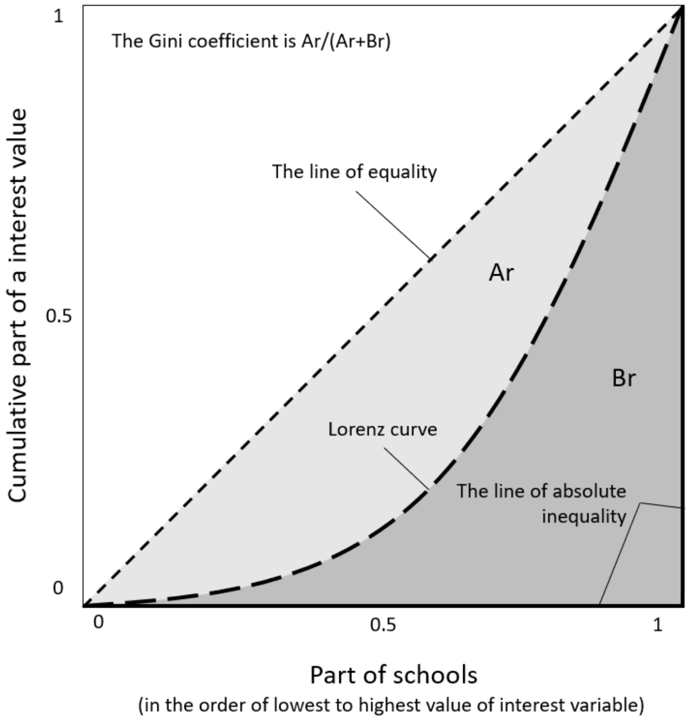


Figure 5.4. Lorenz curve and Gini coefficient

Following other studies on environmental inequalities at school (Baró et al., 2021; Carrier et al., 2014; Fernández et al., 2022; Gallez, Fraile Mujica, et al., 2024; van Velzen and Helbich, 2023; Zhang et al., 2022), we used Spearman's correlation coefficients to assess bivariate associations between socio-economic index (SEI) and the environmental variables across different subsets. All analyses were performed using R software for statistical computing version 4.1.2 (R Core Team, 2024).

We used regression models to explore the joint association of territorial typology (regional scale), neighbourhood median income (neighbourhood scale) and school socio-economic index (individual campus level) with environmental quality around schools. We focused on primary schools, and used the proportion of vegetation within a 300 m radius around each school campuses address as dependent variable. We used beta regression with a logit-link function, which is well suited for continuous variables bound within the unit interval. Models were computed using the R package *betareg* (Cribari-Neto and Zeileis, 2010). Three separate models were fitted on subsets of the data: (i) Dutch-speaking community, within Flanders and Brussels-Capital Region (BCR), (ii) French-speaking community, within Wallonia, and (iii) French-speaking community within the BCR. The BCR was grouped with Flanders for Dutch-speaking schools, as the two regions form a contiguous spatial unit. French-speaking schools in the BCR were modelled separately as the BCR is spatially disjointed from Wallonia. Each model also included the log-transformed number of enrolled students to adjust for differences in school size. All two-way and three-way interaction terms between the focal covariates were included. In the model for the French-speaking BCR schools, territorial typology and its interactions were omitted, as nearly all campuses belong to the high-density urban cluster. To account for potential spatial structuring beyond the immediate surroundings, we tested models both with and without an additional covariate: the proportion of vegetation between 300 and 2000 m around each school. This "donut-shaped" buffer, excluding the central 300 m used for the dependent variable, serves as a spatial contextual regressor. It captures broader landscape characteristics without introducing circularity, and acts as a proxy for spatial autocorrelation, helping to absorb unmeasured spatial structure that could bias estimated associations. Model diagnostic included Q–Q plots of residuals (assumed to follow a normal distribution) and spatial mapping of residuals to visually assess whether any spatial patterns remained unexplained. To facilitate interpretation, results were visualized as model-based estimates (expected values and estimated marginal means) of vegetation exposure (300 m buffer) across combinations of SEI and neighbourhood median income, stratified by territorial typology. This format highlights interaction effects and contextual variation in access to green space.

5.3. Results

A total of 8,721 school campuses were included in the study. Due to differences in the origin data for the SEI, French ($n = 3{,}823$) and Flemish ($n = 4{,}898$) school campuses were analysed separately. Additionally, French school campuses located in Wallonia ($n = 3{,}289$) and the Brussels-Capital Region (BCR) ($n = 534$) were placed into two separate groups for analysis due to their geographical disconnection. These three groups are named hereafter Flemish (for Flemish school in Flanders and in the BCR), Walloon (for French school in Wallonia) and Brussels (for French school in BCR) schools. Table 5.2 provides a detailed description of all the variables considered.

Table 5.2. Characteristics of the study population.

	Flemish schools				Walloon schools				Brussels schools (only FR)
	All	High density	Urban	Rural	All	High density	Urban	Rural	
School number	4898	1229	3075	594	3289	792	1362	1135	534
SEI [mean (sd)]	0 (1)	-0.9 (0.94)	0.2 (0.8)	0.83 (0.72)	0.13 (0.95)	-0.63 (0.88)	0.22 (0.93)	0.56 (0.67)	-0.3 (1.08)
NBH med. Income	25664.1 (4153.86)	23521.22 (4303.62)	26175.98 (3875.24)	27447.84 (3496.27)	23198.21 (4637.81)	19693.54 (3092.99)	23371.99 (4333.29)	25435.21 (4419.64)	20432.07 (4068.21)
Number of students	234.93 (179.51)	268.62 (189.26)	236.94 (179.24)	154.81 (128.8)	202.94 (215.89)	251.06 (239.32)	238.27 (235.75)	126.95 (139.95)	375.83 (215.63)
NO2 [mean (sd)]	19.88 (5.18)	26.45 (4.8)	18.15 (2.79)	15.24 (2.54)	15.86 (5.79)	22.6 (3.28)	16.49 (3.63)	10.39 (3.42)	28.44 (4.71)
PM2.5 [mean (sd)]	13.62 (0.96)	13.99 (0.7)	13.55 (0.95)	13.26 (1.24)	9.7 (1.51)	10.85 (1.3)	9.92 (1.27)	8.64 (1.19)	13.19 (0.83)
BC [mean (sd)]	1.03 (0.2)	1.26 (0.2)	0.97 (0.13)	0.86 (0.1)	0.82 (0.24)	1.1 (0.18)	0.83 (0.15)	0.61 (0.12)	1.27 (0.21)
PM10 [mean (sd)]	21.97 (1.69)	22.8 (1.65)	21.78 (1.51)	21.22 (1.96)	16.34 (2.71)	19 (2.15)	16.6 (1.97)	14.16 (1.92)	20.69 (1.35)
Vegetation 100m [mean (sd)]	0.4 (0.18)	0.29 (0.19)	0.42 (0.17)	0.52 (0.14)	0.42 (0.18)	0.29 (0.15)	0.4 (0.16)	0.52 (0.16)	0.35 (0.19)
Vegetation 300m [mean (sd)]	0.47 (0.18)	0.33 (0.19)	0.5 (0.15)	0.59 (0.11)	0.52 (0.18)	0.37 (0.16)	0.49 (0.15)	0.64 (0.14)	0.38 (0.19)
Vegetation 500m [mean (sd)]	0.48 (0.17)	0.34 (0.18)	0.52 (0.14)	0.58 (0.11)	0.54 (0.18)	0.4 (0.15)	0.52 (0.14)	0.66 (0.15)	0.39 (0.19)
Vegetation 1000m [mean (sd)]	0.5 (0.16)	0.37 (0.17)	0.55 (0.12)	0.54 (0.12)	0.55 (0.18)	0.44 (0.13)	0.54 (0.13)	0.64 (0.2)	0.4 (0.18)
Vegetation 2000m [mean (sd)]	0.52 (0.14)	0.41 (0.14)	0.57 (0.11)	0.51 (0.13)	0.55 (0.18)	0.48 (0.1)	0.53 (0.15)	0.63 (0.24)	0.42 (0.16)

Table 5.3. Overview of schools complying with guidelines on environmental quality

			Part of schools non-compliant			
	Recommended level (interim target)	**Source**	**All schools**	**Flemish schools (NL)**	**Walloon schools (FR)**	**Brussels schools (FR)**
NO_2	10 (20)	(WHO, 2021)	93.52% (36.77%)	99.98% (37.40%)	82.85% (26.48%)	100 % (94.38%)
$PM_{2.5}$	5 (10)	(WHO, 2021)	100% (78.38%)	100% (99.40%)	100% (43.60%)	100% (99.81%)
PM_{10}	15 (20)	(WHO, 2021)	86.37% (58.12%)	99.88% (88.30%)	64.03% (0.10%)	100% (79.77%)
Vegetation cover (300m buffer)	30%	(Konijnendijk, 2023)	18,51%	19.66%	13.01%	41.76%

5.3.1. Compliance with guidelines on environmental quality

First, we assessed the compliance of observed green cover and air pollution levels around schools with recommended standards. Our findings indicate that 18.51% of schools have less than 30% vegetation coverage within a 300-meter radius (adapted from Konijnendijk's "3–30 – 300 rule", 2023). Additionally, a majority of schools fall short of meeting the WHO's air quality guidelines (WHO, 2021): 93.52% of schools exceed recommended levels for NO_2, 100% for $PM_{2.5}$, and 86.37% for PM_{10} (Table 5.3). Moreover, clear differences in average socio-economic levels are observed between schools that meet these guidelines and those that do not, with higher levels of SEI found in compliant schools (Figure 5.5).

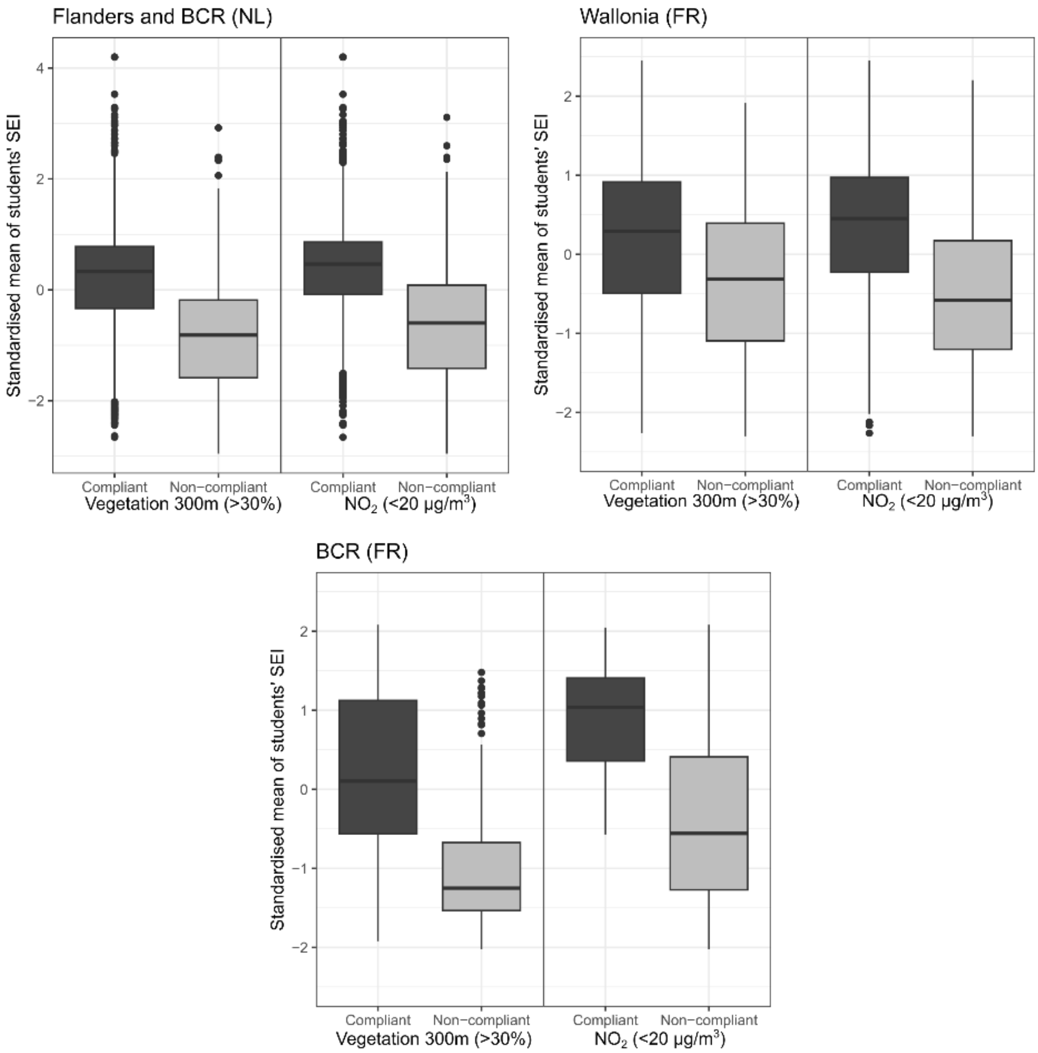


Figure 5.5. Boxplot of SEI according to compliance with guidelines on environmental quality. Please note that the SEIs for the two communities (FR and NL) are not calculated in the same way (see Method).

5.3.2. Inequalities in environmental quality around schools

The distribution of SEI and environmental indicators is represented in boxplots, according to territorial typology (Figure 5.6). Figure 5.6.A shows a clear gradient of SEI across the urban-rural spectrum, with higher socio-economic levels found in more rural areas. A similar distribution is observed when considering vegetation cover within 300 m (Figure 5.6.B). As expected, more urban areas are more polluted, a conclusion that is more evident when considering black carbon (Figure 5.6.D) compared to $PM_{2.5}$ (Figure 5.6.C). These findings confirm the first hypothesis that the urban-rural gradient is also a social gradient, driving a significant part of the unequal distribution of environmental quality. Additionally, on average, Flemish schools present higher air pollution levels than Walloon schools, but Brussels schools (FR) also exhibit high air pollution levels (Table 5.2).

The Gini index was calculated to evaluate the territorial equity of SEI distribution across schools. The Lorenz curves displayed in Figure 5.7 show that the distribution in rural areas deviates least from the line of perfect equality, with lower Gini coefficients (0.1 for Flanders and 0.13 for Wallonia). In contrast, high-density urban areas exhibit the most unequal distribution (Gini coefficient = 0.26 for Flanders and 0.3 for Wallonia). Thus, schools in urban areas face multiple burdens: not only do they have access to lower-quality environments and exhibit lower socio-economic indices, but the distribution of this socio-economic capital is also more unequal.

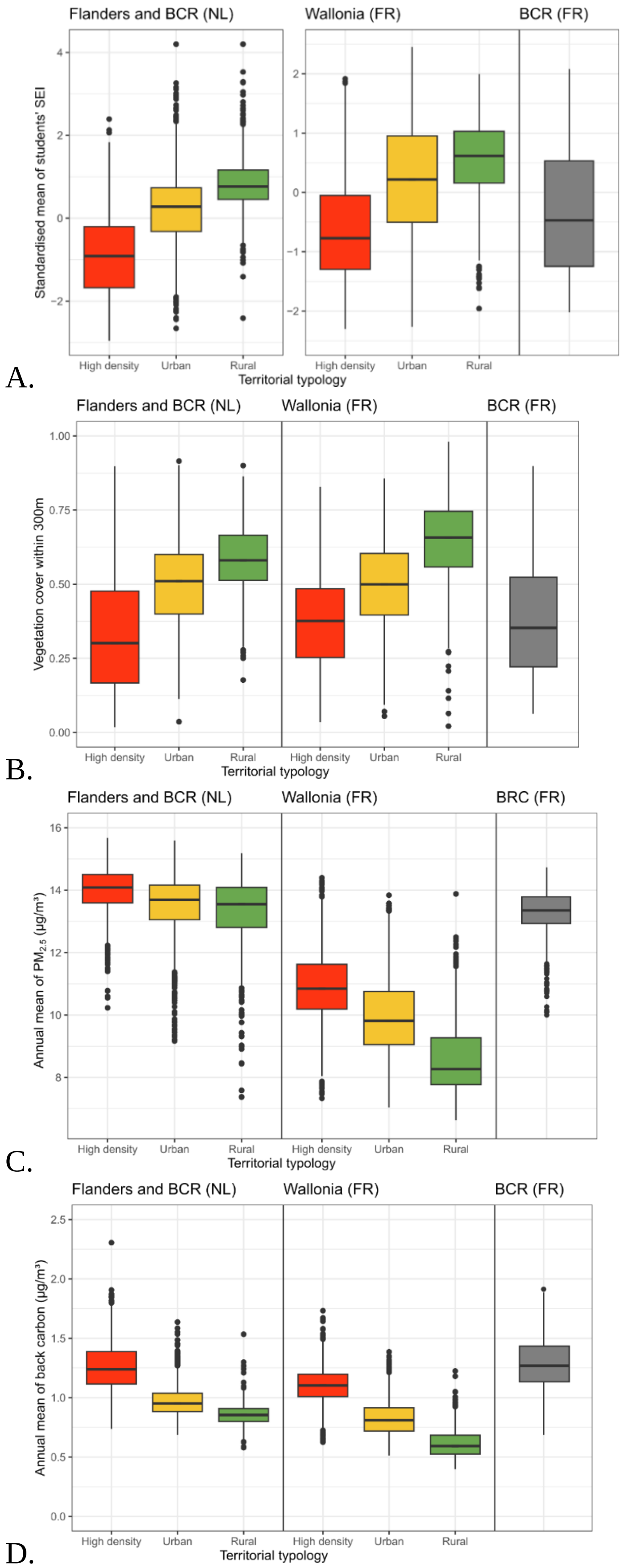


Figure 5.6. Boxplot of (A) SEI, (B) vegetation cover within 300 m, (C) annual mean of $PM_{2.5}$ and (D) annual mean of black carbon according to the different territorial typologies. Please note that the SEIs for the two communities are not calculated in the same way (see Method).

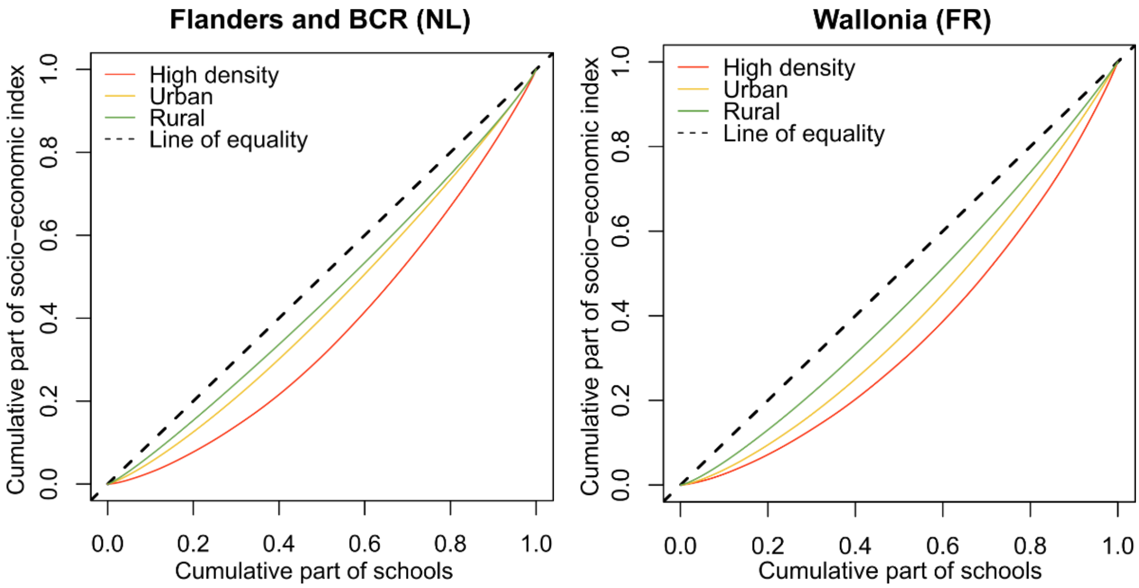


Figure 5.7. Socio-economic index Lorenz curve of the SEI of the three territorial typology.

Figure 5.8 presents the associations between the different variables considered. SEI is positively associated with neighbourhood median income (Spearman's rho = 0.48 in Flanders, 0.53 in Wallonia, and 0.66 in Brussels). Both SEI and neighbourhood median income are correlated with environmental variables as expected: lower SES is associated with more vegetation cover and lower air pollution levels. Generally, the effect size is slightly higher when considering neighbourhood median income, except in Flanders for NO_2 (Spearman's rho = -0.56 for SEI and -0.33 for NBH med. income) and BC (Spearman's rho = -0.55 for SEI and -0.38 for NBH med. income). Vegetation around schools is negatively associated with air pollution, indicating that schools with low vegetation cover also experience high air pollution levels. Air pollution variables are correlated, with NO_2 and BC being more closely associated, as are PM_{10} and $PM_{2.5}$. When examining the spatial patterns of different pollutants (Figure C.1, in the appendices), NO_2 and BC show similar patterns, primarily linked to urban areas. In contrast, PM_{10} and $PM_{2.5}$ exhibit a north-south gradient, which is more related to industrial activities.

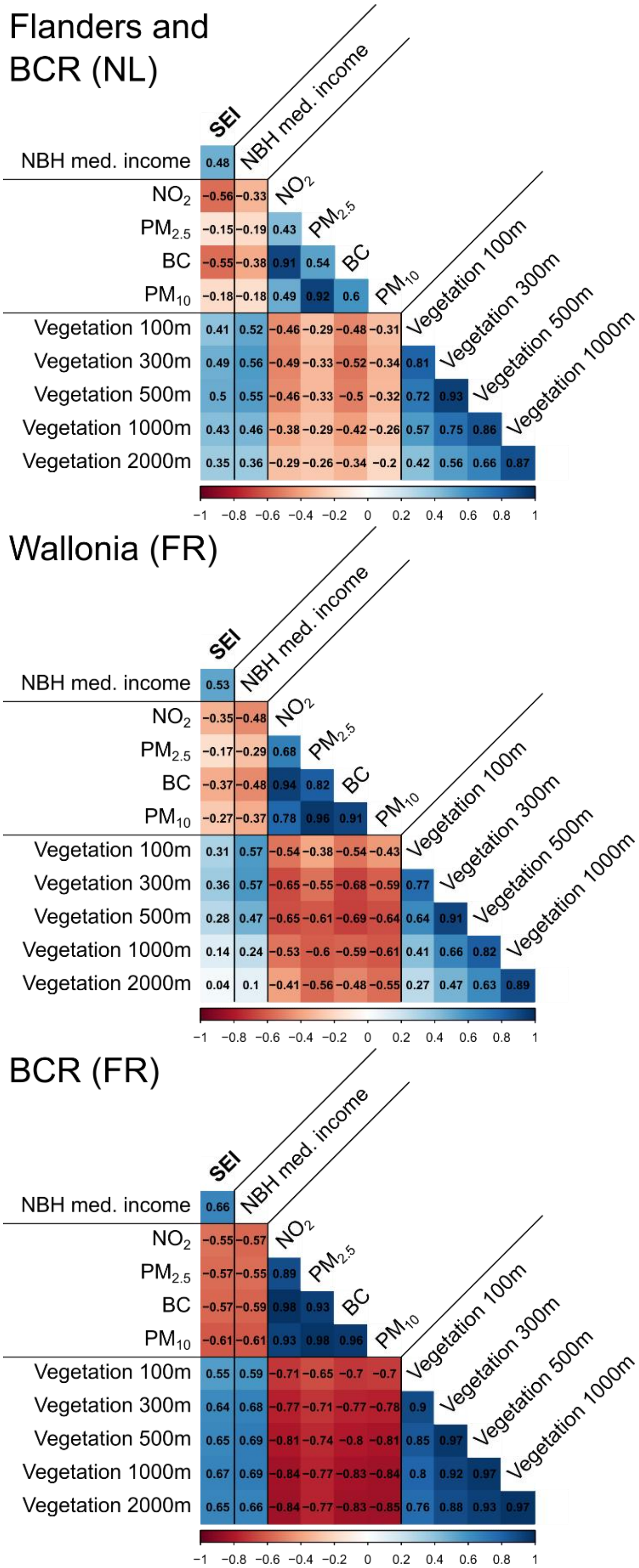


Figure 5.8. Spearman correlation between the different environmental variables and the socio-economic index (SEI). Please note that the SEIs for the two communities are not calculated in the same way (see Method).

The Spearman correlation coefficients between the socio-economic index (SEI) and various environmental variables across different subsets of the dataset are presented in Table 5.4 and Table 5.5. When considering all schools, the correlation results between SEI and environmental variables show several strong associations in Flanders, Wallonia and Brussels. Schools with a low socio-economic index are associated with lower levels of vegetation cover and higher levels of air pollution.

Lower associations are found in the subsets (compared to “All schools”). For Walloon schools, inverse correlations are found with air pollution indicators: rural schools with higher air pollution levels are associated with a higher socio-economic index. A similar trend can be observed for Flemish schools, where rural primary schools with higher air pollution levels are associated with a higher SEI (PM_{10}, Spearman’s rho = 0.19). For Flemish schools, similar associations are found in urban and high density schools compared to the overall dataset. For air pollution, stronger correlations are found with NO_2 and BC both for Flemish and Walloon schools.

Considering the educational level, in general, secondary schools are less green and more polluted than primary or kindergarten schools (Figure 5.9). Walloon primary schools are more unequal compared to Walloon secondary schools, the latter showing low effect sizes for both vegetation and air pollution. The trend is similar between Flemish primary and secondary schools but at a smaller scale.

Table 5.4. Spearman correlation between SEI and environmental variables according to different subsets for Flemish Community schools and French Community schools (excluding Brussels). Please note that the SEIs for the two communities are not calculated in the same way (see Method).

Flanders and RBC (NL)

	N	NO_2	$PM_{2.5}$	BC	PM_{10}	Vegetation 100m	Vegetation 300m	Vegetation 500m	Vegetation 1000m	Vegetation 2000m
All schools	*4666*	−0.56	−0.15	−0.55	−0.18	0.41	0.49	0.5	0.43	0.35
Rural schools	*593*	−0.02	0.1	−0.03	0.11	0.06	0.06	0.05	0.04	0.07
Urban schools	*3074*	−0.28	−0.03	−0.31	−0.05	0.27	0.36	0.38	0.3	0.19
High density schools	*999*	−0.46	−0.05	−0.41	−0.12	0.27	0.3	0.31	0.31	0.37
Primary schools	*2727*	−0.56	−0.12	−0.55	−0.16	0.41	0.51	0.51	0.42	0.34
Rural primary schools	*428*	0.06	0.17	0.07	0.19	−0.02	0.02	0.02	0.05	0.09
Urban primary schools	*1775*	−0.27	−0.01	−0.28	−0.03	0.24	0.37	0.39	0.29	0.19
High density primary schools	*524*	−0.5	−0.08	−0.44	−0.13	0.4	0.43	0.44	0.43	0.46
Secondary schools	*1322*	−0.41	−0.1	−0.41	−0.16	0.1	0.22	0.27	0.3	0.31
Rural secondary schools	*64*	−0.19	−0.06	−0.34	−0.12	0.05	0.18	0.22	0.13	0.08
Urban secondary schools	*894*	−0.16	0.01	−0.21	−0.01	−0.08	0.07	0.14	0.15	0.12
High density secondary schools	*364*	−0.41	0	−0.35	−0.14	0.07	0.09	0.09	0.12	0.23

Wallonia (FR)

	N	NO_2	$PM_{2.5}$	BC	PM_{10}	Vegetation 100m	Vegetation 300m	Vegetation 500m	Vegetation 1000m	Vegetation 2000m
All schools	*3289*	−0.35	−0.17	−0.37	−0.27	0.31	0.36	0.28	0.14	0.04
Rural schools	*1135*	0.27	0.2	0.21	0.25	0.13	0.09	−0.08	−0.22	−0.27
Urban schools	*1362*	−0.05	0.08	−0.13	0	0.14	0.19	0.13	0.09	0.05
High density schools	*792*	−0.03	0.04	−0.07	−0.03	0.05	0.04	0.04	−0.03	−0.08
Primary schools	*2272*	−0.35	−0.18	−0.37	−0.26	0.36	0.4	0.3	0.12	0.02
Rural primary schools	*949*	0.31	0.24	0.26	0.29	0.12	0.05	−0.11	−0.26	−0.31
Urban primary schools	*861*	−0.07	0.05	−0.17	−0.04	0.18	0.26	0.2	0.12	0.07
High density primary schools	*462*	−0.12	−0.02	−0.11	−0.06	0.21	0.21	0.19	0.12	0.02
Secondary schools	*641*	−0.26	−0.09	−0.29	−0.22	0.18	0.23	0.22	0.23	0.17
Rural secondary schools	*101*	0.05	−0.04	−0.03	0	0.13	0.29	0.18	0.08	0.06
Urban secondary schools	*329*	0.01	0.14	−0.05	0.06	0.1	0.09	0.03	0.08	0.03
High density secondary schools	*211*	−0.06	0.12	−0.16	−0.08	−0.06	−0.03	0	−0.06	0.01

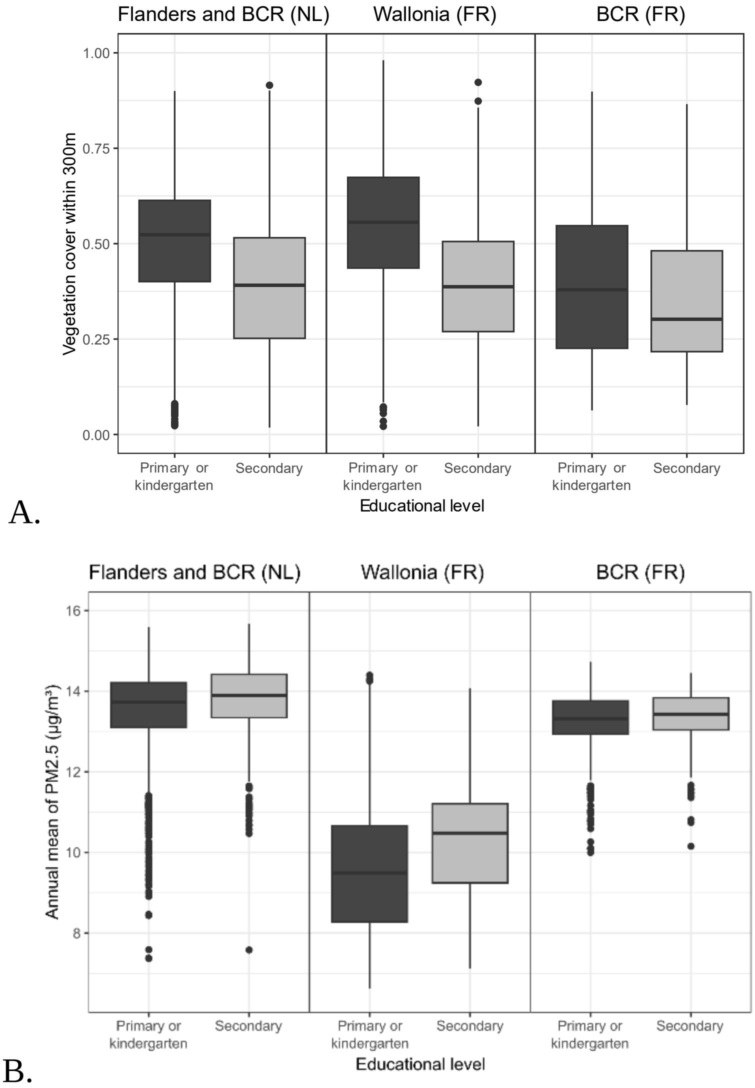


Figure 5.9. Boxplot of environmental quality according to the educational level. (A) Difference in vegetation covert around 300 m and (B) difference in annual mean of PM2.5.

5.3.3. High density urban area

Considering the extensive environmental and socio-economic pressures on urban areas, we applied the same analysis to high density clusters. Within the French community schools (Table 5.6.B), Brussels emerges as the most unequal city regarding both air pollution and vegetation levels, whereas Walloon cities show weak correlations between these environmental factors and socio-economic indicators. In Flemish schools (Table 5.6.A), both Antwerp and Brussels reveal strong correlations between socio-economic index (SEI) and both vegetation coverage and air pollution levels. Ekeren and Ghent display strong correlations with air pollution alone, while Ostend shows strong correlations only with vegetation.

Table 5.5. Spearman correlation between SEI and environmental variables according to different subsets for French Community schools in the Brussels-Capital Region.

	N	NO_2	$PM_{2.5}$	BC	PM_{10}	Vegetation 100m	Vegetation 300m	Vegetation 500m	Vegetation 1000m	Vegetation 2000m
All schools	*534*	−0.55	−0.57	−0.57	−0.61	0.55	0.64	0.65	0.67	0.65
Primary schools	*309*	−0.58	−0.6	−0.6	−0.65	0.58	0.67	0.68	0.7	0.69
Secondary schools	*154*	−0.51	−0.53	−0.55	−0.56	0.5	0.61	0.63	0.62	0.6

Table 5.6. Spearman correlation between SEI and environmental variables according to different subsets of schools located in high density clusters.

A. Flemish Community schools

	N	NO_2	$PM_{2.5}$	BC	PM_{10}	Vegetation 100m	Vegetation 300m	Vegetation 500m	Vegetation 1000m	Vegetation 2000m
Antwerpen	*431*	−0.29	−0.43	−0.32	−0.41	0.35	0.39	0.4	0.36	0.43
Brussel	*280*	−0.4	−0.41	−0.42	−0.44	0.36	0.36	0.39	0.4	0.41
Gent	*189*	−0.31	−0.3	−0.31	−0.33	0.12	0.06	0.05	0.09	0.07
Brugge	*102*	0	−0.2	−0.04	−0.19	0.12	0.19	0.19	0.25	0.25
Oostende	*69*	−0.4	0.01	−0.2	0.02	0.48	0.62	0.59	0.53	0.35
Mechelen	*65*	0.05	−0.07	0.03	−0.15	−0.03	−0.14	−0.1	−0.14	−0.18
Leuven	*65*	−0.26	−0.05	−0.25	−0.05	0	−0.04	−0.01	0.11	0.08
Aalst	*63*	−0.15	0	−0.13	−0.06	−0.25	−0.18	−0.13	−0.09	0.23
Antwerpen − Ekeren	*38*	−0.61	−0.63	−0.51	−0.62	0.44	0.47	0.35	0.27	0.35
Machelen	*31*	−0.03	0.07	−0.02	0.08	0.32	0.46	0.49	0.26	0.3

B. French Community schools

	N	NO_2	$PM_{2.5}$	BC	PM_{10}	Vegetation 100m	Vegetation 300m	Vegetation 500m	Vegetation 1000m	Vegetation 2000m
Bruxelles	*586*	−0.5	−0.52	−0.53	−0.56	0.48	0.57	0.59	0.61	0.6
Liège	*343*	−0.02	−0.01	−0.02	−0.03	0.14	0.16	0.17	0.11	0.03
Namur	*62*	−0.01	−0.08	−0.03	−0.05	−0.01	−0.09	−0.07	−0.13	−0.06
Charleroi	*204*	0.06	−0.08	−0.04	−0.06	−0.01	−0.07	−0.1	−0.14	−0.09
Verviers	*57*	−0.07	0.15	0.01	0.07	0.21	0.16	0.03	−0.03	0.19
La Louvière	*74*	0.07	0.08	0.08	0.08	−0.07	−0.03	0.08	0.06	−0.06
Colfontaine	*65*	−0.01	−0.06	−0.03	−0.07	−0.11	0.11	0.14	0.19	−0.05
Mouscron	*52*	−0.21	−0.21	−0.32	−0.25	0.03	0.15	−0.11	−0.26	−0.3

A. Flanders and BCR (NL)

B. Wallonia (FR)

C. BCR (FR)

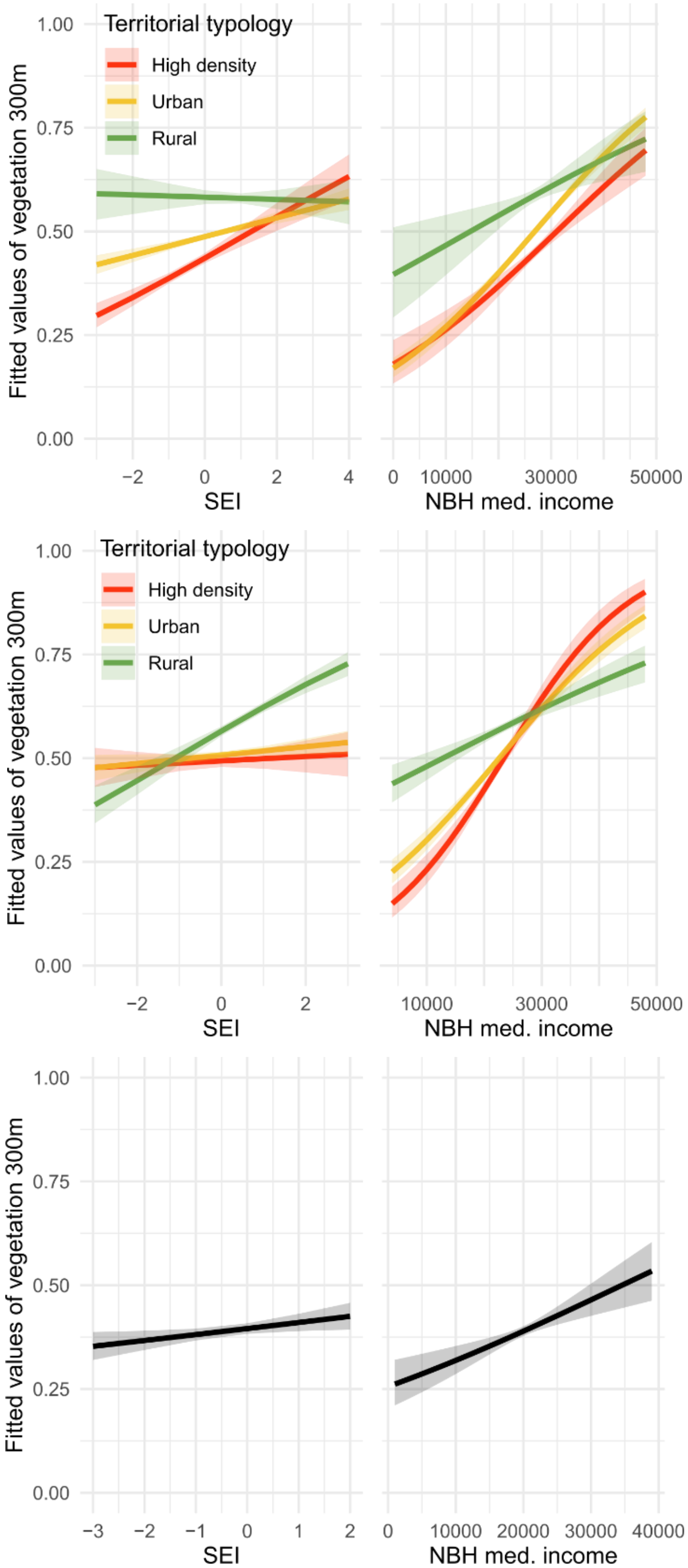


Figure 5.10. Model-based estimates (expected values and estimated marginal means) of vegetation exposure (300 m around primary school address) for different combinations: SEI and neighbourhood median income stratified by territorial typology (except for BCR (FR)).

5.3.4. Multiple associations with environmental quality

Figure 5.10 presents model-based estimates of vegetation exposure from the model including the spatial regressor. This approach allows us to observe how vegetation exposure varies jointly across multiple levels of socio-economic and territorial differentiation, while statistically controlling for their interactions within a unified model. This version of the model was selected because it significantly improved model performance, as evidenced by higher pseudo R^2 values and lower AIC. For comparison, results from models without the spatial regressor are provided in the appendices (Figure C.2), along with residual maps, pseudo R^2 values, and AIC scores.

In Dutch-speaking primary schools (Figure 5.10.A), vegetation cover increases with both the school-level socio-economic index and neighbourhood median income, but the strength of this association varies across territorial contexts. When comparing the two panels, the slope is generally steeper for neighbourhood median income (right) than for SEI (left), suggesting that neighbourhood characteristics may exert a stronger influence on vegetation disparities than the socio-economic composition of the school itself. In high density urban areas (red), the positive gradient is particularly marked, indicating that both school- and neighbourhood-level disadvantage are associated with lower vegetation coverage. Conversely, in rural areas (green), vegetation levels are higher overall and show no clear association with SEI, reflecting a more uniform distribution of green space regardless of social context. Notably, the expected difference in vegetation coverage between territorial typologies (i.e. more green coverage in rural area, less in urban settings) is more pronounced among the most disadvantaged schools (either comparing the socio-economic level of the school itself or of the school neighbourhood), suggesting that environmental inequalities are amplified among socially vulnerable schools.

In French-speaking primary schools in Wallonia (Figure 5.10.B), vegetation cover increases more clearly with neighbourhood median income (right panel) than with school-level SEI (left panel), especially in urban and high density areas where the association with SEI appears weak. In contrast, in rural areas, the association with SEI is strong and even more pronounced than that with neighbourhood income, indicating a different structuring of inequality in these less dense environments. As in Dutch-speaking schools, the expected difference in vegetation coverage between territorial typologies (i.e. more green coverage in rural area, less in urban settings) is more pronounced among the schools within the most disadvantaged neighbourhoods. Conversely, for school-level SEI, this spatial gradient is more pronounced among the most advantaged schools.

In French-speaking primary schools in the BCR (Figure 5.10.C), results are not stratified by territorial typology due to limited variation – most schools are located in high-density urban areas. As in the two other models, vegetation cover increases more clearly with neighbourhood median income (right panel) than with school-level SEI (left panel). An interesting finding in this case is that, unlike in the Flemish and Walloon models, the version without the spatial regressor (Figure C.2.C, in the appendices) shows much stronger associations. This indicates that vegetation spatial patterns in Brussels are closely intertwined with socio-economic spatial structures. When the spatial regressor is excluded, the model reveals stronger socio-economic gradients, which are otherwise partially absorbed by spatial autocorrelation.

It is important to emphasize that the response variable – the vegetation cover within 300 m around the school address point does not directly reflect the vegetation within the physical perimeter of the school campus, as reliable campus boundaries are not available for all schools. This distinction should be kept in mind when interpreting the results. For instance, the maps of residuals for Flanders and Wallonia clearly show negative residuals in areas with significant arable land or settlements. Similarly, in Brussels, negative residuals are observed in the most urbanized parts of the region. These patterns suggest that high proportions of arable land or urban settlements within the 300 m buffer result in lower vegetation cover than expected.

5.4. Discussion

Our results show a clear correlation between the school's socio-economic index and the quality of its environment, with poorer schools facing more air pollution and less green surroundings. This finding is especially stark in major cities like Brussels and Antwerp, where disadvantaged schools bear a cumulative burden: lower socio-economic status, limited vegetation coverage, and higher air pollution levels. The particular case of Brussels, compared with other European cities, has already been highlighted in the article by Gallez et al (2024), who put forward the explanation of the "school-related luxury effect" to explain this particularity, according to which wealthier families tend to live in areas offering better environmental conditions.

Contrary to general trends, French-speaking schools in rural areas with higher levels of air pollution are associated with a higher socio-economic index. We propose the following explanation for this inverse relationship with air pollution: rural schools that are slightly more polluted may be located closer to small economic centres or rural towns, which tend to attract a slightly more affluent population compared to schools located in more remote rural areas, with lower levels of air pollution. A clue supporting this hypothesis is the observed inverse correlation between vegetation within 1000 and 2000 m of rural schools and their socio-economic index: rural schools with a higher socio-economic index tend to have less surrounding vegetation within these larger buffers around their address. While these correlations are intriguing, they remain speculative and warrant further investigation to confirm any causal relationships.

The results also indicate that secondary schools, on average, are located in environments of lower quality compared to primary schools. This can be attributed to the fact that secondary schools typically accommodate a larger number of students and are often situated in more central, and thus more urbanized, locations. Indeed, secondary schools are more prevalent in high-density urban areas (27% in Flanders, 33% in Wallonia) compared to primary schools (12% in Flanders, 20% in Wallonia). Additionally, the spatial distribution of secondary schools is less dispersed, meaning they capture a smaller range of environmental quality contrasts. This explains why environmental inequalities are less pronounced among secondary schools compared to primary schools.

This uneven distribution of environmental quality around schools shown in the results is explained by socio-environmental inequalities present at various levels as demonstrated by the spatial regression models and descriptive statistics. At the regional scale, the urban-rural gradient mirrors a social gradient (H1). This socio-spatial gradient is evident in the data, showing higher socio-economic indices for schools in rural areas, intermediate in urban zones, and lower in high-density urban areas. At the neighbourhood level, wealthier districts tend to have more greenery and less air pollution, and the schools within these neighbourhoods reflect both the environment and the socio-economic composition of the area (H2). Finally, at the individual school level, once the effects of the two broader scales are accounted for, the same pattern can still be observed in many cases: students from higher socio-economic backgrounds are more likely to attend schools located in better-quality environments (H3).

The literature agrees with our findings that the urban-rural gradient in Belgium mirrors a social gradient (H1). Post-World War II suburbanization, driven by automobile proliferation and private property promotion, has led to affluent residential peripheries contrasting with economically disadvantaged central urban areas

(Grimmeau et al., 2007). The Brussels-Capital Region, as the country's most populous urban residential complex, attracts international populations and continues to experience urban exodus, a pattern also seen in other major cities (Vanderstraeten and Van Hecke, 2019). Urban agglomerations offer employment to a wealthier class that prefers suburban green spaces to live and commutes to city centres. Conversely, economically vulnerable populations are concentrated in older industrial urban neighbourhoods or neglected urban margins (Grimmeau et al., 2012). Suburban Belgian communes are characterized by individual housing in green environments and a relatively affluent population (Vanderstraeten and Van Hecke, 2019).

At the neighbourhood level, residential segregation drives environmental inequalities (H2). The housing market influences land use decisions, resulting in low socio-economic groups experiencing poor air quality due to the devaluation of properties near pollution sources (Deguen and Zmirou-Navier, 2010). Conversely, while urban green space strategies aim to address environmental justice issues by making neighbourhoods healthier and more aesthetically pleasing, they can also raise property values, potentially leading to gentrification and the displacement of the very residents these strategies were designed to benefit (Wolch et al., 2014). Since schools are typically located near students' residences (Boussauw et al., 2014; Verhetsel et al., 2009), these patterns are reflected in the distribution of environmental inequalities between the schools.

Finally, our study shows that school segregation can also have an additional effect on environmental inequalities (H3). There are several possible explanations for this. In Belgium, the organization of the school system, including parental choice of school, the possibility for schools to differentiate and define their educational offer and the funding of schools according to the number of pupils enrolled (Agirdag et al., 2016; Dupriez et al., 2018), leads to a "quasi-market in education". Each school develops its own "educational niche" to attract a specific student population. In addition, the preferences of high socio-economic parents for high socio-economic peers are also a key factor driving segregation (Franck and Nicaise, 2018; Gazmuri, 2024). These two factors could explain an amplification of the environmental inequality phenomena seen at the regional and neighbourhood level.

Compared to what is discussed in the literature, the situation observed in schools does not differ greatly from what is observed at the residential level. The lack of compliance with guidelines in schools mirrors what is seen in the general population, where 100% of people are exposed to $PM_{2.5}$ levels exceeding the WHO target value (WHO, 2021), 75% for PM_{10}, and 85% to NO_2 levels (Sciensano, 2024). To our knowledge, no study has compared air pollution levels and the socio-economic profile of the population on a national/regional scale. A study on Ghent showed that deprived neighbourhoods are more exposed to air pollution (Verbeek, 2019). Regarding vegetation cover, Greenpeace Belgium (2024) conducted a study assessing compliance with the 3-30-300 vegetation guidelines (Konijnendijk, 2023) and comparing it with median income across the 100 most populated municipalities. While the indicators differ slightly and are not directly comparable, their conclusions align with ours: the least affluent municipalities are those with the fewest buildings complying with the 3-30-300 rule. Moreover, in 72% of municipalities, fewer than 10% of buildings meet the 3-30-300 rule.

Improving the environmental quality around schools and more particularly around low-SES schools is then urgent, even beyond the reduction of environmental inequalities. Indeed, there is evidence that contact with good air quality (Deguen and Zmirou-Navier, 2010; Landrigan et al., 2018) and green space (Rigolon et al., 2021) may disproportionately benefit disadvantaged populations by attenuating the toxic effect of poverty. Students with a low-SES may be more sensitive to air pollution and lack of green space because of the higher prevalence of existing diseases and because it's cumulative with the environment they already experienced at home (Bolte et al., 2010; Carrier et al., 2014).

In Belgium, there are already initiatives to greening schoolyards (Bruxelles environnement, 2021; GoodPlanet Belgium, 2024; MOS, 2024) and reduce traffic around schools (Durieux et al., 2023). However, improving the environmental quality around schools faces several challenges: lack of environmental awareness, difficulties in securing funding, limited time and expertise in the schools, complexity of the bureaucratic processes, and lack of political will (Giezen and Pellerey, 2021). Additionally, there is a social justice component, as low-SES schools generally struggle to build capacity and skills within their already stretched budgets and staff, receive less parental support, and experience higher staff turnover (Dumay, 2014). Considering this and the fact that, as described above, low-SES schools disproportionately benefit from a high-quality environment, general greening and air quality policies should be designed to address these disparities. These efforts should begin by prioritizing schools situated in low-quality environments and having disadvantaged populations. At the same time, given the freedom of school choice, an improvement in environmental quality around schools could contribute to a gentrification effect, where certain schools become more attractive and experience shifts in their student demographics as a result. To our knowledge, no study has yet explored this aspect. Monitoring current greening initiatives and analysing changes in the socio-economic composition of schools over time could provide valuable insights into these potential dynamics.

While this study provides robust results, contributing valuable insights to the evidence based on environmental inequalities in schools, some limitations exist. Firstly, we used the school's address as a proxy to calculate environmental quality indicators due to the lack of data on exact school parcel boundaries. Although this approximation may be less accurate for certain schools, it is generally acceptable for the majority, and we are confident that this limitation does not significantly alter our findings. Nevertheless, for more detailed analyses and to implement equitable policies, this aspect would require further refinement. Secondly, our definition of vegetation cover is relatively coarse and would need to be refined for policy applications. Several other studies have employed more detailed indicators (Baró et al., 2021; Gallez, Canters, et al., 2024), which could provide additional insights and improve the accuracy of vegetation assessments for targeted interventions.

5.5. Conclusion

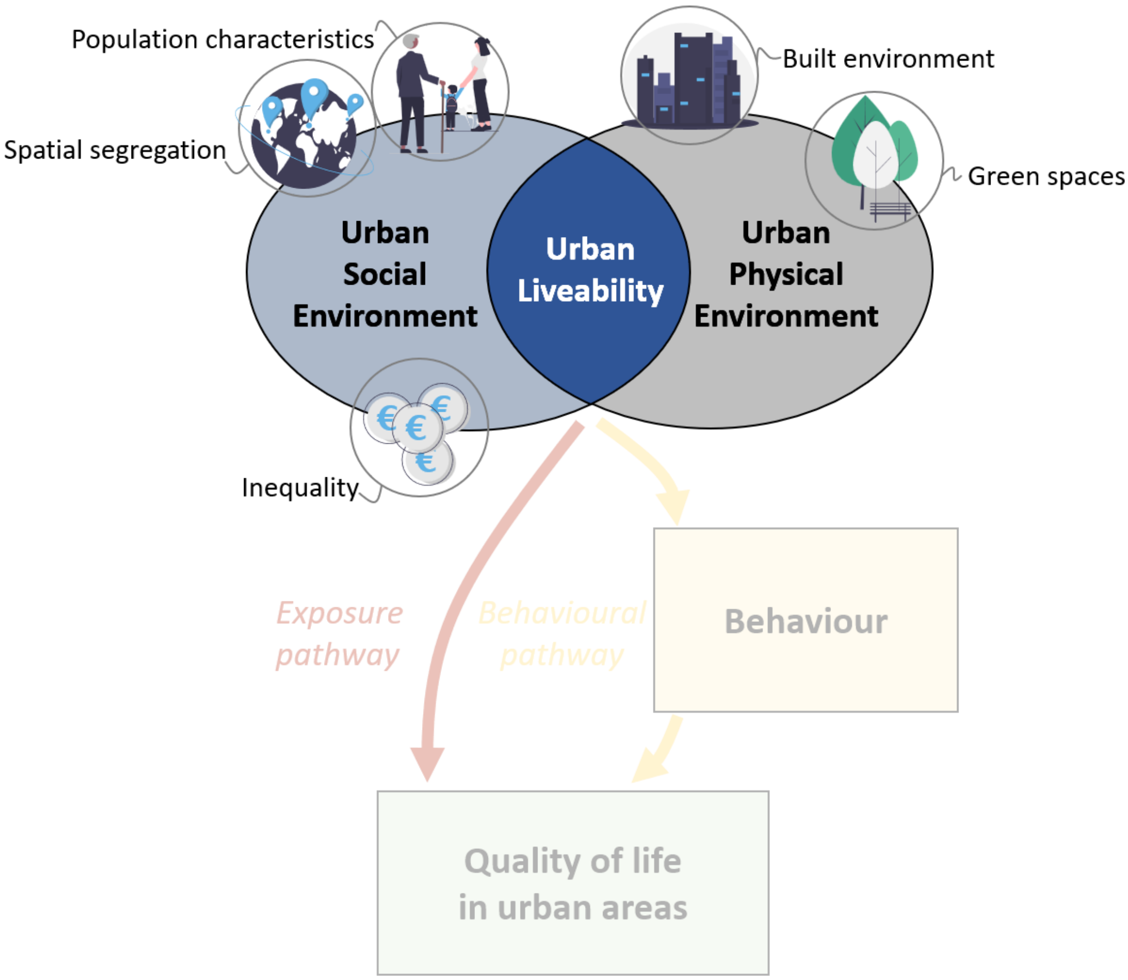
Addressing the importance of socio-environmental inequalities, authorities must prioritize and allocate resources to establish fair environmental quality at schools. By focusing on enhancing the school environment, authorities can actively contribute to mitigating these inequalities. Creating and maintaining green spaces within school premises can provide students with direct exposure to nature, resulting in improved mental well-being, reduced stress levels, and enhanced concentration during academic tasks. This effort can help narrow the gap in opportunities and experiences among diverse socio-economic groups, ensuring that every student has access to a healthy and supportive learning environment.

As a perspective, it would be interesting to monitor the greening and air quality policy to see whether it is targeting the schools that need it most. It would also be interesting to track the socio-economic trajectory of schools that have been improved.

6

Bridging streetscape and socio-economic clusters. A new approach to socio-spatial disparities in Brussels

The abstract of this chapter has been accepted for a full submission to Belgeo for the special issue on "*Environmental Justice in Europe, Spatial Dimensions*." The chapter is co-authored by Thomas, I., and Vanwambeke, S. O.



Abstract

The overall objective of this study is to evaluate the association between the urban environment and socio-spatial segregation aspects in Brussels at a fine scale. While previous research has shown that the uneven spatial distribution of living environment quality contributes to distinct patterns of segregation between poverty and affluence, no fine-scale studies have yet linked the urban environment with multiple socio-demographic variables in a comprehensive manner in Brussels. To address this gap, we combined a detailed streetscape typology of Brussels urban fabrics with socio-economic micro-data at the individual level. We described the distribution of social characteristics across the urban fabrics and established social profiles to identify socio-spatial patterns within the urban space. Specifically, we aimed to determine whether different types of urban fabrics exhibit distinct social structures. Our findings confirm well-known spatial trends in Brussels but offer a more nuanced perspective on socio-spatial segregation at the street level. Two key examples illustrate these disparities: first, the city centre presents clear socio-economic contrasts, with historic urban fabric housing lower income, predominantly non-European residents, while modern office districts accommodate a transient young European workforce with low residential density. Second, green and low-density environments, including the garden districts originally designed for affordable housing, are predominantly inhabited by highly educated, middle- to high-income Belgian residents.

6.1. Introduction

Rising evidence underscores the positive influence of a high-quality urban environment on well-being and health, while, conversely, polluted, densely built, and poorly greened environments have been associated with negative health outcomes, exacerbating stress, respiratory diseases, and overall lower quality of life (Berke and Vernez-Moudon, 2014; Nieuwenhuijsen, 2020; Pacione, 2003). However, studying the relationship between environmental quality and well-being presents a major challenge: the effects of the urban environment are deeply intertwined with social and economic factors. Disentangling the independent impact of environmental conditions from broader socio-spatial inequalities remains complex. One way to address this is to adopt a finer spatial scale that offers a different perspective on the relationship between urban form, quality of life, and social context – one that is more closely centred on individuals than on traditional administrative units. Administrative spatial units at which socio-economic data is often distributed, such as statistical neighbourhoods, may not always correspond with the scale at which urban environment affects human behaviour, well-being, and social interactions (van Kamp et al., 2003; Pacione, 2003). Several authors have highlighted the value of the street-level perspective – centred on the pedestrian – as a complementary scale for modelling urban environments and examining their impact on human-related phenomena (Araldi and Fusco, 2019; Harvey and Aultman-Hall, 2016). The recent widespread availability of high-resolution spatial data has facilitated an increase in research at finer spatial scales (Ferreira and Vale, 2024).

Environmental justice has emerged as a framework to address disparities in access to environmental benefits and exposure to environmental burdens, which are often shaped by socio-economic inequalities. Geographers have made significant contributions to understanding these issues, highlighting the spatial dimensions of environmental inequality and the need for context-specific approaches (Harvey, 1996; Walker and Bulkeley, 2006). Initially, this field focused heavily on the burden of pollution and environmental risks, with research primarily developed in the United States (Coolsaet and Bullard, 2021). Over time, it has expanded to other regions (Fairburn et al., 2019) and broader areas of study, encompassing access to green spaces (Schüle et al., 2019), essential services, and overall quality of living environments (Dubois and Van Criekingen, 2007; Lejeune et al., 2016). Several authors have proposed typologies to clarify the different forms environmental inequality can take. These typically distinguish between inequalities of exposure (to environmental harms), inequalities of access (to environmental benefits), and inequalities of participation (in environmental decision-making). Other dimensions include historical inequalities, vulnerabilities to socio-ecological risks, or the unequal effects of environmental policies (Blanchon et al., 2009; Emelianoff, 2006; Laurent, 2015). While this article acknowledges the multifaceted nature of environmental inequalities, it specifically focuses on inequalities of access to high-quality urban environments, and more precisely, their uneven distribution across Brussels.

There are parallels between the framework of environmental justice, or ecological inequalities as it is sometimes referred to in Europe, and the perspective of social segregation and social disparities, widely studied by geographers. Brussels, in particular, has inspired a substantial body of literature on social segregation (Costa and de Valk, 2021; Dujardin et al., 2008; Imeraj and Gadeyne, 2024; Van Criekingen, 2006; Vanneste et al., 2007). Among Belgian cities, Brussels also stands out for its stark socio-environmental inequalities. Brussels is an urban agglomeration characterized by a pronounced socio-economic gradient, with a concentration of low-income populations in its deprived central areas (Costa and de Valk, 2021). These disparities are driven by socio-spatial segregation, where housing market dynamics, migration patterns, and uneven distribution of urban living environments all play central roles (Haandrikman et al., 2023). Brussels reflects Belgium's broader housing challenges, rooted in liberal housing policies that prioritize homeownership while leaving the rental market largely deregulated (De Decker, 2008). This system disproportionately affects low-income households, who are often confined to poorer-quality rental housing in disadvantaged neighbourhoods. Social housing, while a potential counterbalance to these inequalities, remains insufficient, with long waiting lists and limited availability (De Decker, 2008). Efforts to promote social mixing through area-based interventions, which often target central deprived neighbourhoods (Dessouroux et al., 2016), have been implemented. However, there is no evidence that these policies effectively reduce segregation (Haandrikman et al., 2023). Migration dynamics further amplify these inequalities. Brussels serves as a gateway city, attracting a highly diverse population, including many non-EU migrants. Ethnic and socio-economic segregation often overlap, as low-income migrants cluster in central neighbourhoods where housing is affordable but often substandard. These areas, while offering community networks and accessibility, also concentrate vulnerabilities, reinforcing patterns of exclusion (Costa and de Valk, 2021). Finally, the uneven spatial distribution urban environment quality (Guyot, Araldi, et al., 2021; Lauriks et al., 2022; Stessens et al., 2017; Van de Voorde, 2017) contributes to distinct patterns of segregation between poverty and affluence, producing sharp contrasts in environmental quality across Brussels.

Approaches focused on socio-spatial disparities resonate with the principles of environmental justice, highlighting differences in residential environments and urban accessibility exacerbates broader patterns of segregation and exclusion. As research increasingly emphasizes the connections between urban environments and well-being, it underscores the importance of addressing these disparities to ensure equitable access to healthy living conditions. In Belgium, research on environmental justice remains sparse, whether academic (Cornut et al., 2007; Dozzi et al., 2008; Lejeune et al., 2016; Verbeek, 2019) or conducted by environmental organizations (Greenpeace Belgium, 2024; Lauriks et al., 2022). While inequalities in access to urban environmental quality in Brussels are frequently discussed in the literature (e.g. Costa and de Valk, 2021; Imeraj and Gadeyne, 2024; Stessens et al., 2017), few quantitative applied studies have integrated both environmental and socio-economic indicators (Gallez, Canters, et al., 2024; Greenpeace Belgium, 2024; Lauriks et al., 2022). Previous studies on the relationship between urban morphology and socio-economic variables have primarily focused at an aggregated scale. For example, De Keersmaecker et al. (2003) used fractal dimensions to describe the city, while Dubois and Van Criekingen (2007) examined the social implications of a “sustainable city” agenda in central neighbourhoods.

The overall objective of this study is to evaluate the association between the urban environment and socio-spatial segregation aspects in Brussels at a fine scale. While previous research has shown that the uneven spatial distribution of living environment quality contributes to distinct patterns of segregation between poverty and affluence, no fine-scale studies have yet linked the urban environment with multiple socio-demographic variables in a comprehensive manner in Brussels. To address this gap, we combined a detailed streetscape typology of Brussels urban fabrics with socio-economic micro-data at the individual level. We aimed to describe the distribution of social characteristics across these urban fabrics and establish social profiles to identify socio-spatial patterns within the urban space. Specifically, we investigate whether different types of urban fabrics exhibit distinct social structures.

6.2. Data and methods

6.2.1. Study area

Brussels is the capital city of Belgium, centrally located in the country. The morphological agglomeration has no official clear-cut delineation and extends into three administrative regions: the Brussels-Capital Region (BCR), Flanders and Wallonia (Thomas et al., 2012). We here focus on the urban centre, the area encompassed within the administrative border of the BCR. The BCR is divided into 19 municipalities. It covers 161.38 km² and counts 1.2 million inhabitants (source: Statistics Belgium), for an average density of 7438 inhabitants per square kilometre.

6.2.2. Data

All individuals residing in the Brussels-Capital Region as of January 1, 2017, were included in the data set. The date of 2017 was chosen to be as the most recent with all variables considered. It is also consistent with the streetscape typology, mostly elaborated using data from 2017.

Data were extracted from multiple sources by Statbel, the Belgian statistical office, which supplied anonymized individual datasets, where each line of the database contains the data for one person. The "Registre national des personnes physiques" (national register of natural persons) (RNPP), managed by the SPF Intérieur, provided information for the variables *Origin*, *Age* and *Household size*. The RNPP is an information system that stores individuals' identification data. The *Income* variable was derived from personal income tax records provided by SPF Finances, and the *Educational level* variable was obtained from the 2021 Census (Statbel). The dataset was further enhanced with *Streetscape typology* and *Statistical neighbourhood* variables (describe below), which were linked to the geographical coordinates of the residential address using Geographic Information Systems (GIS). To ensure anonymity, these geographical identifiers were provided separately to the author by Statbel, thereby reducing the risk of individual re-identification that could result from linking precise location data with detailed socio-demographic attributes.

Only residents aged 25 and older were included in the analysis, as preliminary results indicated a strong correlation between age and educational level for individuals under 25, which could introduce bias into the analysis. Additionally, the educational level variable is only reported for individuals aged 15 and above.

This population comprises Belgian and non-Belgians who have been allowed or authorized to settle or to stay in the Region. However, it excludes non-Belgians staying for less than three months, asylum seekers, and individuals without legal status.

6.2.3. Socio-economic indicators

To measure individual socio-economic status, we used five variables: *Origin*, *Age* and *Educational level*, which are specific to each individual, and *Household size* and *Income*, for which each individual is assigned the value corresponding to his or her household. While some variables are derived from household-level data, the analysis was conducted at the individual level to better capture the full range of socio-economic diversity and disparities within the population.

Age was categorized into three classes: 25–44 years, 45–64 years, and 65 years and older.

The *Income* variable is based on the equivalised income statistic, which adjusts total household income to account for differences in household size and composition. This adjustment is performed by Statbel by dividing the total household income by the household's equivalized size, calculated using the modified OECD equivalence scale (Hagenaars et al., 1994). This scale assigns a weight of 1.0 to the first adult, 0.5 to each additional household member aged 14 or older, and 0.3 to each child under 14 years of age. Using this equivalence scale, households (and, by extension, the individuals within them) with the same equivalised income are considered to have a comparable standard of living. For the analysis, income was categorized into three groups: low income (≤ €13,532.59), middle income (€13,532.60 – €26,302.57), and high income (> €26,302.57).

Educational level is defined using a simplified version of the International Standard Classification of Education (ISCED). ISCED levels 0 and 1 were grouped under primary education, levels 2 through 4 were categorized as secondary education, and levels 5 to 8 were classified as tertiary education. It reflects the highest level of education attained according to available administrative records. In cases where no highest level of education could be determined – such as degrees obtained abroad – are categorized as unknown.

Household size refers to the number of people of all ages living in the same household. A household is defined as a group of individuals who usually share the same housing and live together. This can include a person living alone or two or more individuals, regardless of family ties, who share a common living arrangement.

The *Origin* variable categorizes individuals as "Belgian," "EU27," or "Non-EU". These statistics – created by Statbel – are based on the following characteristics: the current nationality, first registered nationality, and the parents' first registered nationality. The starting point for determining origin is current nationality, if not Belgian, the individual is classified as "EU27' or "Non-EU". If the current nationality is Belgian, then the first nationality registered is considered and again, if not Belgian, the individual is classified as 'EU27' or "Non-EU". For individuals with a current and first registered Belgian nationality, the parents' first registered nationality is examined. If at least one parent has a non-Belgian nationality, the individual is assigned to that origin. Those who do not meet these criteria are classified as “Belgian,” having both current and first registered Belgian nationality with no foreign nationality among their parents.

6.2.4. Urban environment

The *Streetscape typology* variable corresponds to the urban fabric (UF) where each studied individual resides. This typology (Figure 6.1) comprises 12 distinct classes (UF1 to UF12) and is based on the morphological characteristics of streets (e.g. layout, building density, and vegetation) (Guyot, Araldi, et al., 2021). Due to the limited number of residents in the last typology (UF12), it was decided to merge this category with UF11 to ensure sufficient representation and statistical robustness.

The *Statistical neighbourhood* variable is derived from the “Monitoring des Quartiers” developed by the Brussels Institute for Statistics and Analysis. Each neighbourhood consists of a set of spatially contiguous statistical sectors – the basic territorial units used in Belgium – and may span across multiple municipalities.

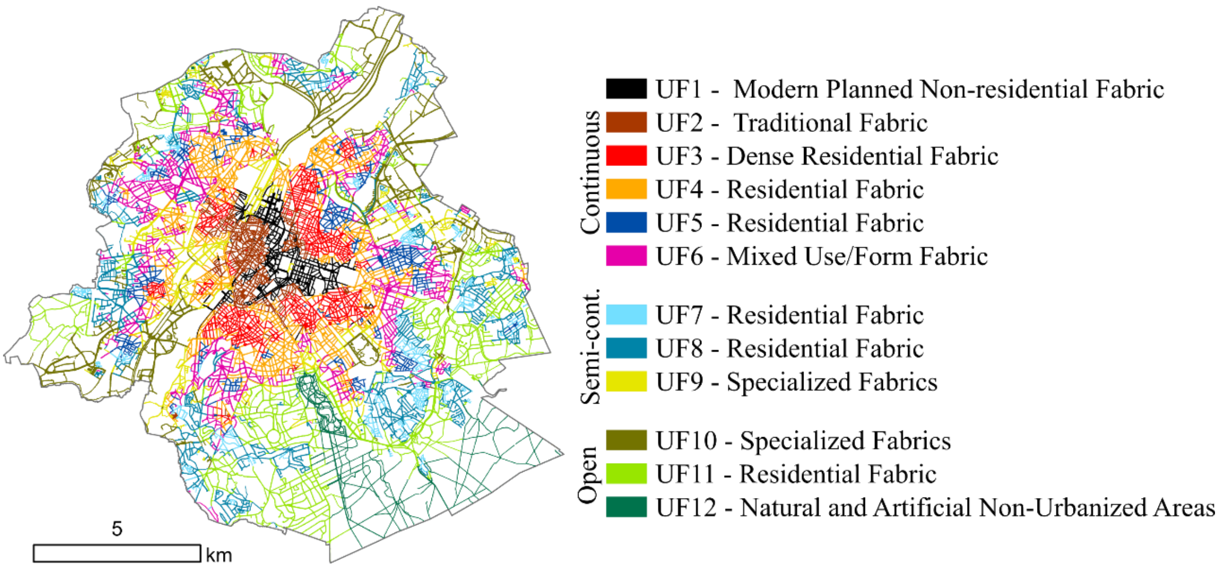


Figure 6.1. Urban fabric map of Brussels (Guyot, Araldi, et al., 2021).

6.2.5. Statistical analyses

Different approaches were used to measure the association of the urban environment, as defined by streetscape typology, with spatial segregation in Brussels. First, we analysed and described the distribution of social characteristics across the different urban fabrics (UFs). Second, we explored the associations between all variables – socio-demographic data and streetscape typology – using a Multiple

Correspondence Analysis (MCA) to uncover underlying patterns. Third, we established social profiles to identify spatial patterns within the urban space by combining MCA, applied exclusively to socio-demographic data, with clustering techniques.

Multiple Correspondence Analysis (MCA) (Husson and Josse, 2014) is a statistical method designed to analyse and summarize categorical data, serving as the categorical equivalent of Principal Component Analysis (PCA). MCA is particularly well suited for exploring relationships among categorical variables, classifying individuals based on their similarities, and providing a joint analysis of individuals and variables to characterize patterns in the data. The method represents individuals as points in a multidimensional space, where the total number of dimensions corresponds to the total number of categories across all variables. Proximity between points reflect the degree of similarity in individuals' category responses, with rare categories exerting a greater influence on these distances. MCA reduces this high-dimensional data into a smaller number of dimensions to facilitate interpretation and visualization, capturing the most relevant information in a simplified form.

Typically, Dimensions 1 and 2 are used for the visualization, as they capture the largest portion of the total inertia (variation) in the data. Although the variance explained by these two dimensions is relatively low, this is typical of MCA, as it handles high-dimensional categorical data, spreading variance across many dimensions. The position of the variable's categories relative to each other indicates their association or similarity.

A k-means clustering analysis was then applied to the results of the MCA performed on the socio-demographic data. The optimal number of clusters was determined by examining the within-cluster sum of squares (WSS). The "elbow method" was used, where the optimal number of clusters corresponds to the point at which the WSS curve begins to flatten, forming an "elbow" shape. Based on this method, four clusters were identified as the optimal solution (see appendices, Figure D.1). This combination of methods (MCA then clustering) is commonly used in the literature for defining social classes (e.g. Doolan and Tonković, 2021; Savage et al., 2013; Yates and Lockley, 2018), offering a framework for analysing and categorizing complex social datasets composed of categorical variables. Finally, we determined the social composition of each UF by calculating the proportion of each socio-economic class within its boundaries.

6.3. Result

On 1 January 2017, there were 814,393 residents over 25 in the Brussels-Capital Region. Table D.1 in appendices describes them with all the variables considered. Table D.2 in appendices presents the distribution of total street length and study population across the different urban fabrics (UF). The table shows varying degrees of correspondence between the spatial extent of each UF and the share of the population residing in them. For example, UF11 covers 21.1% of the total street length while accounting for 6.2% of the population, with a density of 164 inhabitants per kilometre of street. In contrast, UF3 represents 8.51% of the street length and 16.32% of the population, corresponding to 1,077 inhabitants per kilometre of street.

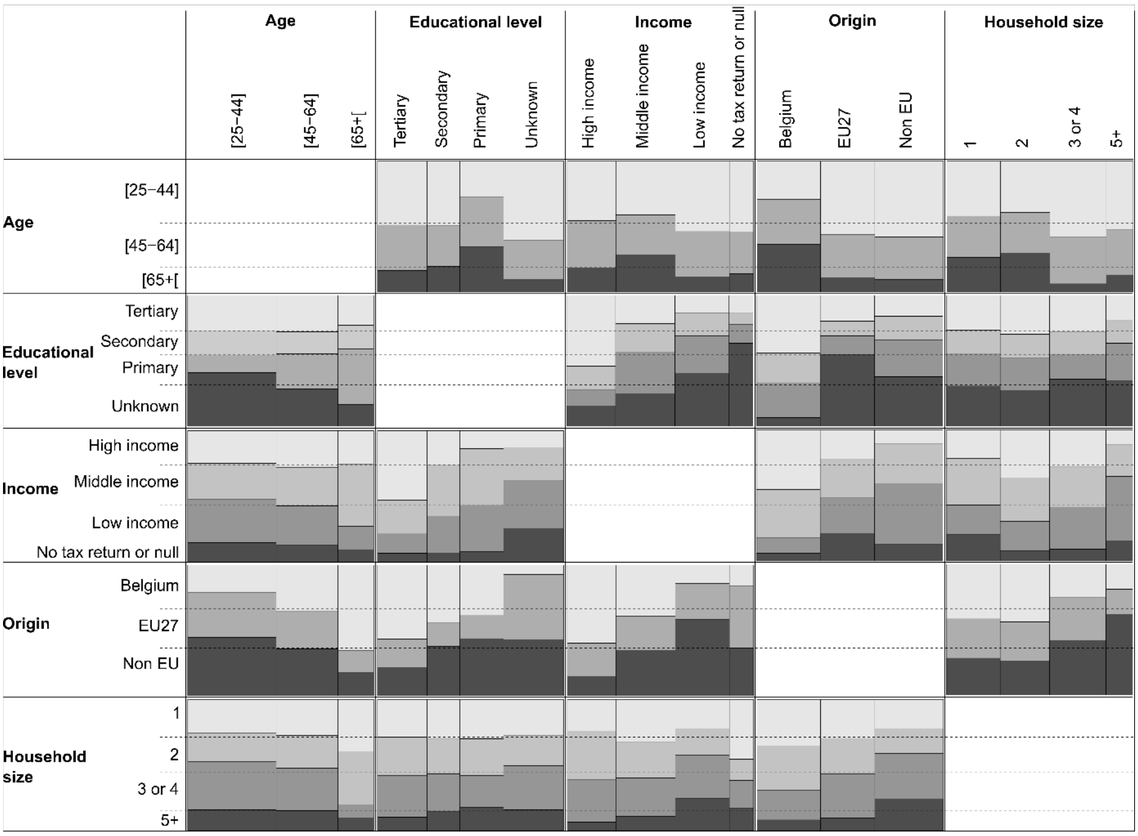


Figure 6.2. Cross-tabulation of socio-economic categories using spineplots. The height of each bar segment represents the proportion within the category, while the total surface area reflects the number of individuals. Dashed lines indicate the reference proportion in the overall study population.

Figure 6.2 illustrates the bivariate relationships between socio-economic variables. The proportions observed are compared to the proportions in the overall study population. Strong associations emerge between education and income: 53% of individuals with tertiary education fall into the high-income category, compared to 28% in the study population. Unknow educational level and “No tax return or null income” are associated and particularly prevalent among individuals of EU27 origin. In the oldest group (65+), middle income is overrepresented (47% versus 32% of middle income in the study population), as is primary education (42% versus 23%). Larger households (5+ members) are more common among non-EU individuals (24% versus 14% of large households in the study population) and within the low-income group (24%). Nationality is also strongly tied to socio-economic status: Belgians are overrepresented in the highest income group (60% versus 34% of Belgian in the study population) and among those with tertiary education (56%), while non-Europeans are disproportionately present in the lowest socio-economic categories (59% of non-EU in the low-income group, versus 37% in the study population).

Figure 6.3 illustrates the distribution of socio-economic variables across the urban fabric (UF). For educational level, the “Unknown” category primarily includes individuals who obtained their degrees abroad, and they are more prevalent in central UFs (UF1 to UF4), potentially representing two distinct populations: migrants and international workers (such as those working for the European or other international institutions). Individuals with tertiary education are overrepresented in the garden districts-like urban fabrics (UF7 and UF8) and the green periphery (UF11). In terms of age, young working-age individuals (25–44 years) are proportionally more numerous in central UFs (UF1 to UF6), while the 65+ age group, though generally less numerous, increases in proportion toward the periphery. One-person households dominate in central UFs (UF1 and UF2), whereas households with three or four members become increasingly common in the second ring (UF5 to UF8). Larger households (5+) remain less frequent overall but are relatively more represented in the historic centre (UF2) and the first ring (UF3 and UF4). Spatial segregation based on origin is particularly evident: Belgians are underrepresented in the central UFs (UF1 to UF4) but form the majority in the garden districts-like urban fabrics (UF7 and UF8) and the green periphery (UF11). Europeans are slightly more concentrated in UF1, with their share decreasing from the centre to the outskirts, while non-EU populations are more represented in the historic centre (UF2) and the first ring (UF3 and UF4).

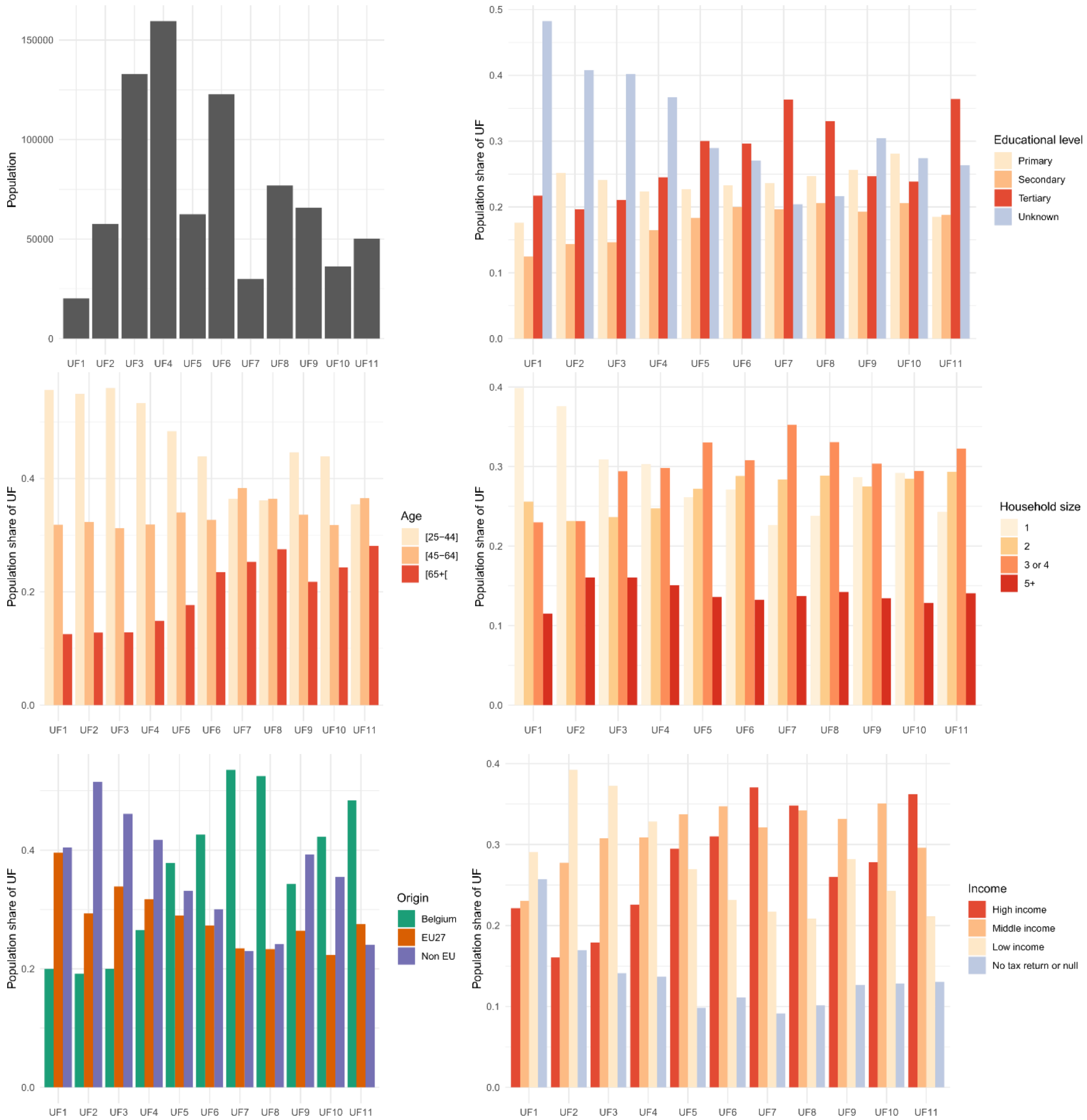


Figure 6.3. Characterizing socio-economic variables among the urban fabric (UF).

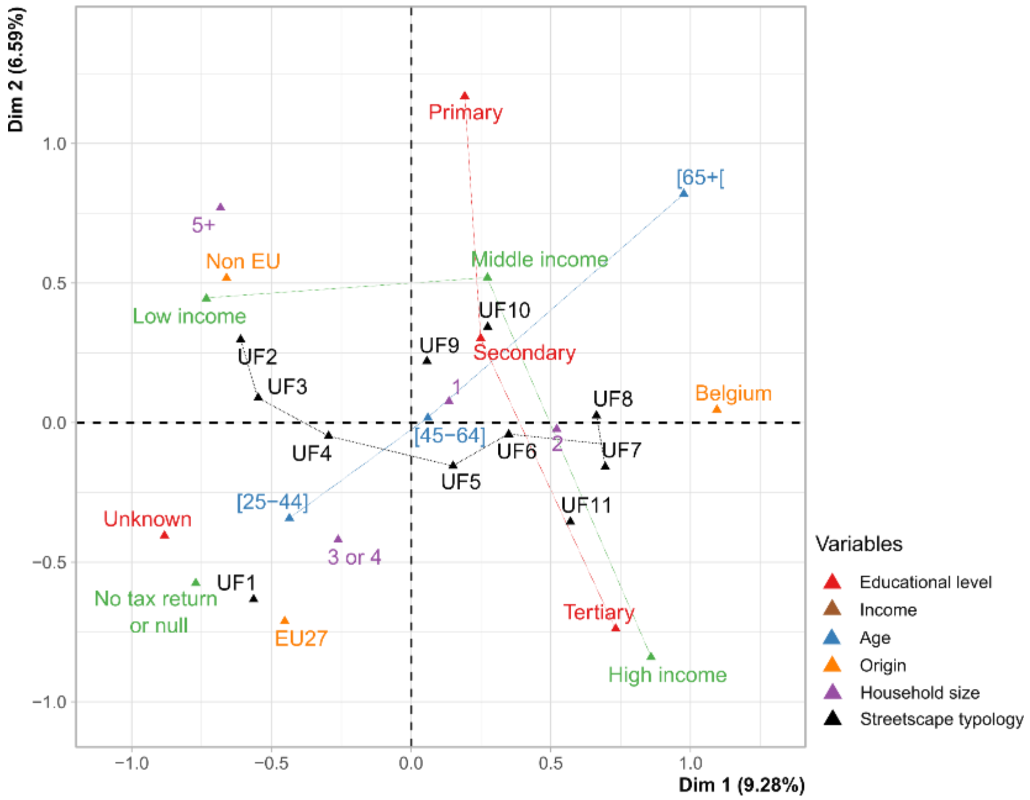


Figure 6.4. Factor map of socio-economic and streetscape typology variables (Dimensions 1 and 2).

Figure 6.4 displays the first two dimensions from the MCA with the socio-economic and streetscape typology variables. Results reveal distinct patterns across the different variables. For *Age* (blue), there is a clear gradient along both Dimension 1 and Dimension 2, with younger age groups positioned in the bottom-left and older age groups in the upper right. For *Origin* (orange), Dimension 1 separates Belgians from non-Belgians. *Income* (green) shows a strong relationship with Dimension 1: lower-income categories and those with no tax return or null are positioned on the left, while middle- and high-income groups are on the right. Dimension 2 associates the “No tax return or null” category with high-income individuals. *Educational level* (red) is closely associated with Dimension 2, while Dimension 1 distinguishes the “Unknown” category from the others. *Household size* (purple) is mainly represented by Dimension 1, which separates larger family members (5+ and 3–4 members) on the left from smaller ones on the right. For *Streetscape typology* (black), the urban intensity inferred qualitatively from these typologies (from UF1 to UF11) generally aligns with Dimension 1. However, there are some exceptions. UF1, which is furthest from the others, represents an office-dominated urban fabric. UF11 also stands out, as it corresponds to the green periphery of Brussels, characterized by villas, which contrasts with the more urban types. UF10 and UF9 are also surprisingly placed, but they represent specialized industrial areas, which follow a different pattern from the more typical urban streets.

Additionally, several associations are evident: in the bottom-left quadrant, younger individuals (25–44 years) with medium-sized families (3–4 members) of European origin, unknown income or educational levels and UF1 are clustered. In the upper-left quadrant, non-Europeans from large families (5+) with low income are grouped and close to UF2 and UF3. High-income individuals with tertiary education are positioned in the upper-right quadrant with UF11 not so far away.

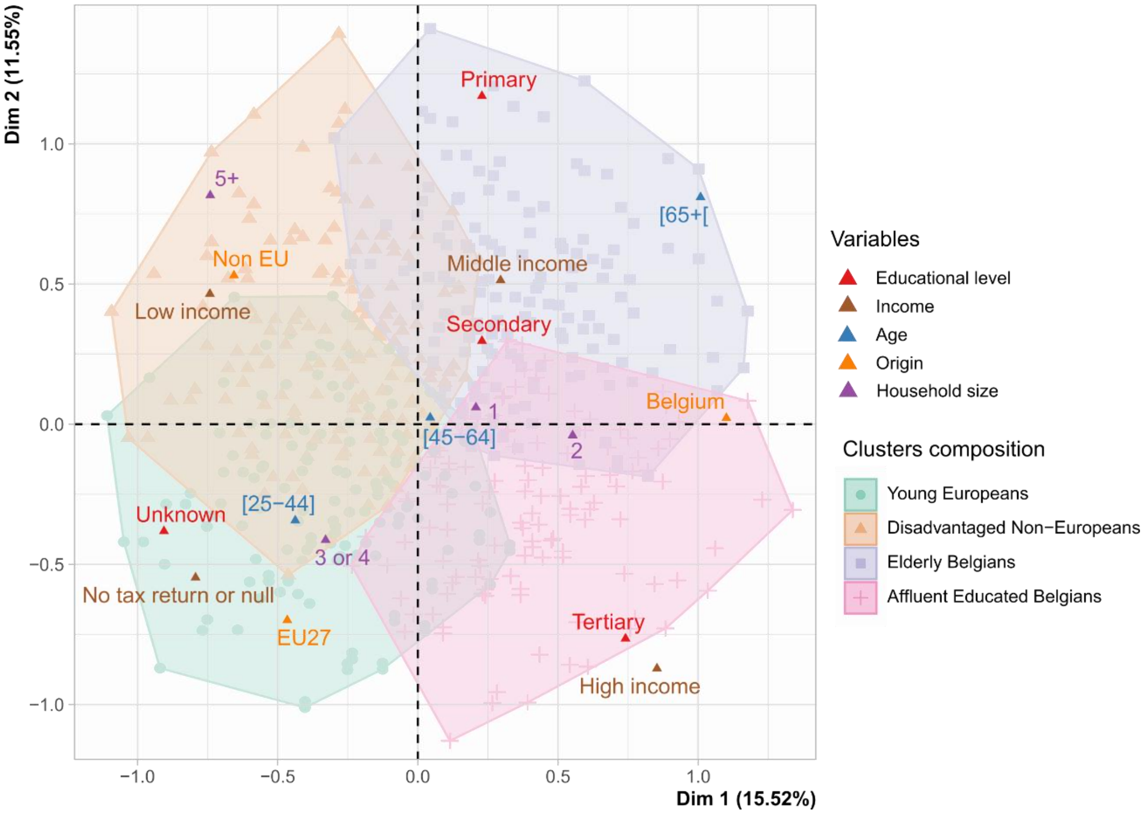


Figure 6.5. Factor map of socio-economic variables (Dimensions 1 and 2) and clusters composition from the HCPC.

Figure 6.5 displays the first two dimensions from the MCA with the socio-demographic variables, out of the three dimensions used for clustering. The number of dimensions was determined by observing the decreasing values of the inertia associated with each subsequent dimension (see appendices, Figure D.2). The barplot shows that the first three dimensions account for a substantially higher share of inertia compared to the following ones, together explaining 37.42% of the total variance. The background points represent individual data points, with colours corresponding to the clusters they belong to. The overlap between clusters is expected, as they were defined in three-dimensional space but are visualized here in two dimensions. Four clusters were identified: the first cluster, labelled *"Young*

Europeans", is characterized by a young (25–44 years, 66%), transient population (82% with unknown educational level, 46% with no or null tax returns), predominantly European (75%) and mostly living alone (41%). The second cluster, *"Disadvantaged Non-Europeans"*, includes a majority of Non-EU individuals (85%), with low incomes (66%), and with a large family (41% with 3–4 members; 33% with 5 or more members). The third cluster, *"Elderly Belgians"*, consists of older individuals (69%), primarily Belgian (70%), with middle incomes (69%) and lower educational level (61% with only primary education), most of whom are living alone (50%) or in couples (37%). Finally, the fourth cluster, *"Affluent Educated Belgians"*, is composed of high-income individuals (77%), highly educated (70% with tertiary education), predominantly Belgian (70%), and in working age groups (25–44 years, 46%; 45–64years, 41%).

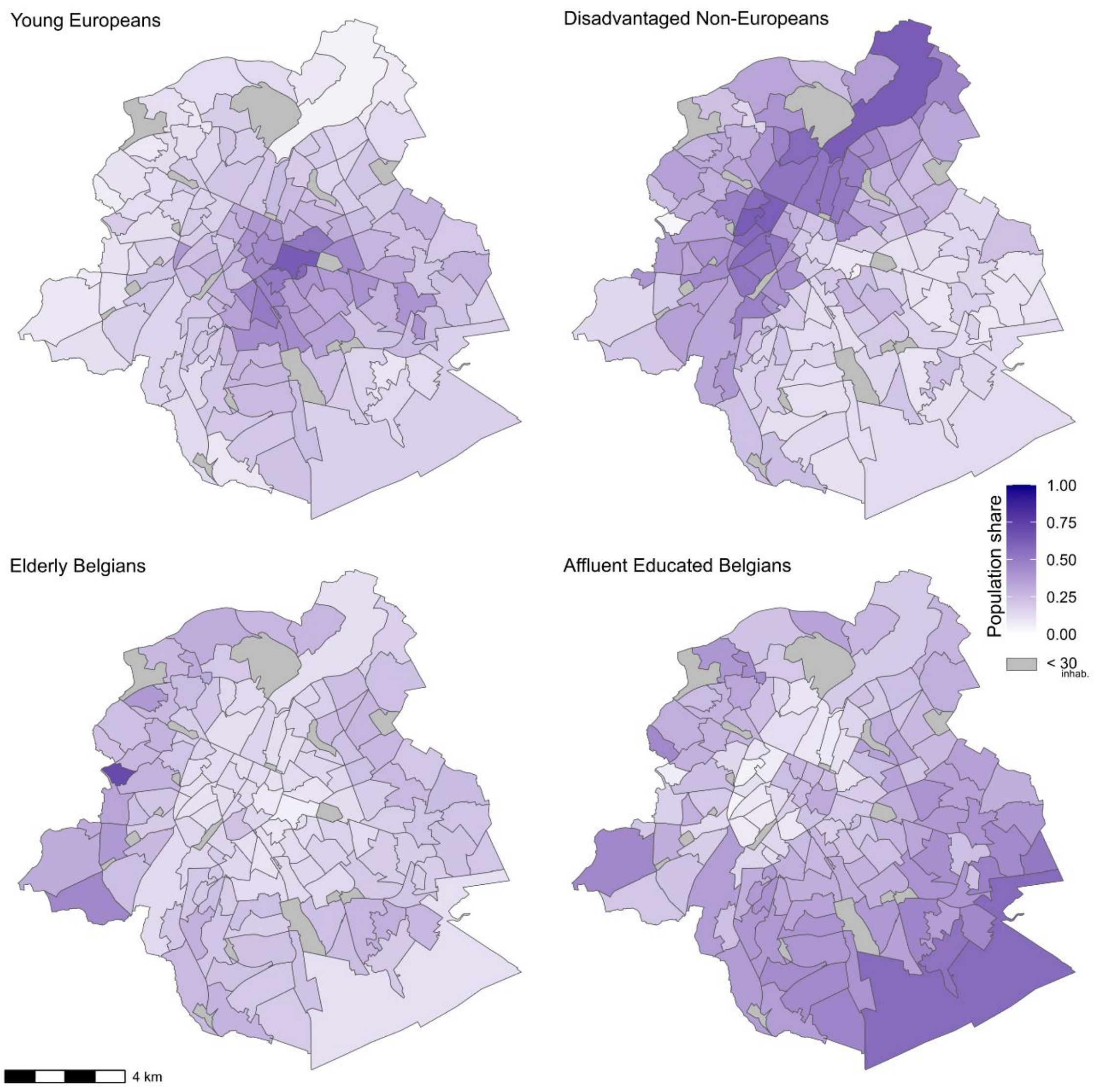


Figure 6.6. Socio-economic cluster composition of each statistical neighbourhood

Figure 6.6 maps the cluster composition of each statistical neighbourhood, providing an overview of their spatial distribution. The *Young Europeans are* predominantly concentrated in the south-east of Brussels, particularly in and around the European institutions. The *Disadvantaged Non-Europeans* are primarily located in the north-west, within the so-called "poor crescent" of Brussels. The *Elderly Belgians* are mostly situated in the periphery of Brussels, with a slightly higher concentration in the north-west outskirts. Finally, the *Affluent Educated Belgians* are primarily located in the peripheral UFs.

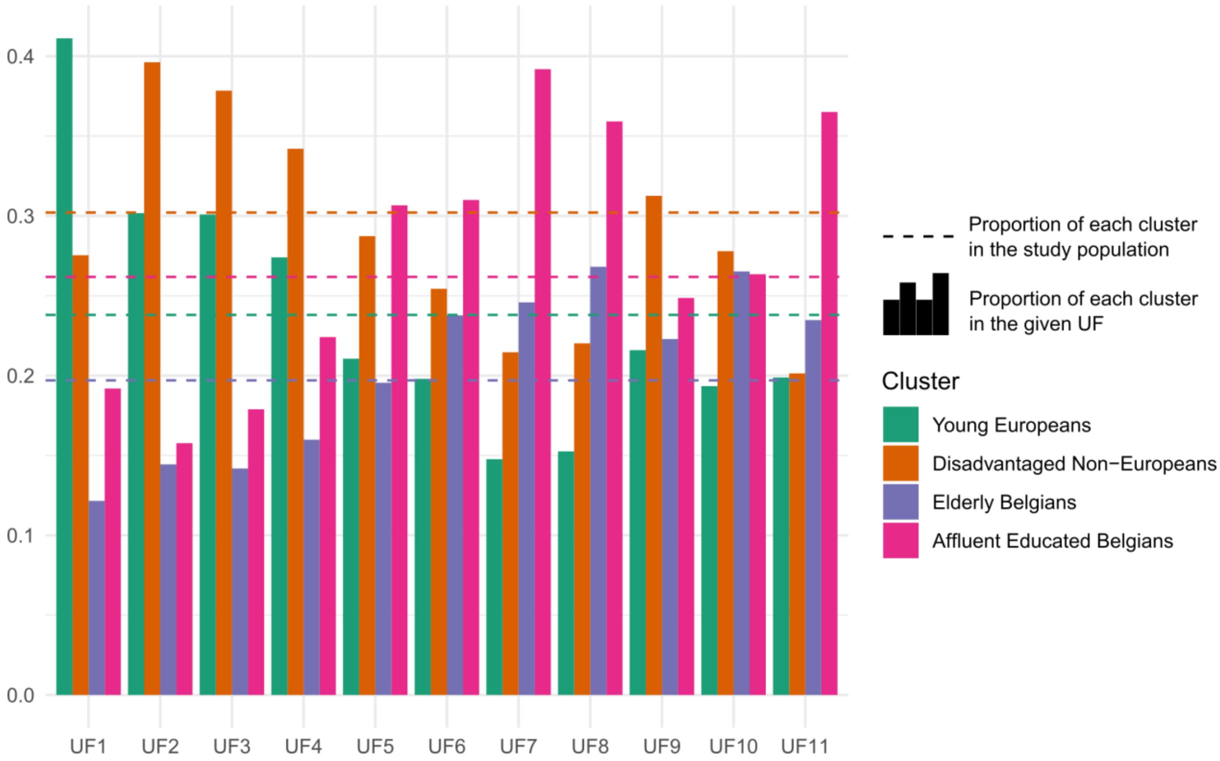


Figure 6.7. Socio-economic cluster composition of each urban fabric (UF).

Figure 6.7 shows the socio-economic cluster composition of each urban fabric (UF). Central UFs attract mostly non-Belgian profiles: Office-dominated areas (UF1) attract *Young Europeans*, while historical and dense townhouse districts (UF2, UF3, UF4) accommodate *Disadvantaged Non-Europeans*. In contrast, *Affluent Educated Belgians* are more prevalent in the greener, more spacious garden districts-like urban fabrics (UF7, UF8) and villa neighbourhoods (UF11). *Elderly Belgians* are found to a greater proportion in the peripheral residential zones.

6.4. Discussion and conclusions

Our study aims to determine whether different types of urban fabrics are associated with distinct social structures. Our findings confirm well-known trends: disadvantaged foreign-origin populations are primarily concentrated in central UFs, while affluent native Belgians benefit from residing in the green periphery. These findings corroborate previous studies on socio-spatial disparities in Brussels, notably the concentration of marginalized populations within the "poor crescent" (Costa and de Valk, 2021). However, this is the first detailed analysis to integrate socio-economic variables with street-level urban form, providing a more nuanced illustration of socio-spatial segregation in Brussels.

Methodologically, the use of Multiple Correspondence Analysis and clustering techniques enables the identification of intricate relationships between socio-economic characteristics and urban forms. This approach synthesizes descriptive analyses and highlights general patterns. The integration of anonymized microdata and a street-level analysis of urban form revealed its value in capturing the micro-geographies of inequality. This method offers significant potential for broader applications, including identifying less visible disparities related to illegal dumping, street vegetation, or infrastructure quality, which often operate at a micro-scale and remain unaddressed in aggregated data.

Brussels's city centre – the Pentagon – is distinctly divided regarding socio-economic profiles and urban form. On one side, it consists of an ageing historic fabric (UF2), while on the other, it is dominated by sparsely inhabited office districts (UF1). Both areas show a relatively low presence of Belgian residents. Although both areas attract *Young Europeans* and *Disadvantaged Non-Europeans*, a notable distinction that aligns with expectations emerges. *Young Europeans* are slightly more concentrated in UF1, whereas *Disadvantaged Non-Europeans* are more prevalent in UF2. This spatial organization can be attributed to two key phenomena. First, Brussels began playing a significant international role starting in 1958 as the host of European institutions, and later, in 1967, as NATO's headquarters (Porotto and Ledent, 2021). These institutions attract a large influx of highly skilled foreign workers who settle near these institutions for limited periods. Second, during the 19th century, industrial development along the canal and the Senne established neighbourhoods with a predominantly working-class population. Although some areas in the historic city centre have undergone gentrification, this former industrial zone remains predominantly inhabited by lower-income populations, many of non-European origin (Dessouroux et al., 2016; Porotto and Ledent, 2021). This spatial segregation reflects the fact that migrants from European and non-European countries live in different neighbourhoods of Brussels (Costa and de Valk, 2021) and, more specifically, in different urban fabrics.

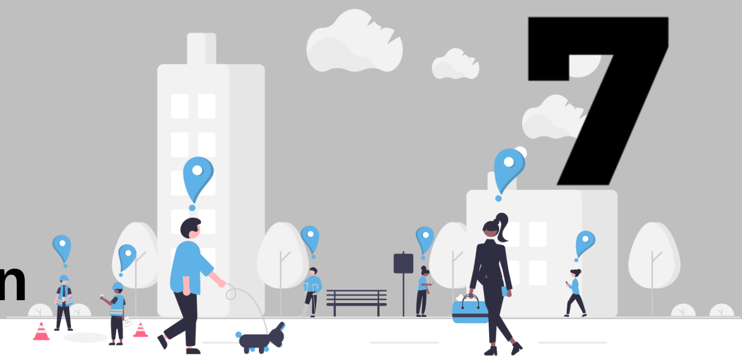
The results reveal that green and low-dense street environments are predominantly accessible to an elite class, highlighting significant socio-spatial disparities. The findings suggest that the garden city ideal of the 1920s – along with urban fabrics inspired by it – has increasingly become associated with higher social classes. Originally developed to address a shortage of affordable housing, Brussels' garden districts were designed as a belt of such neighbourhoods surrounding the city. These developments aimed to counteract the hygiene and overcrowding issues associated with collective housing, while also combating real estate speculation in favour of collective property management (Eggericx and Hanosset, 2003). However, many of these buildings have since been sold off, ranging from a small part, as in the Logis Floréal garden district (Vandermotten and Istaz, 2024), to almost the whole of the Terdelt garden district houses (visit.brussels, 2024). Initially isolated in the countryside, these garden cities are now fully integrated into the expanded urban fabric. The findings indicate that urban fabric associated with garden districts developments, as well as other areas with similar morphology (UF7 and UF8) are predominantly inhabited by Belgians with high or medium incomes, where individuals with higher education degrees are overrepresented. These findings offer a complementary perspective to traditional urban analyses (Pentagon, first ring, second ring, southeast/northwest contrast), revealing socio-spatial dynamics at a different scale.

These findings provide valuable insights for urban planning and governance. Policymakers could benefit from leveraging the granularity of the data used in this analysis to tailor initiatives that address disparities with greater precision. Moreover, the results emphasize the need for trans-municipal policies, as urban morphologies and socio-spatial disparities often transcend administrative boundaries.

Despite its contributions, the study has some limitations. It does not account for non-registered populations, such as individuals without legal status or those officially residing elsewhere. Estimating their exact number is challenging, but certain groups are better documented, such as students: approximately 40,000 living in student housing, of whom an estimated one third are not officially domiciled (Dessouroux et al., 2016). The study does not account for individuals under 25 years. Preliminary results indicated a strong correlation between age and educational level for those younger than 25, which could introduce bias into the analysis. For individuals aged 15–25, the educational level primarily reflects their current progress in the academic system, whereas for those over 25, it generally corresponds to their highest completed level of education. Data on school enrolment rates in the French-speaking education system in 2016–2017 (Wallonia and Brussels-Capital Region) show that slightly over 90% of individuals were still enrolled at age 18, around 70% at age 20, just under 50% at age 22, and slightly over 10% at age 25 (Fédération Wallonie-Bruxelles, 2019b). By setting the threshold at 25 years, we exclude a portion of young people who are no longer in school and have thus reached their final level of education. The analysis is also confined to the Brussels-Capital Region, even though the functional and morphological urban area extends beyond its boundaries. Addressing these gaps in future research could provide an even more comprehensive understanding of urban inequalities in Brussels. Moreover, applying similar methodologies to other cities or expanding the analysis to micro-scale inequalities could offer valuable insights into issues such as informal settlements, street-level disparities, and access to public infrastructure.

The results contribute to the growing body of European research on socio-spatial and environmental justice, emphasizing the importance of detailed, spatially resolved analyses. By uncovering the nuanced socio-economic dynamics at the intersection of urban form and social inequality, this study underscores the transformative potential of urban planning to address deep-rooted disparities and foster more equitable urban environments.

7 General conclusion



7.1. Opening words

This thesis aimed to explore the multifaceted relationship between urban environments and quality of life, with a particular focus on the Brussels-Capital Region. Situated at the intersection of urban geography and public health, the applied research adopted a fine spatial scale perspective while drawing on various data sources. Central to this exploration was the conceptual framework presented in the introduction (Chapter 1). The conceptual framework draws upon established theories (Felce and Perry, 1995; Frank et al., 2019; Galea et al., 2005; Galea and Vlahov, 2005; Pacione, 2003), and link urban environments and quality of life, through the pathways of exposure and behaviour. The findings of this thesis support the framework's relevance by implementing these theoretical principles across empirical chapters. Chapter 2 contributed to modelling the urban physical environment by developing a streetscape typology and Chapter 6 extended this perspective by connecting this streetscape typology to the urban social environment through population characteristics, illustrating how urban morphology interacts with the social environment. Chapter 5 further investigated environmental inequalities, highlighting the association between urban physical environment and urban social environment for schools. Chapter 4 explores the behavioural pathway by examining the association between urban environment and illegal dumping. Finally, Chapter 3 analysed non-response patterns to explore how gaps in data collection can impact our understanding of the relationship between urban physical environment features and mental health outcomes, a case study more related to the exposure pathway.

This chapter will highlight the key messages of this thesis, structuring them into seven core contributions, both scientific and policy-oriented. Several of these contributions also reflect on the study's limitations and outline avenues for future research.

7.2. Key scientific contributions

7.2.1. A fine scale perspective

Throughout this thesis, we adopted a fine spatial scale perspective. We explored a diversity of spatial scales – ranging from the individual to the statistical sector – depending on the research question, conceptual relevance, and data availability. This pluralistic approach reflects both the complexity of urban environments and the methodological challenges inherent to working with heterogeneous data sources.

In several chapters, multiple spatial units were mobilized to examine the same concept (e.g. vegetation or socio-economic context), allowing for a more nuanced understanding of observed associations. In Chapter 3 and the associated NAMED study (Pelgrims et al., 2021), green space – frequently cited in the literature as a factor linked to mental health (Beute et al., 2023; Chi et al., 2022; Lee and Maheswaran, 2011; Vanaken and Danckaerts, 2018) – was measured at different scales: at the address level (*View of green*, derived from Google Street View images), at the street segment level (*Street visible vegetation coverage*), and at the "ego-centred neighbourhoods" level (*Vegetation coverage, 1 km buffer*). This multi-scalar approach was chosen to reflect the idea that each spatial level captures a different way of perceiving or interacting with green space in urban settings – from immediate visual contact, to daily walking environments, to broader residential surroundings. The analysis was deliberately exploratory, as there was no strong a priori assumption about which scale would prove most relevant in relation to mental health outcomes. Despite these multi-scalar efforts, no clear associations with mental health outcomes emerged, prompting further reflection, partly developed in Chapter 3. One perspective not explored here – but which could be promising for future research – is to adopt an intersectional approach to examine whether different spatial scales of environmental exposure are more relevant for specific social groups, inspired by the approach proposed by Rodriguez-Loureiro et al. (2021). However, implementing such an approach requires large and detailed datasets, ideally covering the entire population over extended periods – as was the case in Rodriguez-Loureiro's mortality-based study. In contrast, the health survey data used in this thesis relied on a relatively limited sample, which constrained the feasibility of such stratified analyses.

Chapter 5 also engaged with scale by analysing socio-environmental inequalities around schools using three levels: the school, the surrounding statistical sector, and a territorial typology (urban, rural, and high-density urban areas). While the direction of associations remained consistent across scales, their intensity varied, suggesting that different spatial levels contribute in distinct ways to the observed disparities. The approach here differs from Chapter 3: rather than testing which scale best predicts health outcomes, the objective was to disentangle the relative contribution of multiple socio-spatial levels to the environmental conditions surrounding schools. As discussed later in the conclusion, a mixed-method approach would be valuable to further explore the mechanisms behind these multi-level inequalities.

One of the specific contributions of this thesis lies in the development of indicators at the street segment level – a spatial unit that is gaining traction in geography (Asgarzadeh et al., 2012; De Vries et al., 2013; Harvey et al., 2017). Defined as the portion of a street between two intersections, this unit has the advantage of aligning with how residents commonly experience and navigate urban space. Street segments represent socially meaningful and administratively recognizable units. However, working at this scale raises practical challenges: high-resolution data are required to reaggregate environmental or socio-economic indicators accurately, and such data are not always available. Assessing the relevance of the street segment scale based solely on quantitative results is not straightforward. As shown in the NAMED project, combining qualitative and quantitative methods can help validate spatial assumptions and reveal new analytical pathways (Lauwers et al., 2020). The qualitative part of the project (Lauwers et al., 2021), based on semi-structured walking interviews, enabled participants to describe their lived experiences in relation to their environment and mental well-being. While scale was not explicitly considered in that analysis, several insights proved useful for this thesis. For instance, residents frequently mentioned small-scale green elements – such as planters, individual trees, or pocket parks – as important contributors to their mental well-being. These features, however, are often overlooked by conventional vegetation indicators based on aerial imagery. This highlights the value of alternative indicators that capture greenery from a pedestrian perspective, such as street tree density or green view indices derived from street-level imagery. Moreover, some participants identified illegal dumping as a recurring and distressing feature of their local environment – an issue that later inspired the focus of Chapter 4.

This thesis underscores the value of scale sensitivity in urban health research: different spatial units offer complementary insights, and their choice must remain aligned with both empirical constraints and conceptual assumptions about how people interact with their environments.

7.2.2. Institutional, modelled, and citizen-generated data: opportunities and limitations

This thesis leverages emerging data sources to enable a more detailed characterization of the urban environment and its relationship with individual quality of life. By integrating institutional, modelled, and citizen-generated data, it facilitates disaggregated analyses. Additionally, the thesis explores the opportunities and limitations of using these diverse data sources.

One of the first challenges is data accessibility. The urban fabric typology developed in Chapter 2, along with numerous urban environment indicators used throughout this thesis, relies on institutional open-access datasets, enabling a detailed characterization of the urban environment. The commitment of Brussels and Belgian public authorities to open data significantly enhances research opportunities, facilitating the work of scholars. At the same time, some datasets require additional authorization procedures, as seen with the health surveys used in Chapter 3 and the microdata from Statbel used in Chapter 6. Accessing these datasets involves a long application process, necessitating a clear justification of the request and compliance with strict data security and privacy standards. While these measures are entirely understandable to ensure privacy, they can also restrict research flexibility, requiring researchers to plan data needs well in advance. This may limit creativity and adaptability during the research process, as adjustments and new directions become more difficult.

Most of the large datasets used in this thesis were not originally collected for scientific research, and their intended purposes do not always fully align data needs, as they are used as proxies. Therefore, the analytical approach must be carefully designed to minimize potential biases, and the interpretation of results must take this specificity into account (Ferreira and Vale, 2024; Kitchin, 2013). Chapter 4, which deals with the challenges inherent in using data generated by citizens in a non-scientific purpose, illustrates the adapted analytical approach. One of the key advantages of Fix My Street data – citizen-reported incidents that occur in the public space (e.g. clogged sewer grids, malfunctioning public lamps, or instances of illegal dumping) – lies in its cost effectiveness and the widespread availability of spatial and temporal data, as well as precise location information (xy coordinates). However, Fix My Street app usage exhibits disparities, resulting in data scarcity in certain areas, which limits our insights. To mitigate this selection bias, we compared 46,681 incidents of illegal dumping with 56,069 “control” incidents not involving incivilities. The stability of our results over time attests to the reliability of the associations uncovered, making this method suitable for various applications.

One other challenge is missing data or the absence of essential information. Chapter 3 explicitly addresses the issue of data limitations, particularly in the context of health interview surveys, where partial non-response affects the ability to measure the association between the urban environment and mental health. The non-random spatial and socio-economic distribution of the partial non-response affects the parameter estimates in the statistical models. In a sense, non-responses may be seen as a cause for loss of statistical power, leading to a lower probability to statistically detect differences if such differences existed. In chapter 5, where we used institutional datasets to characterize the average socio-economic level of school campus, we were confronted with the absence of essential information. While these data provided useful aggregated insights about the socio-economic status, we were unable to link them to exact school parcel boundaries, forcing us to use school addresses for computing environmental indicators. Though this approach was reasonable within the study's objectives, it illustrates the broader challenge of relying on pre-existing datasets, where reconstructing missing information is costly. Another example is the microdata from Statbel, which are based on administrative records containing several gaps. For instance, income data only account for officially declared earnings in Belgium, while educational level data include only diplomas obtained within the country, excluding degrees earned abroad. These limitations highlight the incomplete representation of certain populations and emphasize the need for careful interpretation.

All these data sources – whether institutional, modelled, or citizen-generated – offer clear advantages, particularly their widespread availability, often at little to no cost, and their ability to cover large spatial scales with considerable detail. However, it is essential to remain cautious about their relevance (Villeneuve et al., 2018) and reliability (Clews et al., 2016) in addressing specific research objectives. Researchers must be aware of what these datasets truly measure (Le Texier et al., 2018), use appropriate method to analyse them and avoid overgeneralizing beyond their defined limitations (Adam et al., 2019). Despite the abundance and spatial precision of the available data, it is uncertain whether they provide a complete picture of the association between the urban environment and quality of life. Not only is there a lack of comprehensive data on quality of life itself, but there are also inherent challenges in fully accounting for the urban social environment when attempting to assess the impact of urban environments on quality of life in large populations.

7.2.3. Social, environmental and health disparities in Brussels

This thesis has identified and examined social, environmental, and health disparities in Brussels throughout its chapters. To provide a cohesive perspective, we revisit these findings through the conceptual framework introduced in Chapter 1, linking each component to the empirical evidence presented in subsequent chapters.

Regarding the **Urban Social Environment**, socio-economic disparities are very marked in the Brussels-Capital Region (Costa and de Valk, 2021; Dujardin et al., 2008; Imeraj and Gadeyne, 2024; Van Criekingen, 2006; Vanneste et al., 2007). Chapter 6 corroborated existing research on socio-spatial inequalities in Brussels, particularly the concentration of marginalized populations within the so-called "poor crescent". However, this study moves beyond traditional urban divisions by revealing socio-spatial patterns at a fine spatial scale. Two key examples illustrate these disparities. First, the city centre exhibits sharp socio-economic contrasts: historical urban fabric houses a lower income, predominantly non-European population, whereas modern office district houses a transient European workforce and minimal residential density. Second, green and low-density environments in Brussels remain largely exclusive to an elite class. The "garden district" model, originally designed to combat overcrowding and real estate speculation (Eggericx and Hanosset, 2003), are nowadays predominantly inhabited by Belgians with high or medium incomes, where individuals with higher education degrees are overrepresented. Although these areas were meant to promote affordable collective housing (Eggericx and Hanosset, 2003), many garden district homes have been privatized (Vandermotten and Istaz, 2024; visit.brussels, 2024), transforming them into enclaves for highly educated, medium- to high-income Belgian residents. Chapter 5 further illustrated socio-environmental inequalities by comparing the socio-economic status of schools across Belgium with their surrounding environment. The results reveal that Brussels stands out as one of the most unequal cities in Belgium in this regard, with only Antwerp exhibiting a comparable level of disparity.

The Urban Physical Environment, as analysed in Chapter 2, also reveals high spatial disparities. In this chapter, twelve clusters of urban fabrics were identified, divided into three main groups: continuous, semi-continuous and open fabrics. This typology provides a new way of dividing up Brussels that can be linked to several chapters in the history of Brussels, such as the construction of "garden districts" (Eggericx and Hanosset, 2003; Vandermotten and Istaz, 2024) and Brusselization (De Beule and Dessouroux, 2011; Dessouroux, 2008). The urban fabric typology further emphasized the coexistence of strikingly different urban landscapes within close proximity – such as within the Pentagon, where modern, office-dominated spaces stand close to historical Brussels urban fabrics, characterized by lower-quality housing.

Regarding **Behaviour**, findings from Chapter 4 demonstrated clear spatial disparities in illegal dumping occurrences. Results of the extension of Chapter 4 (presented in Guyot et al., 2021) indicated fewer occurrences of illegal dumping in office neighbourhoods and the green periphery, while significantly higher concentrations were observed in historical urban fabrics. Furthermore, the findings highlight that less privileged neighbourhoods are disproportionately affected by illegal dumping. Beyond the visually disruptive impact, uncleanliness generates numerous negative impacts: environmental (Du et al., 2021), social (Innes, 2004), financial (Bruxelles-Propreté, 2022; DECC, 2008) and health-related (Bruxelles-Propreté, 2022; Burdette and Hill, 2008; Lauwers et al., 2021; Lorenc et al., 2012), exacerbating inequalities in urban environments.

Finally, in relation to **Quality of Life in Urban Area**, we explored its link to social disparities, particularly within the NAMED project. The quantitative NAMED study confirmed that socio-economic characteristics of respondents are key determinants of mental health (Pelgrims et al., 2021). Moreover, Chapter 3 suggested that health surveys may even underestimate mental health issues among vulnerable populations, particularly those living in highly urbanized and polluted environments, due to partial non-response bias.

A clear limitation of this thesis is the geographic scope of the study area. The research focuses primarily on the Brussels-Capital Region, whereas the urban agglomeration of Brussels extends well beyond its administrative boundaries. This restricted focus may limit the broader understanding of spatial inequalities and urban dynamics that transcend regional borders.

7.2.4. From environmental disparities to environmental justice

Several chapters of this thesis have examined inequalities in access to environmental resources and in exposure to environmental burdens. The concept of environmental justice offers a valuable framework to interpret these disparities, which are often shaped by socio-economic structures. Geographers have made significant contributions to understanding these issues, highlighting the spatial dimensions of environmental inequality and the need for context-specific approaches (Harvey, 1996; Walker and Bulkeley, 2006). Initially, this field focused heavily on the burden of pollution and environmental risks, with research primarily developed in the United States (Coolsaet and Bullard, 2021). Over time, it has expanded to other regions (Fairburn et al., 2019) and broader areas of study, encompassing access to green spaces (Schüle et al., 2019), essential services, and overall quality of living environments (Dubois and Van Criekingen, 2007; Lejeune et al., 2016).

Several authors have proposed typologies to clarify the different forms environmental inequality can take. These typically distinguish between inequalities of exposure (to environmental harms), inequalities of access (to environmental benefits), and inequalities of participation (in environmental decision-making). Other dimensions include historical inequalities, vulnerabilities to socio-ecological risks, or the unequal effects of environmental policies (Blanchon et al., 2009; Emelianoff, 2006; Laurent, 2015). Within this thesis, some of these dimensions are illustrated to varying degrees. **Inequalities of exposure** are examined in Chapter 4, which shows that illegal dumping is more frequently reported in neighbourhoods with lower median incomes. Chapter 5 also explores inequalities of exposure by analysing environmental disparities between schools, focusing on vegetation coverage and air pollution levels. **Inequalities of access** are addressed in Chapter 6, which investigates disparities in access to quality urban environments across the Brussels-Capital Region. While less directly related, **inequalities of participation** can be linked to Chapter 3. This chapter demonstrates that socially vulnerable populations in Brussels are not only more exposed to mental health risks and live in less green and more polluted environments, but also tend to be underrepresented in health surveys – leading to a partial misrepresentation of their situation in public health data. These empirical findings raise an important question: to what extent do the inequalities documented in this thesis amount to environmental injustice? Inequalities become inequities when they are systemic, socially produced, and avoidable – and thus unjust.

Chapter 5 provides one of the clearest examples of such an environmental inequity. Focusing on schools as sites of environmental exposure, it reveals that pupils do not share equal environmental conditions across the territory, even though access to compulsory education in Belgium is formally free. The results show that schools with lower socio-economic profiles are, on average, located in areas with significantly lower vegetation cover and high air pollution levels. This association remains robust across most subsets, even after accounting for the socio-economic status of the surrounding neighbourhood and the territorial context (rural, urban, or high-density urban). In this sense, the observed socio-environmental gradient is not merely a side effect of broader scale socio-spatial mechanisms (from regional to neighbourhood level); rather, the socio-economic profile of the school itself emerges as a factor associated with the environmental quality of its surroundings. These patterns are particularly concerning given the large body of literature showing that vegetation (Amicone et al., 2018; Engemann et al., 2019; Vanaken and

Danckaerts, 2018) and air pollution (Landrigan et al., 2018; WHO, 2017) significantly affect children's health, well-being, and capacity to learn. This concern is further amplified by the fact that children spend a substantial portion of their daily lives at school (OECD, 2019).

While this thesis does not investigate the causal mechanisms behind these associations, the results raise important questions about the role of the "quasi-market" logic that characterizes the Belgian school system. The organization of the school system, including parental choice of school, the possibility for schools to differentiate and define their educational offer and the funding of schools according to the number of pupils enrolled (Agirdag et al., 2016; Dupriez et al., 2018), contributes to the formation of a competitive educational landscape in which each school develops its own "educational niche" to attract a specific student population. In this context, schools situated in more pleasant environments may reinforce their attractiveness to more affluent families, while disadvantaged schools may become locked into less attractive spaces, with limited means to improve their environmental surroundings.

Further research is needed to investigate these mechanisms more directly. New methodological approaches – such as qualitative interviews with school staff, parent surveys, or participatory fieldwork – would help uncover the institutional logic, historical paths, and spatial constraints that shape the unequal distribution of environmental amenities across the school landscape. Such research would allow us to move beyond documenting disparities and begin to unravel the socio-spatial processes that generate and sustain environmental injustice in schools.

7.2.5. Environmental inequalities complicate the study of quality of life in urban areas

Environmental inequalities present a major challenge when attempting to fully understand the relationship between urban environments and health. In cities like Brussels, where socio-economic disparities in access to high-quality urban spaces are particularly pronounced (Costa and de Valk, 2021; Imeraj and Gadeyne, 2024; Vanneste et al., 2007), as highlighted in Chapter 5 in terms of green spaces and air pollution, it remains uncertain whether any observed association between urban physical environment and quality of life truly reflects an independent relationship or is instead driven by an insufficient adjustment for the urban social environment.

This reflection on the impact of environmental inequalities on our understanding of urban health began when the findings from the quantitative component of the NAMED project, which explored the relationship between urban environments (built environment, air pollution, noise, and green spaces) and mental health, produced mostly inconclusive results (Pelgrims et al., 2021). One possible explanation is the spatial overlap of health issues, poor urban environmental conditions, and vulnerable populations (Andrieux et al., 2020; Missinne et al., 2019), making it extremely difficult to isolate the independent effects of the urban physical environment on health. Complementing this, Chapter 3 shows that the capacity to measure the association between the urban physical environment and health is further complicated by partial non-response in surveys. Participants with low income, low educational levels, lower or higher age or in households with children were less likely to respond. When adjusting for socio-economic variables, non-response was higher in areas which are less vegetated, more polluted or more urbanized. Because the determinants of non-response and depressive disorders were similar, it is reasonable to assume that there will be more people with mental health problems among the non-respondents. The non-random spatial and socio-economic distribution of this bias affects the research findings, underscoring the difficulty of disentangling social and environmental influences on health outcomes.

Not only are socio-environmental inequalities significant in certain cities, but they also manifest at multiple spatial scales. As already mentioned, Chapter 5 discusses how the uneven distribution of environmental quality around schools reflects socio-environmental disparities present at various levels. At the regional scale, in Belgium, the urban-rural gradient mirrors a social gradient (Grimmeau et al., 2007; Vanderstraeten and Van Hecke, 2019). This socio-spatial gradient is evident in the data, showing higher socio-economic indices for schools in rural areas, intermediate in urban zones, and lower in high-density urban areas. At the neighbourhood level, wealthier districts tend to have more greenery and less air pollution (Fairburn et al., 2019; Schüle et al., 2019), and the schools within these neighbourhoods reflect both the environment and the socio-economic composition of the area. Finally, at the individual school level, once the effects of the two broader scales are accounted for, the same pattern can still be observed in many cases: students from higher socio-economic backgrounds are more likely to attend schools located in better-quality environments. These multi-level dynamics and their impact on quality of life, which have not been studied in this thesis, merit further investigation. The impact of area-level socio-economic position on individual health is well documented in the literature explain by differential access to services such as health facilities, supermarkets, and sanitation infrastructure, variations in physical conditions like traffic exposure, overcrowding, and access to green spaces, and differences in social environments, including crime rates, social cohesion, and the presence of vandalized public spaces (Duncan and Kawachi, 2018).

To account for environmental inequalities in studying the relationship between the urban environment and quality of life, the conceptual framework presented in Chapter 1 offers a key advantage: it directly links urban physical and urban social environments, recognizing their combined impact on quality of life. Viewing the urban and social environment as an integrated whole, rather than as separate influences, is a challenging approach, but it may be crucial to gaining a deeper understanding of how these factors shape quality of life.

7.3. Key policy-oriented contributions

7.3.1. Tackling inequalities as part of improving the urban environment

When examining the links between urban liveability and quality of life, it becomes evident that urban social environment is one of the major determinants of population well-being (Aerts et al., 2020; Kirkbride et al., 2024; Silva et al., 2016). This is clearly illustrated in the NAMED project, where, in the quantitative part, individual characteristics were found to have the most significant impact on participants' mental health (Pelgrims et al., 2021). Similarly, in Chapter 4 about illegal dumping, we observe that neighbourhood median income is a key determinant of the presence of illegal dumping. That reaffirms that social deprivation constitutes a risk factor for illegal dumping, as proposed by Bruxelles-Propreté (2012) and widely discussed in the literature (Hodsman and Williams, 2011; Sampson and Groves, 1989). Before focusing on improving the physical environment of streets, it is essential to first address how to enhance the urban social environment – both at the individual and community levels.

This does not mean that improving the urban environment should be neglected. However, any policy aimed at enhancing urban spaces must critically consider for whom these improvements are intended. Equally important is questioning the true motivations behind such policies: are they genuinely designed to improve the environment for all residents, or are they aimed at transforming urban spaces to attract wealthier populations? Ensuring that urban improvements do not contribute to the socio-economic exclusion is key to fostering equitable and inclusive cities.

7.3.2. Prioritize vulnerable groups, but counter gentrification

Improving the urban environments of vulnerable groups should be a priority in urban and environmental policies. This is crucial for two main reasons. First, the most vulnerable population groups are often exposed to environments with limited access to green spaces (Schüle et al., 2019) and higher pollution levels (Fairburn et al., 2019). Second, improving air quality and increasing green spaces have been shown to yield disproportionate benefits for vulnerable groups. Research suggests that exposure to cleaner air (Deguen and Zmirou-Navier, 2010; Landrigan et al., 2018) and green space (Rigolon et al., 2021) have stronger protective effects for disadvantaged populations. This is largely due to their greater dependence on their immediate urban environment, as well as their limited access to other health-promoting resources (Deguen and Zmirou-Navier, 2010) and their already compromised health status resulting from deprivation (O'Neill et al., 2003).

One particularly impactful strategy to improve the living environment of a vulnerable group would be to focus on enhancing environmental quality around schools, as children spend a significant portion of their time at school (OECD, 2019). The analysis in Chapter 5 provides valuable insights into shaping such policies. In Belgium, there are already initiatives to greening schoolyards (Bruxelles environnement, 2021; GoodPlanet Belgium, 2024; MOS, 2024) and reduce traffic around schools (Durieux et al., 2023). However, improving the environmental quality around schools faces several challenges: lack of environmental awareness, difficulties in securing funding, limited time and expertise in the schools, complexity of the bureaucratic processes, and lack of political will (Giezen and Pellerey, 2021). Additionally, there is a social justice component, as low SES schools generally struggle to build capacity and skills within their already stretched budgets and staff, receive less parental support, and experience higher staff turnover (Dumay, 2014). Considering this and the fact that low-SES schools disproportionately benefit from a high-quality environment, general greening and air quality policies should be designed to address these disparities. These efforts should begin by prioritizing schools situated in low-quality environments and having disadvantaged populations.

Initiatives aimed at improving urban environmental quality in vulnerable areas must be carefully designed to prevent both "grey" gentrification (driven by changes in the built environment) and "green" gentrification. As highlighted in Chapter 6, socio-spatial segregation is particularly pronounced in Brussels, shaped by housing market dynamics, migration patterns, and the uneven distribution of urban living environments. Without proactive policies to counteract these mechanisms, any improvement of the urban environment risks intensifying gentrification, ultimately displacing lower-income populations rather than improving their living conditions. The gentrification process is already well underway in Brussels, particularly in central neighbourhoods. Factors such as economic globalization, the city's increasing internationalization, and shifts in salary and employment models have played a significant role in accelerating this trend (Porotto and Ledent, 2021). Moreover, this leads to the gradual erosion of residual affordable housing stock, including privately owned yet modest, often deteriorated, low-rent dwellings, particularly in historically working-class areas (Dessouroux et al., 2016). This thesis did not directly address these questions, but future research should explore longitudinal studies to gain a deeper understanding of these urban dynamics over time. Examining temporal changes in urban environments and quality of life outcomes would provide a dynamic perspective on the effectiveness of urban interventions.

Appendices

The appendices can be found in colour online at https://dial.uclouvain.be/.

A. Appendices of Chapter 2

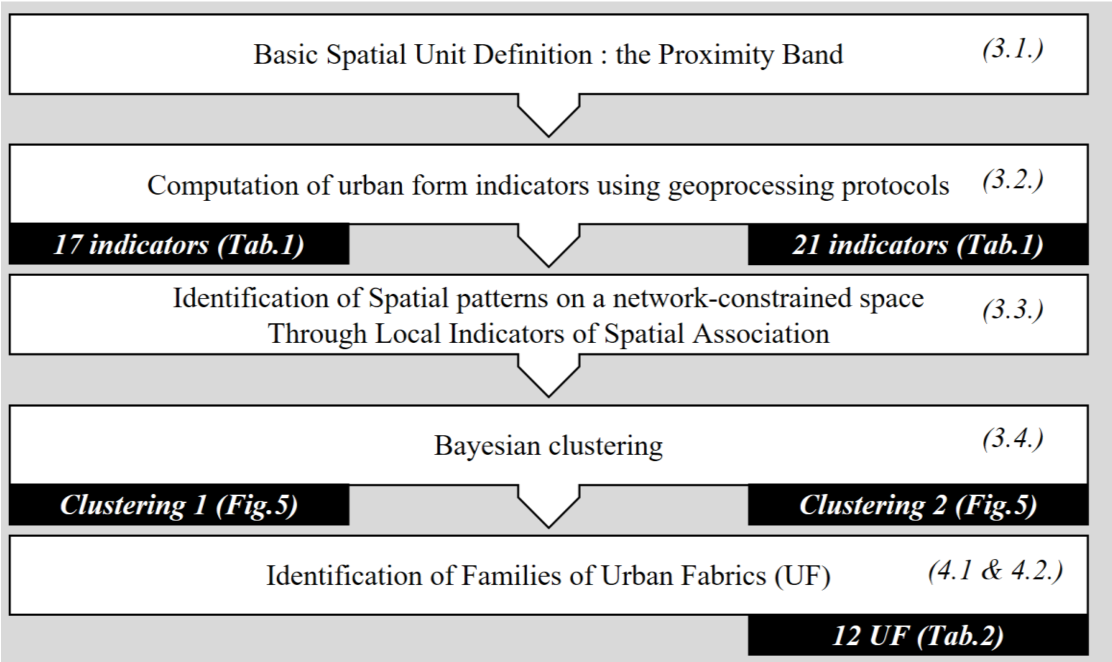


Figure A.1. Flowchart of the MFA protocol in relation to the corresponding sections in the paper

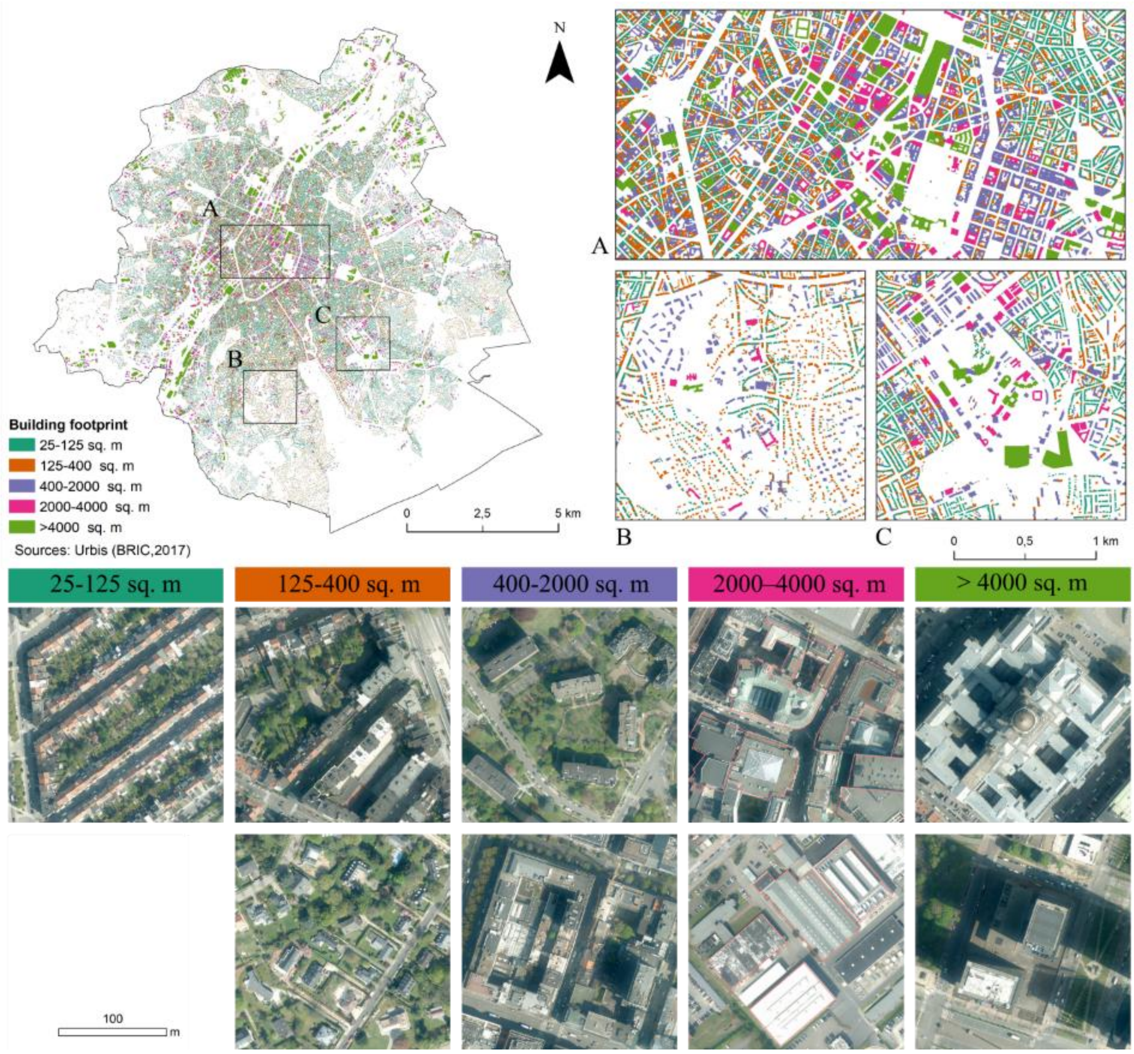


Figure A.2. Segmentation of building footprints used for the five "Prevalence of building types" indicators: general map (above) with zooms on three relevant areas (A,B,C) and examples of aerial images for each segmentation (below)

Table A.1. Contribution of each indicator to the clustering definition in terms of mutual information

Urban fabric component	Name	Clustering 1	Clustering 2
		Mutual information [%]	
Network Morphology	Street length	16,51	16,41
	Windingness	9,12	8,69
	Grid Perpend.	5,92	5,78
	Dead ends	4,74	4,99
	Pedestrian Area		11,47
Built-up Morphology	Build. (<125 sqm)	24,52	19,92
	Build. (125-400 sqm)	7,68	7,93
	Build. (400-2k sqm)	12,91	12,07
	Build. (2-4k sqm)	8,48	8,34
	Build. (>4k sqm)	8,25	8,45
	Build. Coverage	28,42	27,50
	Build. Contiguity	31,76	30,54
	Build. Specialization	3,92	3,33
Network-Building Relationship	Build. Frequency	28,26	27,47
	Build. Height	36,87	33,61
	Average Width	21,89	20,32
	HW ratio	34,08	31,76
	Corridor Effect	24,64	23,25
Vegetation	Trees		4,21
	Veg. within 10m		24,87
	Veg. over10m		22,47

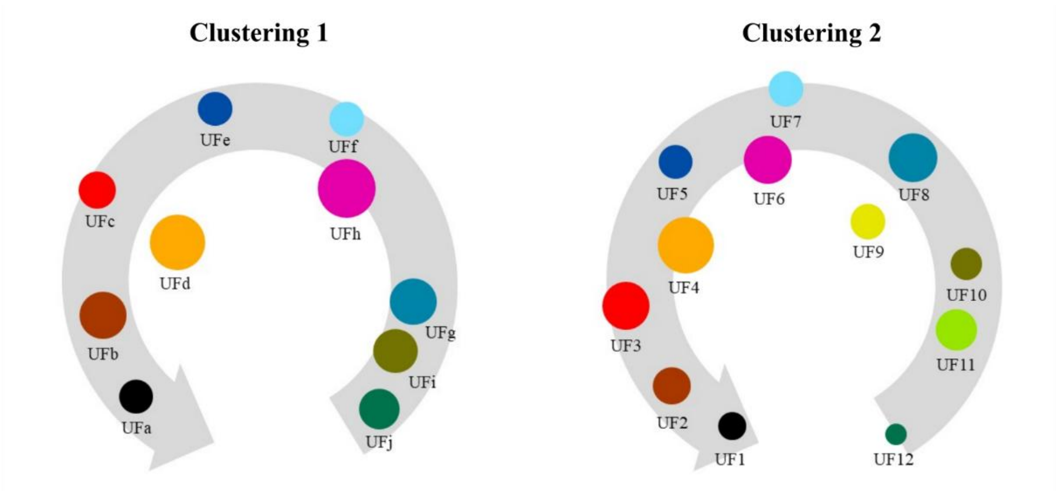


Figure A.3. Projection of the cluster variables in a space of mutual information for clusterings 1 and 2. Cluster size is proportional to the number of spatial units assigned to each urban fabric (UF). The arrows highlight the presence of an urban intensity gradient: UFa and UF1 are the fabrics of the core areas, while HFj and UF12 are the fabrics mainly covered with vegetation.

Table A.2. Characterizing urban fabrics in the BCR (clustering 2) through probabilities of morphological patterns. If p(HH)>0.85 then "H" is entered in the table, likewise for "L' and "NS". If 0.6<p(HH)<0.85, then the second category in terms of probability entered as follows: 'H some L' or "H some NS". If p(HH)>0.4 and p(LL)>0.4, then "H or L' is entered in the table. Similarly for the other combinations.

	UF1	UF2	UF3	UF4	UF5	UF6	UF7	UF8	UF9	UF10	UF11	UF12
Street length	NS some L	L some NS	NS or L	NS	NS some L	NS	NS or L	NS some H	NS some H	H some NS	H some NS	H
Windingness	NS some L	NS some L	L or NS	NS some L	NS some L	NS some L	NS some H/L	NS or H	NS some H	H or NS	NS or H	NS or H
Grid Perpend.	L some NS	L or NS	NS or L	NS some L	NS some L	NS some L	NS some H/L	NS some H	NS some L	NS some H	NS some	NS or H
Dead ends	L or NS	NS or L	L	L some NS	L some NS	L or NS	Mix	NS some L	NS some L	NS some L/H	NS some L	H or NS
Pedestrian Area	NS	NS or H	NS	NS or L	NS some L	L or NS	NS	NS some L	L or NS	L some NS	L or NS	H
Build. (<125 sq. m)	L	L or NS	H some NS	NS	H	NS some H	H	H or NS	L some NS	L some NS	L or NS	L
Build. (125–400 sq. m)	L or NS	NS some L	NS	NS some H	NS some L	NS some H	L or NS	NS or L	Mix	L some NS	H or NS	L
Build. (400-2k sq. m)	H some NS	NS or H	NS some L	NS	L some NS	NS some L	L some NS	NS or L	H some NS	H some NS	NS some L	L some NS
Build. (2-4k sq. m)	H some NS	Mix	NS some L	NS some L	L or NS	NS some L	L some NS	NS or L	NS or H	NS or H	NS or L	L some NS
Build. (>4k sq. m)	H some NS	Mix	L some NS	NS or L	L some NS	L or NS	L	L some NS	Mix	H or NS	L or NS	L
Build. Coverage	H some NS	H	H some NS	NS	NS	NS some L	NS some L	L	NS some L	L	L	L
Build. Contiguity	NS some H/L	H	H	H some NS	H	NS	NS	L some NS	NS or L	L	L	L
Build. Specialization	H or NS	NS or H	NS	NS some L	NS some L	NS some H	NS or L	NS some L	NS some L/H	NS some L/H	NS some L	L some NS
Build. Frequency	NS some L	H some NS	H	NS some H	H some NS	NS	NS or H	NS	L or NS	L	L	L
Build. Height	H	H	H	H or NS	NS some H	NS	NS some L	L	NS	L	L	L
Average Width	NS or L	L	L	NS or L	NS some L	NS some H	NS some H/L	H some NS	NS or H	H	H	H some NS
HW ratio	H	H	H	NS some H	NS	NS	NS	L some NS	NS some L	L	L	L
Corridor Effect	H or NS	H	H	H some NS	H	NS some H	NS some H/L	NS some L	NS or L	L	L	L
Trees	NS some L	L or NS	NS some L	NS some H	NS or H	NS or H	Mix	NS or H	NS some H	Mix	Mix	L
Veg. within 10m	L	L	L	L	L	NS some L	NS or H	H some NS	Mix	NS or H	H	H
Veg. over10m	L	L	L some NS	L some NS	NS some H	NS some H	H some NS	H some NS	Mix	Mix	H	H

B. Appendices of Chapter 4

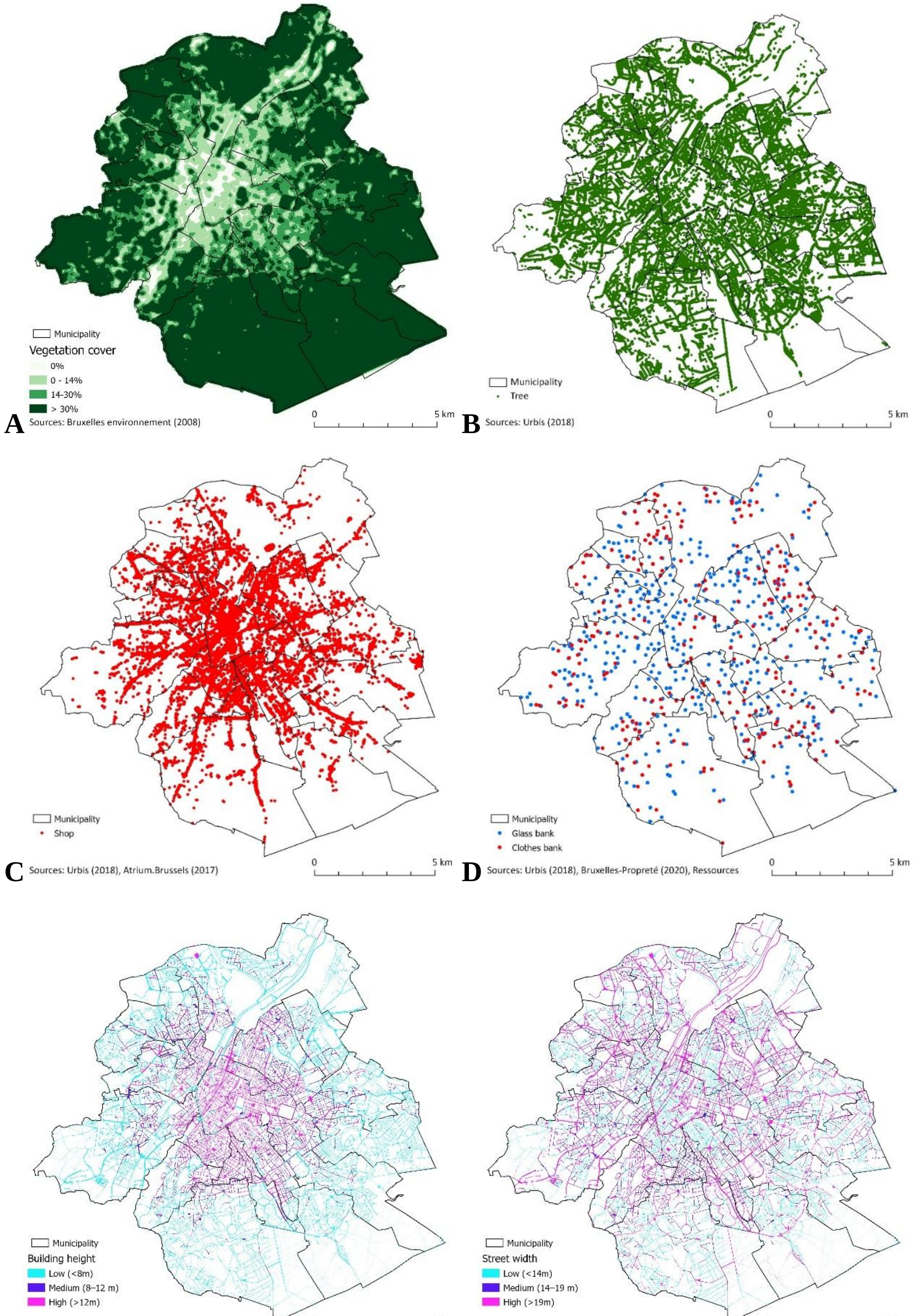


Figure B.1. Map of the indicators used in the models (A to J) and name of the municipality (K).

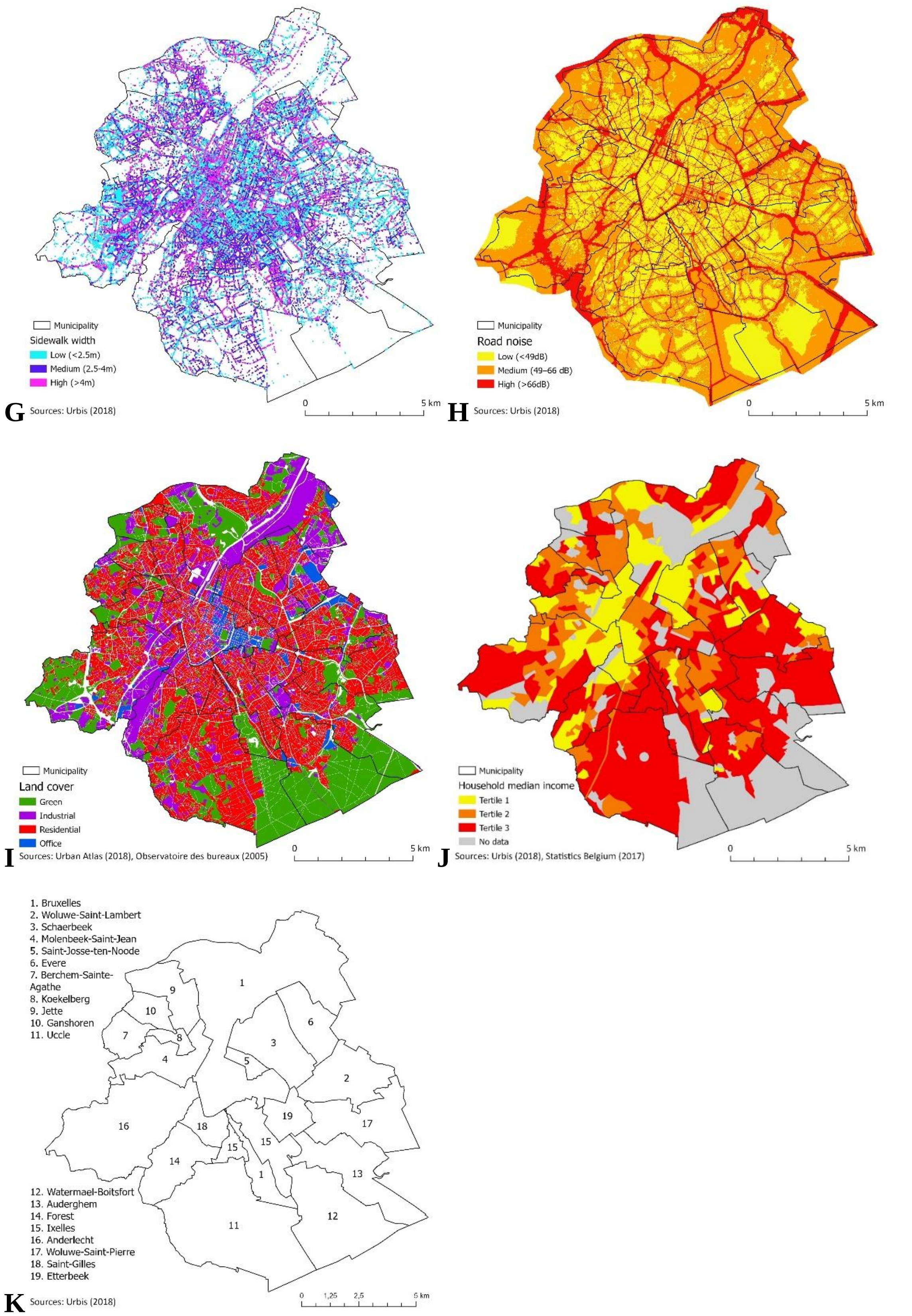


Figure B.1 (continued). Map of the indicators used in the models (A to J) and name of the municipality (K).

Table B.1. Classification of Fix My Street incident categories used in the study into control and Illegal dumping Incidents

Control incidents n = 53,516	**n**
Sewer grid / Covered in concrete	131
Sewer grid / Clogged	3,353
Sewer grid / Missing grid	336
Public lighting / Lamp / Lit on continuously	313
Public lighting / Lamp / Blinking	110
Public lighting / Lamp / Turned off	2,822
Public lighting / Section / Lit on continuously	126
Public lighting / Section / Turned off	1,076
Public furniture / Bollard / Damaged	7,678
Public furniture / Bollard / Missing	1,454
Vegetation / Branch	573
Vegetation / Impeding vegetation	1,112
Coating / Oil on the road	75
Coating / Vanished markings	3,204
Coating / Ice or snow / Roadway – bike path	1,923
Coating / Pothole	3,920
Coating / Damaged coating	12,971
Signage / Bicycle counter	25
Signage / Traffic light	1,723
Signage / Traffic sign	6,141
Signage / Variable message signs	801
Signage / Pole	2,400
Sewer cover / Noisy	471
Sewer cover / Broken	778
Illegal dumping incidents n = 45,569	
Garbage / Illegal dump / Bulky wastes / <1 m^3	27,459
Garbage / Illegal dump / Bulky wastes />1 m^3	14,079
Garbage / Illegal dump / Oil & drums	517
Garbage / Illegal dump / Paint	357
Garbage / Abandoned materials / Construction wastes	3,157

Table B.2. Results of multiple logistic regressions applied to the full database (OR Jul 17-Mar20) and two subsets stratified by incident date: July 2017 to Mid-February 2019 (Jul 17-mid Feb19) and Mid-February 2019 to March 2020 (mid Feb19-Mar20). Significant OR (p <0.5) have been coloured in a gradient of blue (protective factor, OR <1) or red (risk factor, OR>1). The darker the colour, the larger the effect size.

		OR Jul 17-Mar20	N	OR Jul 17-mid Feb19	N	OR mid Feb19-Mar20	N
Vegetation	0%	Reference	10785	Reference	4466	Reference	6319
	<14%	1.88 (1.78-1.99)***	29420	1.76 (1.61-1.91)***	14054	2.09 (1.94-2.25)***	15366
	14–30%	2.14 (2.02-2.27)***	29450	1.86 (1.69-2.03)***	14753	2.62 (2.42-2.83)***	14697
	>30%	1.80 (1.68-1.92)***	29430	1.59 (1.44-1.75)***	16305	2.20 (2.01-2.40)***	13125
Tree	No	Reference	62418	Reference	30948	Reference	31470
	Under a tree	1.27 (1.22-1.31)***	36667	1.23 (1.17-1.29)***	18630	1.32 (1.26-1.39)***	18037
Shop	No	Reference	63559	Reference	32550	Reference	31009
	Yes	0.91 (0.88-0.94)***	35526	0.95 (0.91-1.00)	17028	0.86 (0.82-0.90)***	18498
Recycling bank	No	Reference	96856	Reference	48521	Reference	48335
	Yes	1.22 (1.10-1.36)***	2229	1.18 (1.01-1.38)*	1057	1.24 (1.07-1.43)**	1172
Buildings height	<8m	Reference	33015	Reference	17469	Reference	15546
	8–12 m	1.20 (1.15-1.25)***	33042	1.23 (1.16-1.31)***	16087	1.17 (1.10-1.25)***	16955
	>12m	1.09 (1.04-1.14)***	33028	1.08 (1.00-1.15)*	16022	1.12 (1.04-1.19)***	17006
Street width	<14m	Reference	33022	Reference	16293	Reference	16729
	14–19 m	0.99 (0.95-1.03)	33028	1.03 (0.97-1.10)	16763	0.93 (0.88-0.99)*	16265
	>19m	0.82 (0.79-0.86)***	33035	0.85 (0.80-0.90)***	16522	0.77 (0.73-0.82)***	16513
Sidewalk width	<2.5m	Reference	33025	Reference	16312	Reference	16713
	2.5-4m	1.01 (0.97-1.05)	33027	0.97 (0.91-1.02)	16443	1.06 (1.00-1.12)	16584
	>4m	0.75 (0.72-0.78)***	33033	0.74 (0.70-0.79)***	16823	0.77 (0.72-0.81)***	16210
Road noise	<49dB	Reference	33032	Reference	15333	Reference	17699
	49–66 dB	0.79 (0.76-0.82)***	33016	0.78 (0.73-0.82)***	16733	0.81 (0.77-0.86)***	16283
	>66dB	0.48 (0.46-0.50)***	33037	0.46 (0.44-0.49)***	17512	0.51 (0.48-0.54)***	15525
Land cover	Residential	Reference	81417	Reference	40654	Reference	40763
	Green	0.92 (0.84-1.00)*	3611	1.08 (0.96-1.21)	2019	0.78 (0.69-0.89)***	1592
	Industrial	0.72 (0.69-0.75)***	12522	0.71 (0.66-0.76)***	6174	0.73 (0.68-0.78)***	6348
	Office	0.48 (0.42-0.55)***	1535	0.45 (0.37-0.55)***	731	0.49 (0.41-0.58)***	804
Recurrence	0 or 1	Reference	52854	Reference	28085	Reference	24769
	More than 1	3.12 (3.02-3.22)***	46231	3.33 (3.18-3.49)***	21493	2.87 (2.75-3.00)***	24738
Household median income	Tertile 1 (low)	2.72 (2.60-2.85)***	32506	2.81 (2.63-3.00)***	15506	2.67 (2.50-2.85)***	17000
	Tertile 2	1.80 (1.73-1.88)***	33534	1.65 (1.56-1.75)***	16075	1.96 (1.85-2.08)***	17459
	Tertile 3 (high)	Reference	33045	Reference	17997	Reference	15048

Table B.3. Results of multiple logistic regressions applied to the Brussels-Capital Region (full database) and four municipalities in this region (see Appendices, Figure B.1.K.). Significant OR (p <0.5) have been coloured in a gradient of blue (protective factor, OR <1) or red (risk factor, OR>1). The darker the colour, the larger the effect size.

Variable		Brussel Capital Region	N	Bruxelles	N	Anderlecht	N	Ixelles	N	Etterbeek	N
Vegetation	0%	Reference	10785	Reference	4668	Reference	2024	Reference	179	Reference	24
	<14%	1.88 (1.78-1.99)***	29420	1.98 (1.82-2.16)***	10719	0.79 (0.69-0.91)***	5794	0.58 (0.41-0.83)**	2836	3.86 (1.61-9.25)**	1920
	14–30%	2.14 (2.02-2.27)***	29450	2.90 (2.61-3.23)***	4981	0.74 (0.63-0.86)***	5414	0.51 (0.36-0.74)***	5275	2.91 (1.22-6.94)*	4350
	>30%	1.80 (1.68-1.92)***	29430	3.67 (3.23-4.16)***	3885	0.65 (0.55-0.76)***	6273	0.41 (0.28-0.62)***	2873	1.79 (0.74-4.33)	785
Tree	No	Reference	62418	Reference	16835	Reference	11609	Reference	6794	Reference	4272
	Under a tree	1.27 (1.22-1.31)***	36667	1.61 (1.48-1.74)***	7418	1.08 (1.01-1.17)*	7896	1.24 (1.09-1.41)***	4369	1.14 (1.01-1.30)*	2807
Shop	No	Reference	63559	Reference	13491	Reference	13496	Reference	6511	Reference	4455
	Yes	0.91 (0.88-0.94)***	35526	0.82 (0.76-0.88)***	10762	0.92 (0.84-1.00)	6009	1.50 (1.33-1.70)***	4652	0.87 (0.76-0.98)*	2624
Recycling bank	No	Reference	96856	Reference	23853	Reference	19006	Reference	10955	Reference	6825
	Yes	1.22 (1.10-1.36)***	2229	0.92 (0.72-1.19)	400	1.16 (0.94-1.44)	499	1.39 (0.92-2.05)	208	1.38 (1.00-1.93)	254
Buildings height	<8m	Reference	33015	Reference	5031	Reference	9717	Reference	1262	Reference	678
	8–12 m	1.20 (1.15-1.25)***	33042	0.99 (0.90-1.10)	6596	1.29 (1.18-1.41)***	6172	1.13 (0.91-1.43)	4330	1.42 (1.17-1.73)***	4000
	>12m	1.09 (1.04-1.14)***	33028	0.81 (0.74-0.89)***	12626	1.21 (1.07-1.38)**	3616	1.19 (0.94-1.50)	5571	1.54 (1.25-1.89)***	2401
Street width	<14m	Reference	33022	Reference	9013	Reference	5549	Reference	4193	Reference	2232
	14–19 m	0.99 (0.95-1.03)	33028	0.81 (0.74-0.89)***	6089	1.02 (0.93-1.11)	8886	0.80 (0.69-0.93)**	4476	0.85 (0.73-1.00)*	2120
	>19m	0.82 (0.79-0.86)***	33035	0.59 (0.54-0.65)***	9151	0.79 (0.72-0.88)***	5070	0.71 (0.59-0.86)***	2494	0.73 (0.63-0.85)***	2727
Sidewalk width	<2.5m	Reference	33025	Reference	7921	Reference	5803	Reference	3892	Reference	2670
	2.5-4m	1.01 (0.97-1.05)	33027	0.97 (0.89-1.06)	7140	1.10 (1.00-1.20)*	6998	0.80 (0.69-0.92)**	4457	0.98 (0.85-1.13)	2248
	>4m	0.75 (0.72-0.78)***	33033	0.81 (0.74-0.88)***	9192	0.90 (0.82-0.99)*	6704	0.68 (0.57-0.80)***	2814	0.50 (0.43-0.58)***	2161
Road noise	<49dB	Reference	33032	Reference	10601	Reference	6016	Reference	3215	Reference	2660
	49–66 dB	0.79 (0.76-0.82)***	33016	0.76 (0.70-0.82)***	7373	0.78 (0.72-0.85)***	7700	0.74 (0.64-0.85)***	3769	0.74 (0.65-0.85)***	2584
	>66dB	0.48 (0.46-0.50)***	33037	0.40 (0.37-0.44)***	6279	0.51 (0.46-0.55)***	5789	0.71 (0.61-0.82)***	4179	0.43 (0.37-0.51)***	1835
Land cover	Residential	Reference	81417	Reference	18685	Reference	15291	Reference	9921	Reference	6315
	Green	0.92 (0.84-1.00)*	3611	0.35 (0.28-0.44)***	565	1.37 (1.20-1.56)***	1370	0.40 (0.21-0.70)**	290	0.36 (0.18-0.68)**	56
	Industrial	0.72 (0.69-0.75)***	12522	0.53 (0.49-0.58)***	4251	1.04 (0.94-1.14)	2747	0.75 (0.59-0.94)*	867	0.55 (0.46-0.67)***	645
	Office	0.48 (0.42-0.55)***	1535	0.35 (0.28-0.43)***	752	0.84 (0.54-1.30)	97	0.81 (0.40-1.49)	85	0.80 (0.47-1.37)	63
Recurrence	0 or 1	Reference	52854	Reference	10073	Reference	9010	Reference	5800	Reference	3176
	More than 1	3.12 (3.02-3.22)***	46231	4.64 (4.35-4.96)***	14180	5.04 (4.70-5.41)***	10495	0.57 (0.51-0.64)***	5363	4.38 (3.90-4.93)***	3903
Household median income	Tertile 1 (low)	2.72 (2.60-2.85)***	32506	5.91 (5.40-6.47)***	10791	1.14 (1.01-1.27)*	9999	2.13 (1.79-2.53)***	1630	1.07 (0.41-2.75)	21
	Tertile 2	1.80 (1.73-1.88)***	33534	3.47 (3.17-3.79)***	8222	0.88 (0.79-0.98)*	6709	1.56 (1.36-1.80)***	3816	1.90 (1.68-2.15)***	4383
	Tertile 3 (high)	Reference	33045	Reference	5240	Reference	2797	Reference	5717	Reference	2675

C. Appendices of Chapter 5

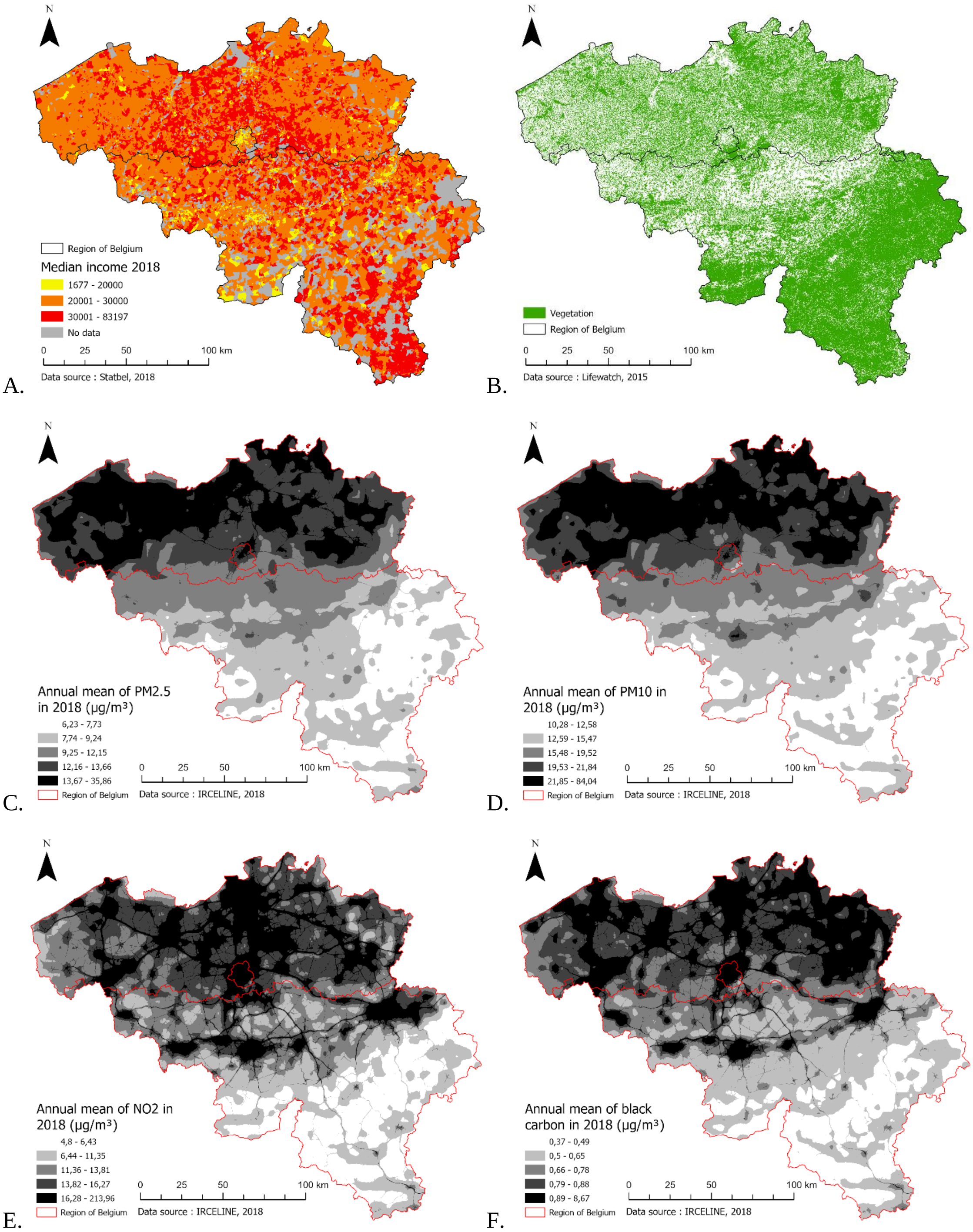
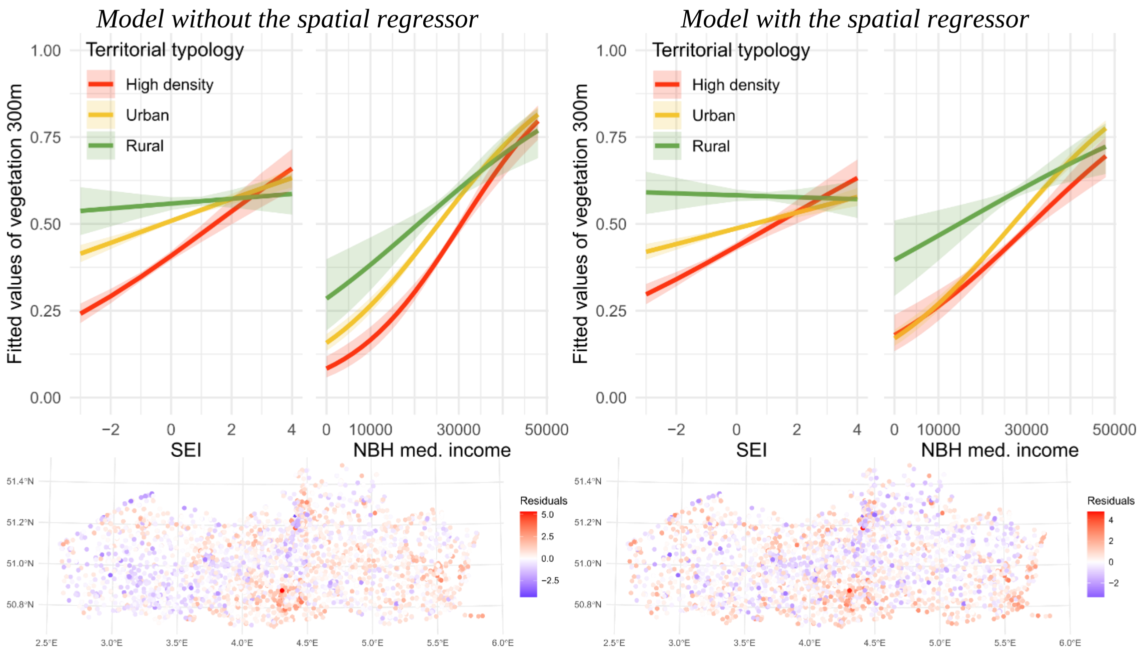


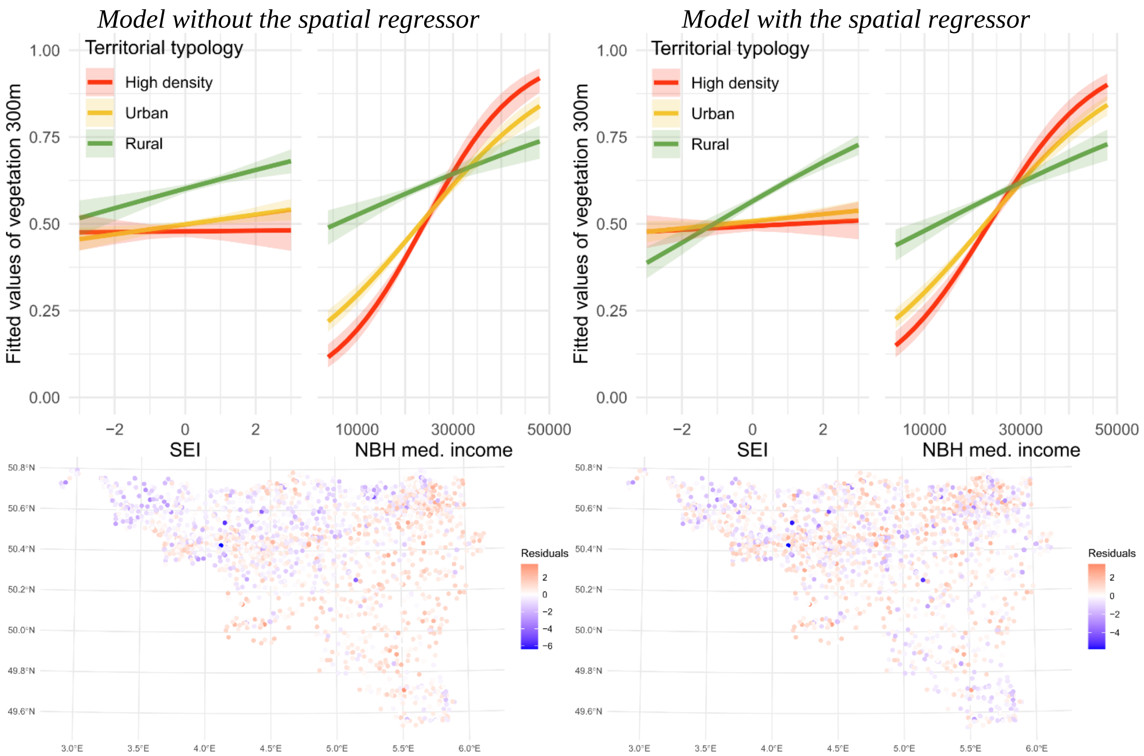
Figure C.1. Map of the neighbourhood median income (A) and all environmental indicators (B to F).

A. Flanders and BCR (NL)



Pseudo R² = 0.44, AIC = -4587.16 Pseudo R² = 0.56, AIC = -5367.99

B. Wallonia (FR)



Pseudo R² = 0.45, AIC =-3527.17 Pseudo R² = 0.56, AIC = -4097.92

Figure C.2. Model-based estimates (expected values and estimated marginal means) of vegetation exposure (300 m around primary school address) for different combinations: SEI and neighbourhood median income stratified by territorial typology (except for BCR(FR)). Results are presented for models with and without the spatial regressor. Residual maps, pseudo R^2 values, and AIC are also shown.

C. BCR (FR)

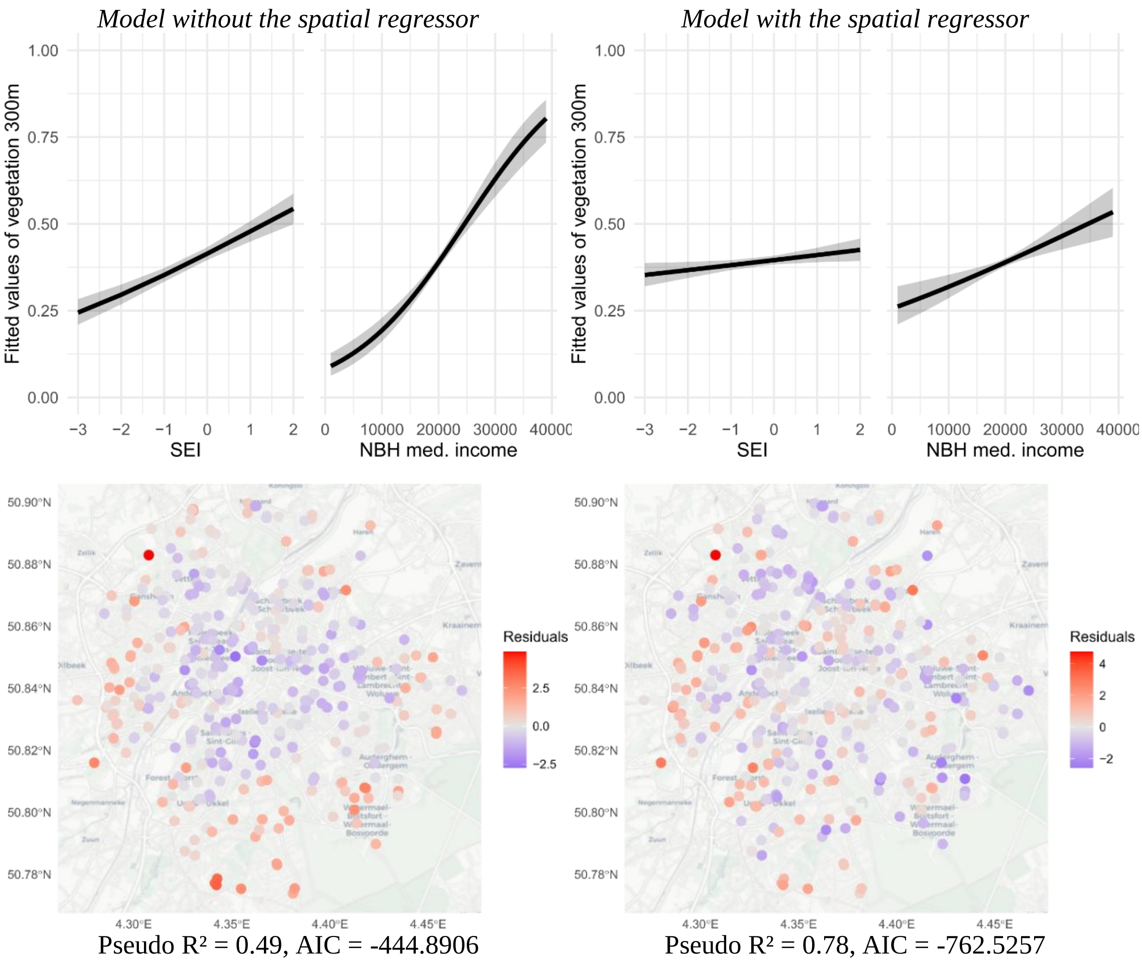


Figure C.2 (continued). Model-based estimates (expected values and estimated marginal means) of vegetation exposure (300 m around primary school address) for different combinations: SEI and neighbourhood median income stratified by territorial typology (except for BCR(FR)). Results are presented for models with and without the spatial regressor. Residual maps, pseudo R^2 values, and AIC are also shown.

D. Appendices of Chapter 6

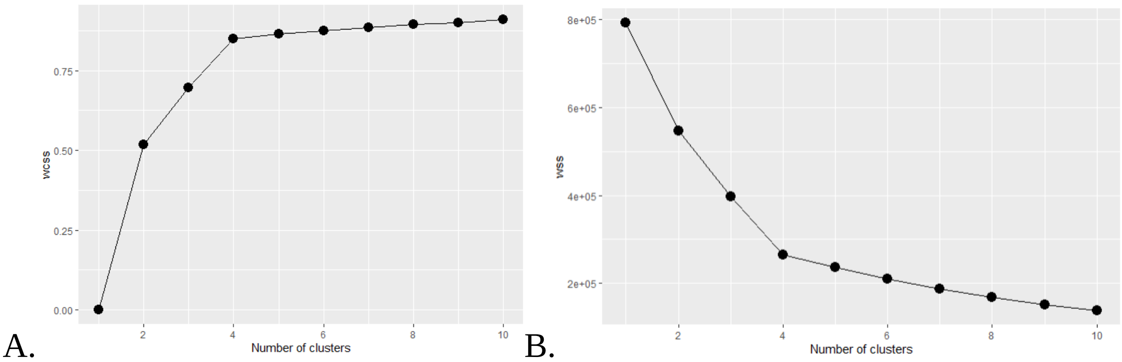


Figure D.1. Determination of the optimal number of clusters using the elbow method. (A) Within-cluster sum of squares (WCSS) and (B) within-cluster sum of squares (WSS). The optimal number of clusters is identified at the point where the curves begin to flatten, forming an “elbow” shape. Based on this method, four clusters were selected as the optimal solution.

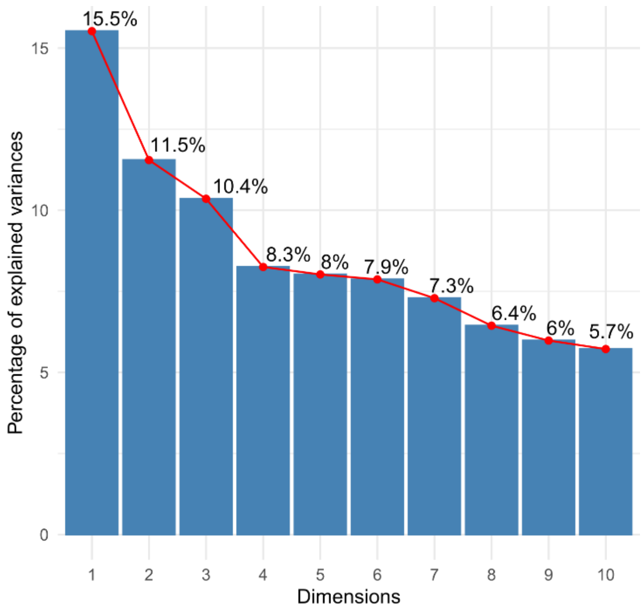


Figure D.2. Proportion of variances retained by the first 10 dimensions (axes) from the MCA.

Table D.1. Descriptive statistics.

Variable	Category	n	%
Educational level	Tertiary	217,340	26.69%
	Secondary	143,782	17.66%
	Primary	190,918	23.44%
	Unknown	262,353	32.21%
Age	[25–44]	387,907	47.63%
	[45–64]	270,051	33.16%
	[65+[	156,435	19.21%
Income	High income	213,182	26.18%
	Middle income	259,852	31.91%
	Low income	236,062	28.99%
	No tax return or null	105,297	12.93%
Origin	Belgium	278,457	34.19%
	European	236,391	29.03%
	Non-European	299,545	36.78%
Household size	1	235,423	28.91%
	2	215,625	26.48%
	3 or 4	245,954	30.20%
	5+	117,391	14.41%
Streetscape typology	UF1	20,166	2.48%
	UF2	57,639	7.08%
	UF3	132,916	16.32%
	UF4	159,449	19.58%
	UF5	62,442	7.67%
	UF6	122,686	15.06%
	UF7	29,895	3.67%
	UF8	76,881	9.44%
	UF9	65,771	8.08%
	UF10	36,307	4.46%
	UF11	50,241	6.17%

Table D.2. Street length and study population distribution across urban fabric (UF)

	# kilometres	% kilometres	# inhabitant	% inhabitant	inh/km
UF1	55.08	3.80%	20166	2.48%	366.12
UF2	73.69	5.08%	57639	7.08%	782.18
UF3	123.35	8.51%	132916	16.32%	1077.55
UF4	178.08	12.29%	159449	19.58%	895.38
UF5	76.06	5.25%	62442	7.67%	820.96
UF6	151.46	10.45%	122686	15.06%	810.02
UF7	66.88	4.61%	29895	3.67%	446.99
UF8	167.76	11.58%	76881	9.44%	458.28
UF9	106.81	7.37%	65771	8.08%	615.78
UF10	144.12	9.94%	36307	4.46%	251.92
UF11	305.99	21.11%	50241	6.17%	164.19

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