FROM COMPLAINTS TO INSIGHTS: A GEOGRAPHICAL ANALYSIS OF ILLEGAL DUMPING BY CITIZEN SENSOR DATA

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

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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.

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 (Pacione, 1990; van Kamp et al., 2003). 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 & 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 & 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

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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 & 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 & 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 & 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 & 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 & 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's 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 & 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 et al. (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.

2. Data and method

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 km^2, 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/km^2. 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).

2.2. Fix My Street

Fix My Street Brussels is a web and mobile platform (Fig. 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). Fig. 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.

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 appendix (Supplementary File 2). 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"

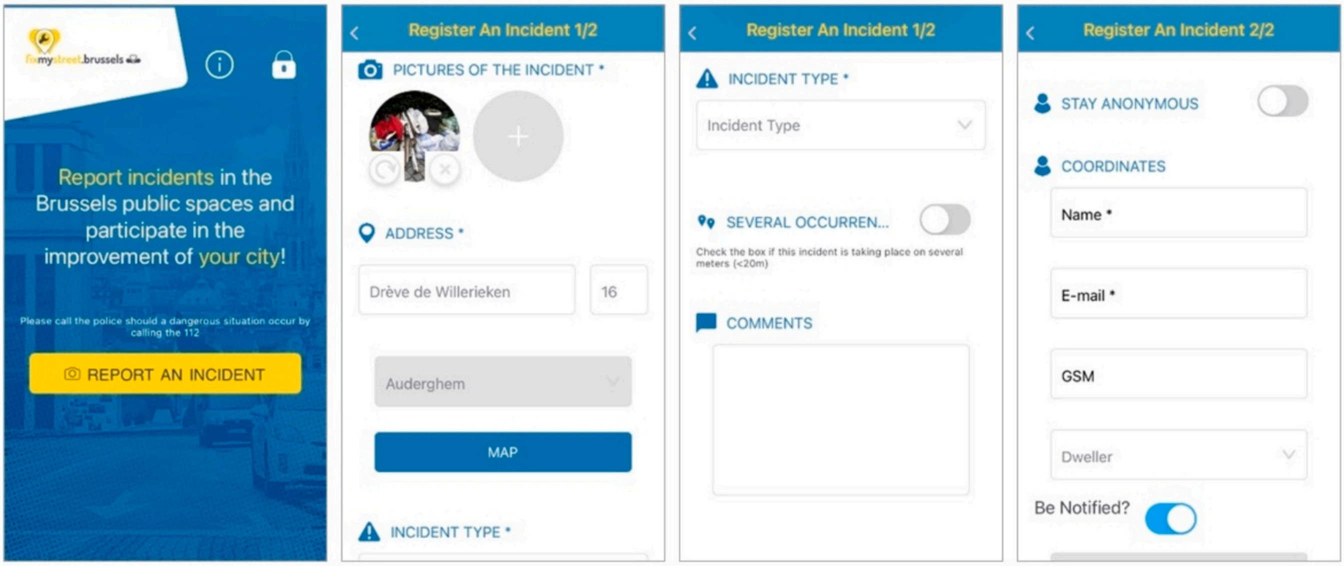

Fig. 1. Smartphone interface of the Fix My Street Brussels app (Source: Fix My Street, Brussels).

Fig. 2. Examples of illegal dumping reported in Fix My Street (Source: Fix My Street, Brussels).

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).

2.3. *Urban environment and "broken window" indicators*

We computed a selection of urban environment indicators (Table 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* (Supplementary File 1.B) or a *Recycling bank* (Supplementary File 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 with an incident: within 10 m of a tree (point data from Urbis: BRIC, 2017) and within 20 m 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

Table 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 & 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[a] (€).	Statistics Belgium (2017a)
	Tenant ratio	Value of the statistical sector[a] (%).	Census (Statistics Belgium, 2011)
	Population density	Value of the statistical sector[a] (hab/km^2)	Statistics Belgium (2017b)

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

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* (Supplementary File 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 m of a shop (point data from Atrium. Brussels, 2017). *Road noise* (Supplementary File 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 (Supplementary File 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 & 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 & Sullivan, 2001). The ratio of *Vegetation cover* (Supplementary File 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 & 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* (Supplementary File 1. E), *Street width* (Supplementary File 1. F) *and Sidewalk width* (Supplementary File 1. G) as representative of street configuration. The computation methods are detailed in Table 1. These indicators were categorized in tertiles. Street lighting would have been an interesting indicator (Welsh & Farrington, 2008) but no comprehensive database was available for Brussels.

We also considered the "broken window" or disorder effect (Kelling & 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 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'.

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 & Groves, 1989) or social deprivation: *Household median income* (Supplementary File 1. J), *Tenant ratio*, and *Population density* (Table 1). The computation methods are detailed in Table 1. These indicators were categorized in tertiles.

We included the municipality where the incident occurred (Supplementary File 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.

2.5. Statistical methods

Among all the potential explanatory variables presented in Table 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 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 was 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

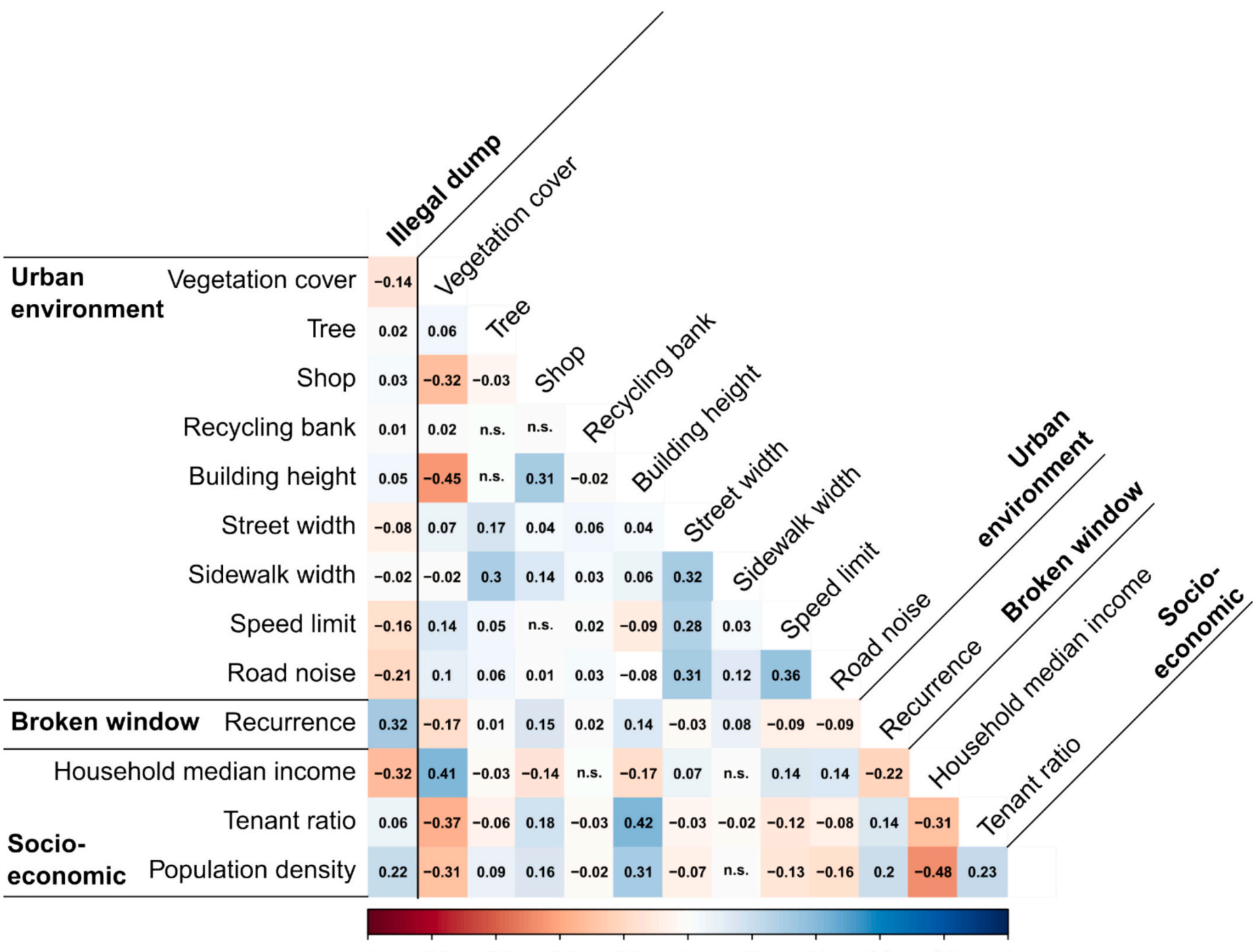

Fig. 3. Spearman's correlation matrix between ordinal variables, n.s. = non-significant correlation (Bonferroni adjusted p-value).

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.

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 (Fig. 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).

Table 2 presents the outcomes of the univariate, adjusted, and multiple models. The outcomes of multiple models are also provided based on subdivided datasets within Supplementary File 3 (data split in two based on the date) and Supplementary File 4 (data from the four municipalities with the highest number of incidents).

The association between the independent variables and *Illegal dumping* remains consistent across the global models present in Table 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 (Supplementary File 3): 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 (Supplementary File 4). 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 Fig. 4. Table 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*, Fig. 4.

Table 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			*n*
		Univariate	Adjusted[a]	Multiple[b]	
Vegetation cover	No (0%)	Reference	Reference	Reference	10785
	Low (<14%)	1.69 (1.62-1.77)***	1.8 (1.71-1.89)***	1.88 (1.78-1.99)***	29420
	Medium (14–30%)	1.16 (1.11-1.21)***	1.96 (1.86-2.07)***	2.14 (2.02-2.27)***	29450
	High (>30%)	0.67 (0.64-0.70)***	1.56 (1.47-1.65)***	1.80 (1.68-1.92)***	29430
Tree	No	Reference	Reference	Reference	62418
	Yes (under a tree)	1.08 (1.05-1.11)***	1.15 (1.12-1.19)***	1.27 (1.22-1.31)***	36667
Shop	No	Reference	Reference	Reference	63559
	Yes	1.14 (1.11-1.17)***	0.97 (0.94-1)	0.91 (0.88-0.94)***	35526
Recycling bank	No	Reference	Reference	Reference	96856
	Yes	1.19 (1.09-1.30)***	1.15 (1.05-1.27)**	1.22 (1.10-1.36)***	2229
Building height	Low (<8 m)	Reference	Reference	Reference	33015
	Medium (8–12 m)	1.53 (1.48-1.58)***	1.39 (1.33-1.44)***	1.20 (1.15-1.25)***	33042
	High (>12 m)	1.29 (1.25-1.33)***	1.12 (1.08-1.17)***	1.09 (1.04-1.14)**	33028
Street width	Low (<14 m)	Reference	Reference	Reference	33022
	Medium (14–19 m)	0.91 (0.88-0.94)***	0.9 (0.87-0.93)***	0.99 (0.95-1.03)	33028
	High (>19 m)	0.69 (0.66-0.71)***	0.63 (0.61-0.66)***	0.82 (0.79-0.86)***	33035
Sidewalk width	Low (<2.5 m)	Reference	Reference	Reference	33025
	Medium (2.5–4 m)	1.02 (0.99-1.05)	1.09 (1.06-1.13)***	1.01 (0.97-1.05)	33027
	High (>4 m)	0.92 (0.90-0.95)***	0.81 (0.78-0.84)***	0.75 (0.72-0.78)***	33033
Road noise	Low (<49 dB)	Reference	Reference	Reference	33032
	Medium (49–66 dB)	0.67 (0.65-0.70)***	0.74 (0.72-0.77)***	0.79 (0.76-0.82)***	33016
	High (>66 dB)	0.35 (0.34-0.36)***	0.43 (0.41-0.44)***	0.48 (0.46-0.50)***	33037
Land cover	Residential	Reference	Reference	Reference	81417
	Green	0.61 (0.57-0.66)***	0.62 (0.58-0.68)***	0.92 (0.84-1.00)*	3611
	Industrial	0.76 (0.73-0.79)***	0.57 (0.55-0.6)***	0.72 (0.69-0.75)***	12522
	Office	0.45 (0.41-0.51)***	0.42 (0.37-0.47)***	0.48 (0.42-0.55)***	1535
Recurrence	No (0 or 1)	Reference	Reference	Reference	52854
	Yes (more than 1)	3.83 (3.73-3.93)***	3.05 (2.96-3.14)***	3.12 (3.02-3.22)***	46231
Household median income	Low	5.55 (5.37-5.74)***	–	2.72 (2.60-2.85)***	32506
	Medium	3.47 (3.35-3.59)***	–	1.80 (1.73-1.88)***	33534
	High	Reference	–	Reference	33045

Signif. codes: 0 "***" 0.001 "**" 0.01 "*" 0.05.

[a]With household median income and municipality.

[b]With municipality.

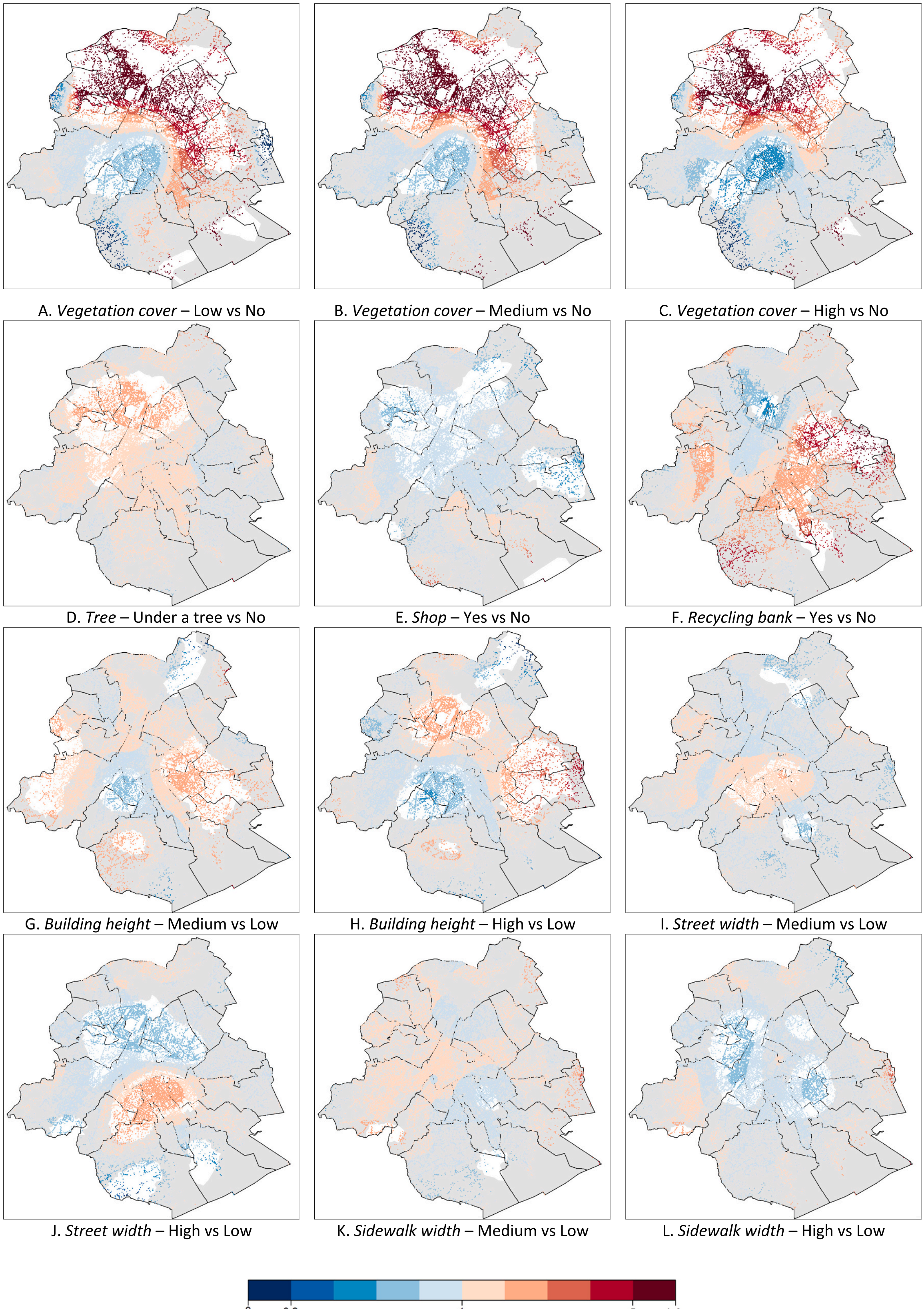

Fig. 4. Maps of GWR odd ratios. Red colour indicates risk factors, blue indicates protective ones. Values in grey areas are not significant (p>0.05). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

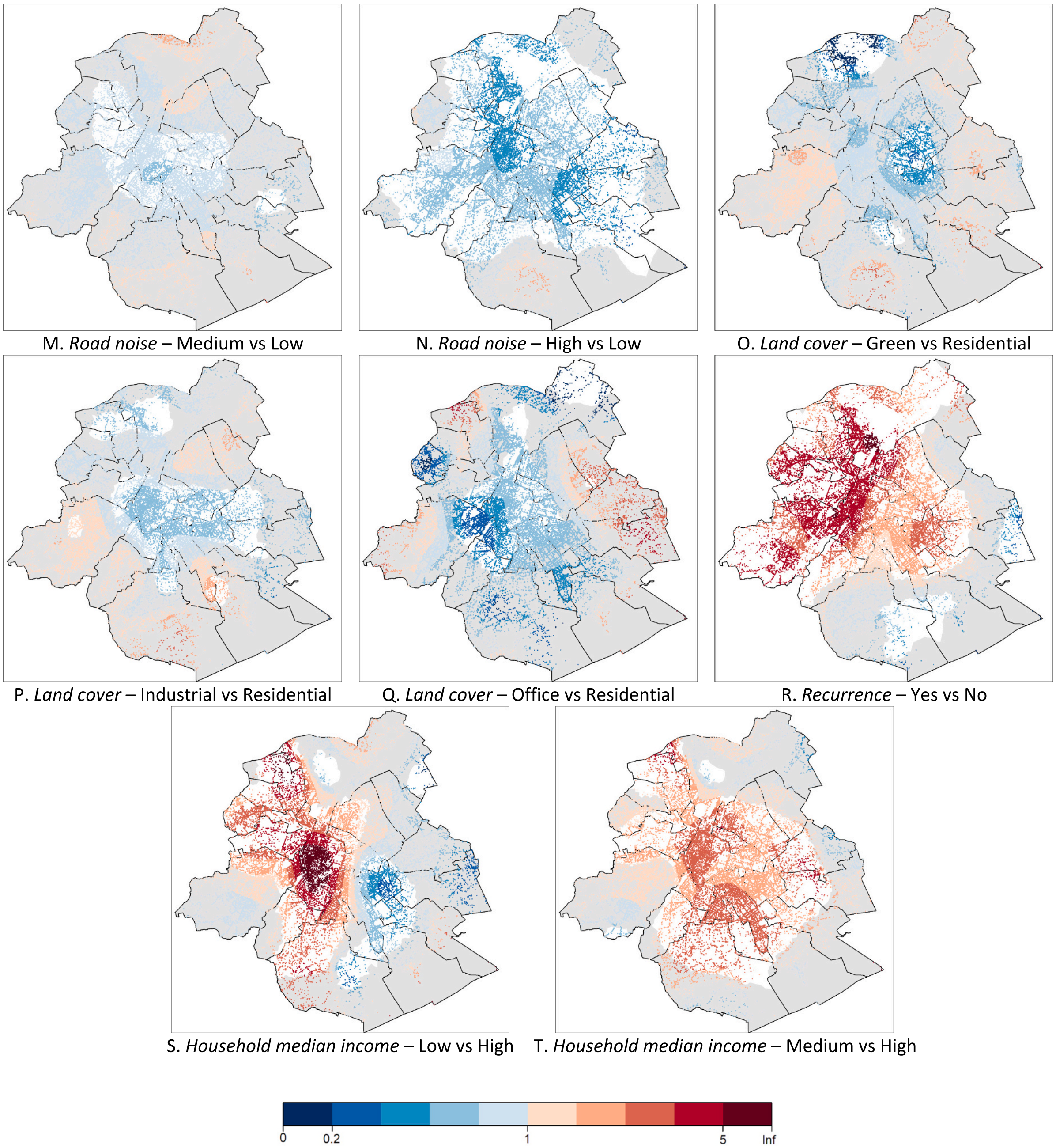

Fig. 4. (*continued*).

N) acts as a protective factor across the majority of the BCR, with 91.8 % of incidents exhibiting a positive association (Table 3). Medium income neighbourhoods (*Household median income* – *Medium* vs *High*, Fig. 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*, Fig. 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*, Fig. 4. E) is positively associated with illegal dumping for 43.76 % of incidents. Wide sidewalks (*Sidewalk width* – *high* vs *low*, Fig. 4. L) exhibit a positive association in 43.56 % of cases. The presence of a tree (*Tree* – *yes* vs *no*, Fig. 4. D) reveals a negative association in 40.17 % of incidents. Office area (*Land cover* – *office* vs *residential*, Fig. 4. Q) is linked to a positive association in 45.71 % of incidents, and industrial areas (*Land cover* – *industrial* vs *residential*, Fig. 4. P) results in a positive association in 46.17 % of cases.

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 (Supplementary File 1. K) and its surroundings in the spatial model (Fig. 4. C). Furthermore, in all models this association is nonlinear, as the effect size does not increase linearly between the different classes.

4. Discussion

This paper offers a twofold contribution. Firstly, we identified both

Table 3
Percentage of incidents according to the odd ratio obtained for the geographically weighted regression. Cells are coloured in grayscale according to percentage values, with darker tones indicating higher percentages.

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
Building 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

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 (Fig. 4. P), compared with the map of industrial zones (Supplementary File 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 & Williams, 2011; Sampson & Groves, 1989). The robust association between illegal dumping and recurrence aligns with the "broken windows" or disorder effect literature (Kelling & 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 & Kwon, 2015; Kuo & 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 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 modeling 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 situation 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.

CRediT authorship contribution statement

Madeleine Guyot: Writing – original draft, Visualization, Formal analysis. **Isabelle Thomas:** Writing – review & editing, Supervision, Conceptualization. **Sophie O. Vanwambeke:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary files

Supplementary files to this article can be found online at https://doi.org/10.1016/j.cities.2025.105892.

Data availability

The authors do not have permission to share data.

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