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Article

Unequal residential exposure to air pollution and noise: A geospatial environmental justice analysis for Ghent, Belgium

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ABSTRACT

Following the growing empirical evidence on the health effects of air pollution and noise, the fair distribution of these impacts receives increasing attention. The existing environmental inequality studies often focus on a single environmental impact, apply a limited range of covariates or do not correct for spatial autocorrelation. This article presents a geospatial data analysis on Ghent (Belgium), combining residential exposure to air pollution and noise with socioeconomic variables and housing variables. The global results show that neighborhoods with lower household incomes, more unemployment, more people of foreign origin, more rental houses, and higher residential mobility, are more exposed to air pollution, but not to noise. Multiple regression models to explain exposure to air pollution show that residential mobility and percentage of rental houses are the strongest predictors, stressing the role of the housing market in explaining which people are most at risk. Applying spatial regression models leads to better models but reduces the importance of all covariates, leaving income and residential mobility as the only significant predictors for air pollution exposure. While traditional multiple regression models were not significant for explaining noise exposure, spatial regression models were, and also indicate the significant contribution of income to the model. This means income is a robust predictor for both air pollution and noise exposure across the whole urban territory. The results provide a good starting point for discussions about environmental justice and the need for policy action. The study also underlines the importance of taking spatial autocorrelation into account when analyzing environmental inequality.

Introduction

In recent decades, the impact of the built environment on health and well-being receives increasing research interest (Jackson, 2003). Concerns about levels of physical activity, respiratory disease, sleep disturbance and stress strongly identify urban design and associated activity patterns as a public health issue (Dannenberg et al., 2012; Frumkin, 2003).

Conclusive empirical evidence is available on the negative health impact of air pollution and noise. Exposure to air pollution has been related to asthma, deficits in lung development and allergy development in children; and a higher mortality and coronary disease risk for the whole population (Health Effects Institute, 2010). Recently, also effects on cognitive performance and neuropsychological development, especially in children, have been established (Suades-González, Gascon, Guxens, & Sunyer, 2015). For noise exposure, conclusive associations have been found with annoyance, sleep disturbance, cognitive impairment of children and increased risk of hypertension and coronary heart

disease (Basner et al., 2014).

Both impacts have the largest health burden out of all environmental risk factors in developed countries. In a European research project comprising six countries, the included environmental risk factors accounted for about 3 to 7% of the total annual burden of disease (Hänninen et al., 2014). Air pollution was the leading environmental risk factor associated with 6000–10,000 disability-adjusted life years (DALYs) per million people per year. Together with second-hand smoke, traffic noise came second, with estimate ranges between 600 and 1200 DALYs per million people per year – considerably lower than the health burden of air pollution.

Environmental Justice and Pollution

Together with the growing empirical evidence on the causality of effects, also the spatial and social distribution of environmental burdens gets attention. While environmental justice research initially focused on the relationship between race and the distribution of waste and

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industrial sites in the United States, its scope has expanded and diversified, with a growing focus on all kinds of socio-demographic difference in environmental impact exposure (Brulle & Pellow, 2006). In this light, Schweitzer and Valenzuela (2004) made the case for more quantitative environmental justice research on the (environmental) costs and (economic) benefits of transportation. This was followed by continued attention to the topic in recent years, also in Europe, where research interest mainly goes to environmental justice issues concerning the impact of (traffic-related) air pollution and noise. For both impacts, the substantial local variation in exposure and the mutual production by all of us, open up discussions on fairness.

Moreover, exposure is considered to interact with vulnerability, producing a “triple jeopardy” of low socioeconomic position, polluted environment and impaired health. This means that groups with a lower socioeconomic position that already experience a compromised health status due to material deprivation and psychosocial stress, also receive the highest exposure; and this exposure then exerts larger effects on their health than it does on the average population (Laurent, Bard, Filleul, & Segala, 2007; O’Neill et al., 2003; Pearce, Richardson, Mitchell, & Shortt, 2010; Walker, 2012). Vice versa, well-off populations, regardless of their residential exposure to noise or air pollution, are likely to perceive less annoyance or health effects than their neighbors, because they can afford to protect themselves by equipping their dwelling with sound proofing or air purification and are often not at home during the day (Havard, Reich, Bean, & Chaix, 2011). Moreover, for noise specifically, subgroups in socially lower positions may tend to complain less about environmental noise due to habituation to chronic residential noise exposure or adoption of coping strategies, leaving problematic situations underexposed (Kohlhuber, Mielck, Weiland, & Bolte, 2006; Riedel, Scheiner, Müller, & Köckler, 2014). In this way, air pollution and noise may aggravate social health inequalities, forming an additional argument in discussions on fairness of environmental impact distribution and underlining the importance of empirical studies.

Quantitative environmental justice studies on air pollution and noise

Today, an abundance of American empirical studies relatively consistently suggests that exposure to air pollution – usually operationalized through NO₂ concentration – is not evenly distributed and that individuals with a low socioeconomic position, a low income or a non-white background may generally be more exposed (Bell & Ebisu, 2012; Chakraborty, 2009; Clark, Millet, & Marshall, 2014; Su, Larson, Gould, Cohen, & Buzzelli, 2010). In studies from New Zealand and Canada the same association with deprivation and income was usually found, but only a weak or even inverse association for ethnicity (Crouse, Ross, & Goldberg, 2009; Kingham, Pearce, & Zawar-Reza, 2007; Pearce & Kingham, 2008; Su et al., 2010). In European studies results are more varied overall (Deguen & Zmirou-Navier, 2010; Hajat, Hsia, & O’Neill, 2015). Some European studies are in line with the American studies and reported a (weak) global relation between high exposure and low socioeconomic status or non-white ethnicity (Brainard, Jones, Bateman, Lovett, & Fallon, 2002 (UK); Briggs, Abellan, & Fecht, 2008 (UK); Chaix et al., 2006 (Sweden); Fecht et al., 2015 (UK & the Netherlands); Goodman, Wilkinson, Stafford, & Tonne, 2011 (UK); Jephcote & Chen, 2012 (UK)). Other studies found a higher exposure for mid-level deprivation areas (Havard et al., 2009 (France)), a lower exposure for mid-level deprivation areas (Mitchell & Dorling, 2003 (UK)) or inconsistent results depending on the city (Padilla et al., 2014 (France)).

In their 2009 paper, Havard et al. stressed the need to take spatial autocorrelation into account in ecological studies. Spatial autocorrelation occurs when locations close to each other exhibit more similar values than those further apart. If the pattern remains present in the residuals of a statistical model based on such data, the key assumption that residuals are independent and identically distributed is violated

(Dormann et al., 2007). Ignoring spatial autocorrelation may lead to biased and unreliable estimates and thus erroneous conclusions. Havard et al. (2009) were among the first authors to account for spatial autocorrelation in environmental justice studies. Using spatial autoregressive models in addition to ordinary least square (OLS) regression models, they found similar results, but with much weaker coefficients. Also other (already mentioned) authors applied methods to correct for spatial autocorrelation, such as geographically weighted regression (Jephcote & Chen, 2012 (UK)), generalized additive models (Padilla et al., 2014 (France); Su et al., 2010 (Canada/US)) and three-level random intercept models (Goodman et al., 2011 (UK)). These models are very different in the way they take spatial autocorrelation into account. For example, in spatial autoregressive models an additional explanatory variable is added to the global regression function to capture the spatial effect, while in geographically weighted regression a unique regression function is calculated for each spatial unit, assuming that there is a different relationship between the independent variables in different parts of the study area. Accounting for spatial autocorrelation in environmental justice studies generally led to weaker coefficients, but also revealed localized variations in associations. For example, Goodman et al. (2011) found a reversed relation between socioeconomic status and air pollution exposure in central city areas.

In contrast to air pollution, relatively few studies examined inequalities in environmental noise exposure. While some North American studies and one Asian study indicated a relatively strong association between noise levels, household income and percentage of non-white/minority residents (Carrier, Apparicio, & Séguin, 2016; Dale et al., 2015; Lam & Chung, 2012; Nega, Chihara, Smith, & Jayaraman, 2013), the evidence in European studies is mixed. Some studies showed that more deprived or non-white populations might be subjected to a higher modelled noise exposure, but associations are generally very weak (Brainard, Jones, Bateman, & Lovett, 2004 (UK)), dependent on the type of noise source (Kruize, Driessen, Glasbergen, & van Egmond, 2007 (the Netherlands)) or only valid for medium-sized cities and not for large cities (Fyhri & Klæboe, 2006 (Norway)). Conversely, two French studies reported the highest noise exposure levels for middle-class neighborhoods (Bocquier et al., 2013) and more advantaged neighborhoods (Havard et al., 2011). Of the European studies, only the latter two applied spatial regression models to control for spatial autocorrelation. They both found a better fit and reductions of the regression coefficients, but the shape of the relations remained the same.

Housing market dynamics and residential preferences might help explain why some subgroups suffer from a higher exposure to noise or air pollution and others buy themselves free of pollution (Deguen & Zmirou-Navier, 2010). However, there is few research available to support this hypothesis, and most studies did not include spatial autocorrelation effects. In a case study in Hong Kong, Lam and Chung (2012) found that renters on the private housing market were generally exposed to higher levels of traffic noise. Since no multiple regression analysis was performed, it is not possible to verify whether this effect is independent from the relation between socioeconomic status and noise exposure. In a case study in Phoenix, neighborhoods with a higher proportion of renters were exposed to higher levels of air pollutants (Grineski, Bolin, & Boone, 2007). A multiple regression analysis showed that the percentage of renters explained additional variability in air pollution exposure that ethnicity and income could not explain. For this particular study area it meant that also more privileged groups would generally bear a higher exposure to air pollution in case they rent their house. We found one study that did account for spatial autocorrelation, examining the association between home ownership rate and air pollution related health risks (lifetime cancer risk and a respiratory hazard index) (Chakraborty, 2009). In a multiple spatial error regression model, a robust relation was found between higher home ownership and lower air pollution related health risks.

Research objectives

The presented overview of empirical studies provides evidence of city-specific spatial inequalities that relate to the historical socio-economic make-up of the cities and their evolution (Padilla et al., 2014). The mixed results highlight the need to study the diversity of patterns of environmental inequalities across various economic, social and cultural contexts (Bocquier et al., 2013). Our empirical study on the city of Ghent presents the first environmental justice analysis on a Belgian city, adding to the growing evidence base from various European countries. Moreover, whereas most studies limit their focus to a single environmental impact, we simultaneously analyze the spatial distribution of air pollution and noise – the two most important environmental stressors – using the same methodology. Finally, unlike several other studies, we run spatial regression models to correct for the effects of spatial autocorrelation.

This study aims to determine the association between residential exposure to air pollution and noise, and different socioeconomic and housing variables. We specifically assess whether unequal exposure is linked to having a lower socioeconomic status and being of foreign origin. Furthermore, by including housing variables, we explore the role of the housing market in explaining differences in exposure. We opt for a geostatistical analysis using geospatial tools available in the GeoDA software package and apply Local Indicators of Spatial Association (LISA), correlation analysis, multiple OLS regression models and spatial autoregressive models that account for the possible effects of spatial autocorrelation. We conclude with discussing the results from an environmental justice perspective and explore ethical concerns and policy implications.

Materials and methods

Study area

Ghent is a medium-sized city with a population of about 250,000 in the Flanders region, the northern part of Belgium (Fig. 1). The city lies north of the intersection of two important international highways (E17 and E40) and is further characterized by a busy urban ring road (R40), a suburban ring road (R4) and an economically important port area north of the city center, all contributing to local hotspots of air and noise pollution. Interestingly, the municipal territory is characterized by a

gradient that goes from a rather small urban core with high densities over lower-density suburban neighborhoods to semi-rural areas, particularly on the southwestern edge of the city.

The city is also known for its ambitious policy on sustainable urban development. In 2010, a Ghent Local Air Quality Plan 2010–2015 was developed, including fifty concrete actions for cleaner air (City of Ghent, 2010). In 2014, an equally ambitious Ghent Local Noise Action Plan 2014–2019 was drawn up, including the explicit aim to decrease the traffic noise level at all houses below 70 dB(A) by 2030 (while in 2014 about 15% of the city's population was still exposed to these levels) (City of Ghent, 2014). One of the most important actions in reaching the air quality and noise targets is a new Circulation Plan, which splits the city center into six disconnected traffic zones, eliminating through traffic and discouraging cars to enter the city center (City of Ghent, 2015). Considering these far-reaching and ambitious plans, a thorough environmental justice analysis prior to the implementation of concrete actions would yield an important reference measurement to which a future analysis can be compared.

Finally, the choice for the study area is supported by the availability of detailed and full coverage modeled data for exposure to air pollution and environmental noise, which makes it possible to calculate address-based exposure values.

Data

Air pollution

To quantify exposure to air pollution, data on air quality were derived from the ATMOSYS annual air quality maps for road traffic-related air pollution (ATMOSYS, 2013). The air quality maps result from the combination of two data sources: the spatial interpolation of air quality measurements (RIO-interpolation technique) and the calculation of air pollutant concentrations based on meteorological data and the emissions of air pollutants (IFDM-model) (Lefebvre et al., 2013). The RIO-interpolation technique primarily provides data on the background concentration, while the IFDM-model reveals local differences in air quality caused by traffic. Although validation tests gave reliable results, both data sources have limitations and uncertainties. A disadvantage of the IFDM-model is its focus on air pollution by road traffic, not including other sources like industry or households. While other sources are still partly captured in the RIO-model, this can lead to underestimation of the actual concentrations and mitigation of local

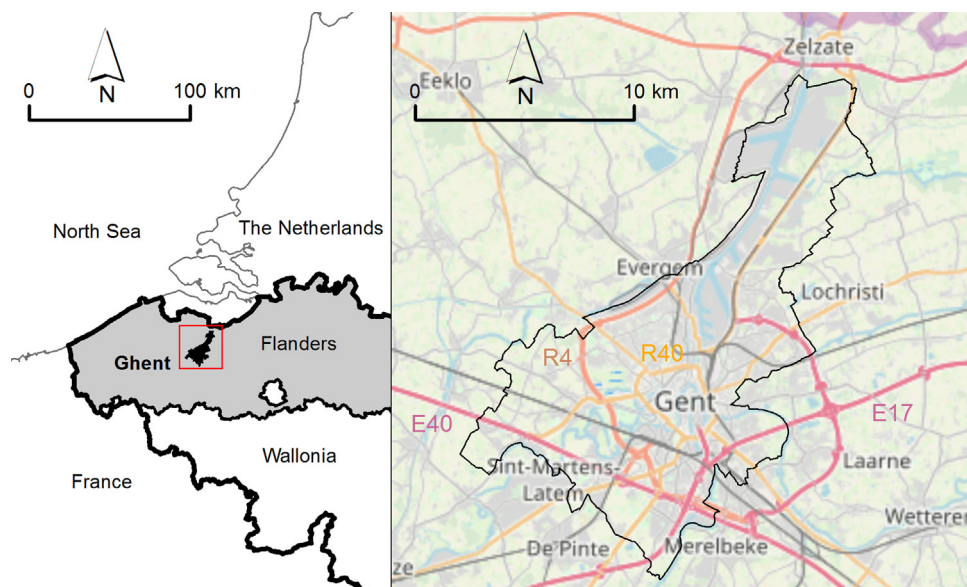


Fig. 1. Location of Ghent in Flanders; location of highways and major roads around Ghent (black line: municipal boundary; basemap: © OpenStreetMap (and contributors, CC-BY-SA).

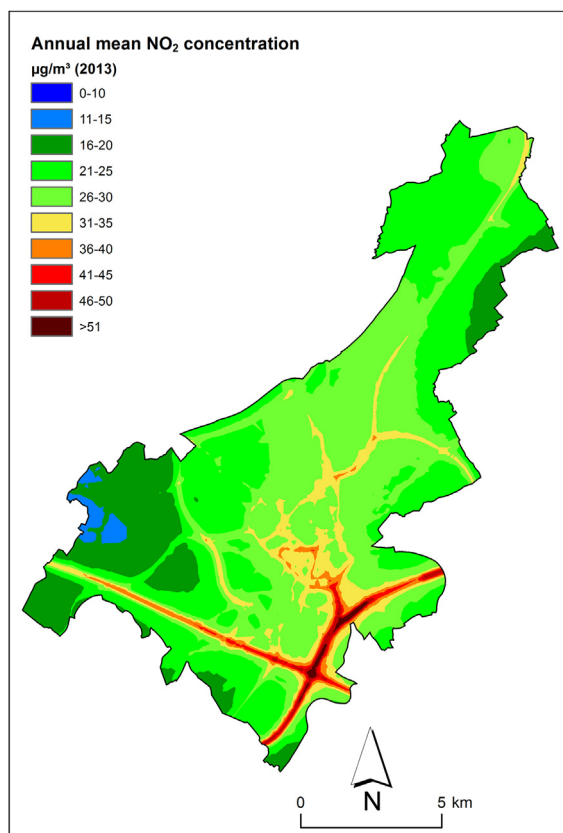


Fig. 2. Distribution of annual mean NO₂ concentration (2013) (based on: [ATMOSYS, 2013](#)).

differences. Most importantly, the RIO-IFDM model is an “open street” model that does not consider the effect of obstacles alongside roads (buildings, continuous urban fabric, trees) that can cause the street canyon effect. This means that in narrow inner-city streets with a lot of traffic, where the dispersion of polluted air goes slower, the model will probably underestimate the concentrations.

The ATMOSYS project provides rasterized georeferenced data on several pollutants, with a resolution of 10×10m. In further analysis, the annual mean concentration (µg/m³) of NO₂ (nitrogen dioxide) for the year 2013 was used as proxy indicator for traffic-related air pollution. NO₂ has proven to be a good indicator for traffic-related air pollution, showing more spatial variation than other modeled pollutants ([Goodman et al., 2011](#)). Probably the occurrence of NO₂ is correlated with a specific mixture of particulate matter typical for traffic-related air pollution and the associated health effects ([Health Effects Institute, 2010](#)). Thus, NO₂ can be considered a good proxy indicator and accordingly limit values have been adopted by the World Health Organization and the European Commission. Both bodies use a maximum limit value of 40 µg/m³ for annual mean NO₂ concentration.

When NO₂ concentrations are mapped for the city of Ghent ([Fig. 2](#)) an uneven distribution across the city is visible, with higher values around the highways and just south of the city center. In a small area the limit value of 40 µg/m³ is exceeded.

Noise

To quantify noise exposure the urban noise maps of the city of Ghent were used, taking road, railway and industry noise into account. These were created for the first time in 2010 following the EU Environmental Noise Directive 2002/49/EC, which stated that for all agglomerations with more than 250,000 inhabitants, detailed noise maps had to be made. In 2014, the noise maps were revised by the same consultants [AIB-Vinçotte Environment nv](#) and [GIM nv](#) (2014). They

combined noise measurements with a 3D model containing topography and buildings, and also performed an extensive quality control with model validation on the field. Their approach followed the *Good Practice Guide for Strategic Noise Mapping and the Production of Associated Data on Noise Exposure* produced by the European Commission’s Working Group – Assessment of Exposure to Noise ([WG-AEN, 2007](#)).

In further analysis, L_{den} (2014) was used as the principal proxy variable for environmental noise. L_{den} is the standard harmonized noise indicator for assessing annoyance and sleep disturbance, measuring the average equivalent sound level over a 24-hour period, with a 5 dB(A) penalty added for noise during the evening hours of 19:00 to 23:00 and a 10 dB(A) penalty for noise during the nighttime hours of 23:00 to 07:00. In the analysis “L_{den} total” was used, combining road, railway and industry noise, though in most parts of the city mainly representing the first two. Data are in georeferenced raster format and have a resolution of 10×10m. In Belgium and Europe no legally binding standards for traffic-related environmental noise exist. Only target and reference values are defined, with the most important ones the Flemish “fundamental reference values” of L_{den} = 65 dB(A) for existing situations and L_{den} = 55 dB(A) for new situations. The World Health Organization (WHO) advocates a limit value of L_{den} = 55 dB(A) to indicate serious annoyance, while for new developments it recommends a limit value of L_{den} = 40 dB(A) ([WHO, 1999](#)). Note that these limit values are considerably lower than the 2030 target value of 70 dB(A) in the Ghent Local Noise Action Plan 2014–2019 ([City of Ghent, 2014](#)).

In [Fig. 3](#) the distribution of “L_{den} total” across the city is shown, displaying a dispersed pattern across the municipal territory. In large parts of the city, especially along the major roads and railways, the WHO limit value of L_{den} = 55 dB(A) is exceeded.

Covariates

To operationalize the covariates, data were collected at the level of

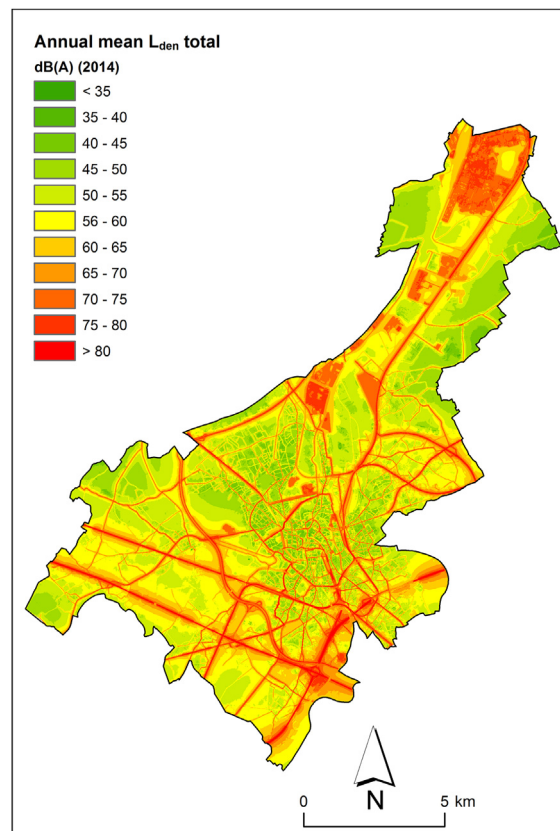


Fig. 3. Distribution of annual mean L_{den} total (2014) (based on: [AIB-Vinçotte Environment nv](#) and [GIM nv, 2014](#)).

Table 1
Descriptive statistics for covariates and environmental impact indicators, at statistical sector level (N = 164).

	Min	Max	Mean	Std. dev.
Median household income (€)	15,151	39,067	24,876	5015
Unemployment pressure (%)	0.00	18.00	6.32	4.07
% foreign origin	2.10	78.90	22.03	17.44
% EU15 origin	0.00	27.20	4.50	2.84
% EU13 origin	0.00	18.50	3.10	3.82
% Turkish/Maghreb origin	0.00	52.90	7.68	10.14
% other origin	0.00	28.70	6.75	5.76
% rental houses	5.60	96.30	41.12	21.07
Number of house moves per 1,000 inh.	29.41	739.49	244.67	129.78
Annual mean NO ₂ concentration (µg/m ³)	15.07	40.77	26.52	5.10
Annual mean L _{den} total (dB(A))	47.53	70.03	57.94	3.92

statistical sectors. The city of Ghent counts 201 statistical sectors, which have been defined by sociological and spatial characteristics, with an average population of about 1,200 respondents. It is the finest spatial division for which census data are available and is representative of natural neighborhoods. Opting for this level of analysis thus follows the recommendations regarding the Modifiable Area Unit Problem (MAUP) in environmental justice research (Baden, Noonan, & Turaga, 2007). Indicators on socioeconomic vulnerability and housing are publicly available on a website of the city of Ghent (<http://gent.buurtmonitor.be/>). Table 1 lists summary statistics for the covariates, and for the air pollution and noise indicators.

Socioeconomic position was operationalized by median household income and unemployment pressure (the share of non-working job-seekers between 18 and 64 years old relative to the total population between these ages). Being of foreign origin was operationalized by a general indicator representing the percentage of people of foreign origin – which means the father, mother or individual had a foreign nationality at birth – and by four specialized indicators on the percentage of people with EU15 (countries that entered the EU before 2004), EU13 (countries that entered the EU after 2004), Turkish-Maghreb and other foreign origin. Finally, we chose to focus the aspect of housing on the aspect of temporary or unstable housing, by selecting a variable on the percentage of rental houses and the number of house moves per 1000 inhabitants per statistical sector. Apart from the percentage of rental houses, which is based on data from 2011, all data are from 2012.

Of the 201 statistical sectors in Ghent, 17 do not contain any residential buildings and consist of parks, waterways, infrastructure or industrial land. Of the 184 remaining sectors, 19 sectors with incomplete data were excluded and one sector was excluded because it had an extreme outlier value on the indicator of house moves (due to planned residential development taking place in a previously unpopulated statistical sector). The most important exclusion criterion was formed by the median income variable. For privacy reasons, income data is not made publicly available if a statistical sector contains less than 20 taxpayers. As such, 1,216 citizens were excluded from the analysis, which is less than 0.5% of the total population. In all subsequent analyses we only report on the 164 remaining statistical sectors.

The descriptive statistics in Table 1 show a wide range of values for all variables (including the two environmental indicators), underscoring the variety of the different neighborhoods across the city. In Table 2 associations between the nine different socioeconomic and housing variables are summarized. Almost all correlation coefficients are significant, but they are not equally strong. One of the strongest associations exists between median income and unemployment pressure per sector ($r = -0.823^{**}$). Both variables also show relatively strong correlations ($0.7 < r < 0.9$ or $-0.9 < r < -0.7$) with percentage of rental houses and percentage of people of foreign origin. Also the correlations between percentage of rental houses and percentage of

people of foreign origin resp. number of house moves per 1000 inhabitants are relatively strong ($r = 0.641^{**}$ and $r = 0.692^{**}$). The number of house moves per 1000 inhabitants, in turn, shows moderately strong correlations with median income, unemployment pressure and percentage of people of foreign origin ($0.5 < r < 0.6$ or $-0.6 < r < -0.5$). The specialized foreign origin variables show patterns similar to the combined variable, though with weaker correlation coefficients, and with the people of EU15 origin being a clearly better-off socioeconomic group.

Methods

The data analysis was carried out at statistical sector level with environmental impact indicators based on average residential exposure values (Table 1). To calculate average residential exposure values per sector, a spatial data set containing all residential addresses for the year 2013 was obtained from the City of Ghent. Making use of ArcGIS9.3, to each address point the respective values were added of the rasterized air pollution and noise data. In this operation bilinear interpolation was used. These residential address-based exposure values were subsequently averaged at statistical sector level. This approach calculates a fairly accurate estimation of residential exposure at statistical sector level, by accounting for the local differences in household density. Parts of a statistical sector where the household density is very high (e.g. apartment blocks) will have a higher weight in calculating the aggregated value for the statistical sector.

As a first step in our geostatistical analysis, the constructed environmental exposure variables were analyzed for global spatial autocorrelation by calculating the univariate global Moran's I statistic. The significance of the Moran statistical values was obtained through calculating pseudo p-values based on 999 random permutations. Subsequently, Local Indicators of Spatial Association (LISA) were applied to each statistical sector for the detection of spatial patterns, i.e. spatial clusters of high or low values or spatial outliers (Anselin, 1995). Contiguity-based spatial weights were used, standardized by neighbor count and applying the queen criterion, which defines neighbors as spatial units sharing a common edge or common vertex. We also calculated the bivariate Moran's I coefficients for the two environmental exposure variables. The bivariate tool determines whether there is spatial autocorrelation between two variables. It more specifically evaluates the correspondence between the value of one variable in one location and the values of the other variable in neighboring locations (i.e. the lagged variable). Finally, also the spatial patterns of the most important covariates were analyzed using the Moran's I statistic and LISA maps. In addition, we calculated correlation coefficients between the covariates and the environmental indicators.

Next, multiple regression methods were applied to discern the different explanatory value of socioeconomic and housing variables, and the relation between them. We applied ordinary least square (OLS) regression models and subsequently spatial autoregressive models to control for spatial autocorrelation. We used the values of the Lagrange Multiplier and Robust Lagrange Multiplier (LM and Robust LM) tests, calculated using the residuals from the OLS models, to evaluate the need for either a spatial lag or spatial error model (Anselin & Bera, 1998).

- When it is assumed that the autoregressive process occurs only in the response variable, a spatial lag model is applied. In this model the values of the dependent variable in neighboring locations (WY) are included as an additional explanatory variable with a parameter ρ (with Y the dependent variable, X the covariate, β the regression coefficient, β_0 the intercept, ε the error and W the weights matrix).

$$Y = \beta_0 + \rho WY + \beta X + \varepsilon$$

- When it is assumed that the autoregressive process occurs only in

Table 2

Bivariate correlations between the covariates, at statistical sector level (N = 164) (Pearson correlation coefficients) (** correlation significant at the 0.01 level; * correlation significant at the 0.05 level).

		1	2	3	4	5	6	7	8	9
1	Median household income (€)	1	–	–	–	–	–	–	–	–
2	Unemployment pressure (%)	–.823**	1	–	–	–	–	–	–	–
3	% people of foreign origin	–.750**	.865**	1	–	–	–	–	–	–
4	% people of EU15 origin	–.106	.217**	.251**	1	–	–	–	–	–
5	% people of EU13 origin	–.614**	.676**	.881**	.104	1	–	–	–	–
6	% people of Turkish/Maghreb origin	–.645**	.733**	.892**	–.082	.823**	1	–	–	–
7	% people of other origin	–.677**	.773**	.749**	.339**	.503**	.435**	1	–	–
8	% rental houses	–.761**	.758**	.641**	.381**	.414**	.399**	.774**	1	–
9	Number of house moves per 1,000 inh.	–.539**	.577**	.573**	.480**	.519**	.322**	.586**	.692**	1

the error term, a spatial error model is applied. In this model the values of the residuals in neighboring locations ($W\epsilon$) are included as an extra term in the equation, with a parameter λ (and ξ being “white noise”).

$$Y = \beta_0 + \beta X + \lambda W\epsilon + \xi$$

To compare the different models and evaluate the relative quality we applied the Akaike Information Criterion (AIC) (Akaike, 1974) (with k = the number of coefficients in the regression equation, normally equal to the number of independent variables plus one for the constant term).

$$AIC = 2k + n[\ln(\text{Residual Sum of Squares})]$$

Statistical analyses were carried out in SPSS (Version 22) and GeoDA (see <https://geodacenter.github.io/>).

Results

Exploratory geospatial data analysis

The correlation between residential exposure to air pollution and noise ($r = 0.387^{**}$) is rather weak, showing that both indicators have a different distribution across the study area. An exploratory geospatial data analysis can give more insight in the specificities of the spatial patterns. We first calculated the Global Moran's I coefficient for residential exposure to air pollution (annual mean NO_2 concentration) and noise (annual mean L_{den} total). While both variables show significant spatial autocorrelation, the spatial distribution of air pollution (Moran's $I = 0.78$, $p < 0.01$, 999 randomizations) is much more clustered than the spatial distribution of noise (Moran's $I = 0.34$, $p < 0.01$, 999 randomizations). These results show that spatial dependencies should be accounted for when developing regression models.

We further explored the spatial patterns of residential exposure to air pollution and noise by employing Local Indicators of Spatial Association (LISA), using the Local Moran's I statistical test to define clusters and outliers (Fig. 4). Statistical sectors shown in dark red are sectors with high values surrounded by sectors with equally high values, indicating a cluster. Statistical sectors with a dark blue color are sectors with low values, surrounded by sectors with equally low values, indicating a cluster. Statistical sectors shown in light red or light blue represent spatial outliers, with a high value surrounded by low values or vice versa. The statistical sectors colored in grey represent non-significant spatial patterns, while the sectors colored in white were excluded from the analysis because of lack of data and a very low population.

The maps show rather different spatial patterns for residential air pollution and noise exposure. For air pollution, the Local Moran's I statistical test identified a high clustering of air pollution exposure in the southeast, where there is a high concentration of major road infrastructure, and in the city center. Observed annual mean NO_2 concentrations in this zone of high clustering range from 26.65 to 40.77 $\mu\text{g}/\text{m}^3$, values all above the city's mean of 26.50 $\mu\text{g}/\text{m}^3$ (Table 1).

The western part of the municipality of Ghent, which has a relatively rural character, consists of a cluster with a very low exposure to air pollution, with values from 15.07 to 25.15 $\mu\text{g}/\text{m}^3$. There is only one specific outlier in the west, where air pollution exposure is significantly higher than in neighboring areas (33.12 $\mu\text{g}/\text{m}^3$).

The Local Moran's I statistical test for noise exposure identified a more dispersed pattern with several smaller clusters next to two large clusters. A large cluster of high values is situated south of the city center, similar to the air pollution map. However, the city center itself did not come out as an area with significantly higher values. Values of annual mean L_{den} total in this contiguous cluster range from 58.23 to 70.03 dB(A), above the city's mean of 57.93 dB(A) and well above the limit value of 55 dB(A) advised by the WHO. Spatial clustering of low values of residential noise exposure can be found in some suburban neighborhoods north of the city center. This zone is clearly different from the spatial clustering of low values in the air pollution map. Values of annual mean L_{den} total in the largest cluster range from 47.53 to 55.61 dB(A), which means these sectors almost comply with the advised limit value of the WHO. Finally, the map indicates seven outliers, particularly in the southern part of the city. Most of these outliers are located near major road infrastructures, but they – or the majority of homes in these neighborhoods – are not directly adjacent to them. This illustrates the more pronounced local differences in noise, while higher and lower concentrations of air pollution form larger clusters (see Figs. 2 and 3). However, there clearly is some overlap between the spatial patterns of both indicators. This is confirmed by the bivariate Global Moran's I coefficient for exposure to air pollution and the lagged noise variable (Moran's $I = 0.25$, $p < 0.01$, 999 randomizations), and for exposure to noise and the lagged air pollution variable (Moran's $I = 0.23$, $p < 0.01$, 999 randomizations).

In addition, we calculated Global and Local Moran's I for four covariates: median household income, percentage of people of foreign origin, percentage of rental houses and the number of house moves per 1,000 inhabitants. Percentage of foreign origin is the most clustered variable (Moran's $I = 0.69$, $p < 0.01$, 999 randomizations), followed by the number of house moves (Moran's $I = 0.67$, $p < 0.01$, 999 randomizations), percentage of rental houses (Moran's $I = 0.62$, $p < 0.01$, 999 randomizations) and median household income (Moran's $I = 0.46$, $p < 0.01$, 999 randomizations). A LISA analysis for these covariates (Fig. 5) shows that especially the spatial cluster of low air pollution exposure overlaps very well with a cluster of high income, low percentage of foreign origin people, low residential mobility and a low percentage of rental houses. The spatial cluster of high air pollution exposure corresponds fairly well with the cluster of high percentage of rental houses and low residential mobility. These spatial correspondences help interpreting spatial regression models.

Correlation analysis

To get more insight into the possible explanatory value of the different covariates we first employed a bivariate correlation analysis,

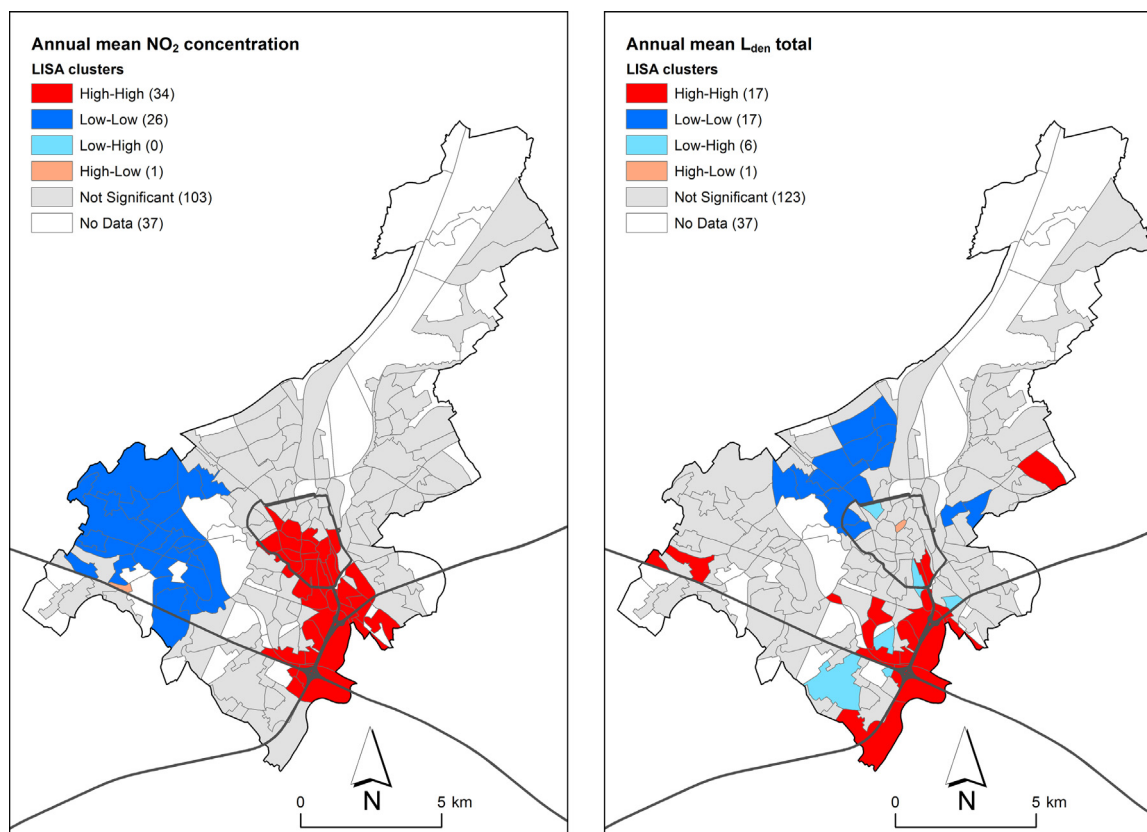


Fig. 4. Local Moran's I cluster and outlier analysis for residential exposure to air pollution (left) and noise (right) (p -value < 0.05) (highways and urban ring road added for spatial reference).

with Pearson correlation coefficients calculated at statistical sector level (Table 3).

For air pollution, moderate to strong correlations with the covariates can be noted, at least for social research (Cohen, 1988). All correlation coefficients are highly significant. A higher residential exposure to air pollution is associated with a lower median household income ($r = -0.452^{**}$), a higher unemployment rate ($r = 0.480^{**}$) and a higher share of people of foreign origin ($r = 0.464^{**}$). Remarkably the association with foreign origin is strongest for the share of people with "other origin" (mainly Asia, Africa and the Americas) and not for the important minority group with Turkish/Maghreb origin. As for housing variables, there is a relatively strong correlation of residential exposure to air pollution with the relative number of house moves per sector ($r = 0.607^{**}$) and with the percentage of rental houses ($r = 0.553^{**}$).

For noise, we only found one significant weak correlation, with the percentage of people with "other origin" ($r = 0.159^*$). This shows again that noise is much more equally spread across the city.

Multiple spatial regression

To analyze the combined effect of the covariates we applied multiple regression techniques. First, conventional ordinary least square (OLS) regression was applied, starting from a model with two covariates, median household income and percentage of people of foreign origin per statistical sector. Because of the very high correlation between income and unemployment pressure and between the different specialized foreign origin variables (Table 2), adding the other socio-economic variables would lead to unacceptably high levels of multicollinearity. Tables 4 and 5 show the multiple regression models, with NO₂ concentration and L_{den} total as the respective dependent variables. While the residuals of the models for residential noise exposure follow a

normal distribution, the residuals of the models for air pollution exposure violate this assumption (not shown in table). However, since the violation of normality is not severe, the sample is quite large, and we are mainly interested in predicting the average value for the coefficients (and not the prediction intervals), we consider the models as valid.

The first regression model for air pollution (OLS_AIR_1) is significant, with the two covariates explaining 24% of the variance ($R^2 = 0.24$, $F(2,161) = 25.26$, $p < 0.01$). We found that median household income per sector significantly predicts residential exposure to air pollution ($\beta = -0.24$, $p < 0.05$), as did percentage of people of foreign origin per sector ($\beta = 0.08$, $p < 0.01$). According to this model, the annual mean NO₂ concentration decreases with $1 \mu\text{g}/\text{m}^3$ when the median household income increases with € 4000 or when the percentage of foreign origin people decreases with 12.5%. For residential noise exposure, the regression equation (OLS_NOISE_1) turned out to be non-significant ($F(2,161) = 1.24$, $p = 0.29$).

Next, we added the two housing variables to the model. For air pollution, the regression equation (OLS_AIR_2) is again significant ($F(4,159) = 27.25$, $p < 0.01$), with an R^2 of 0.41. This means an additional 17% of the variation in residential exposure to air pollution can be explained by adding the two housing variables. Both percentage of foreign origin and median household income do not significantly contribute to the model anymore. Instead, the number of house moves turns out to be a highly significant predictor ($\beta = 0.02$, $p < 0.01$), while the contribution of the (correlated) percentage of rental houses almost reaches statistical significance ($\beta = 0.05$, $p = 0.06$). This means the relation of median household income with exposure to air pollution can largely be explained by its correlation with the housing variables. According to the model, the annual mean NO₂ concentration increases with $1 \mu\text{g}/\text{m}^3$ when there are 50 more moves per 1000 inhabitants and when the percentage of rental houses increases with 20%. Again, for residential noise exposure, the regression equation (OLS_NOISE_2) is

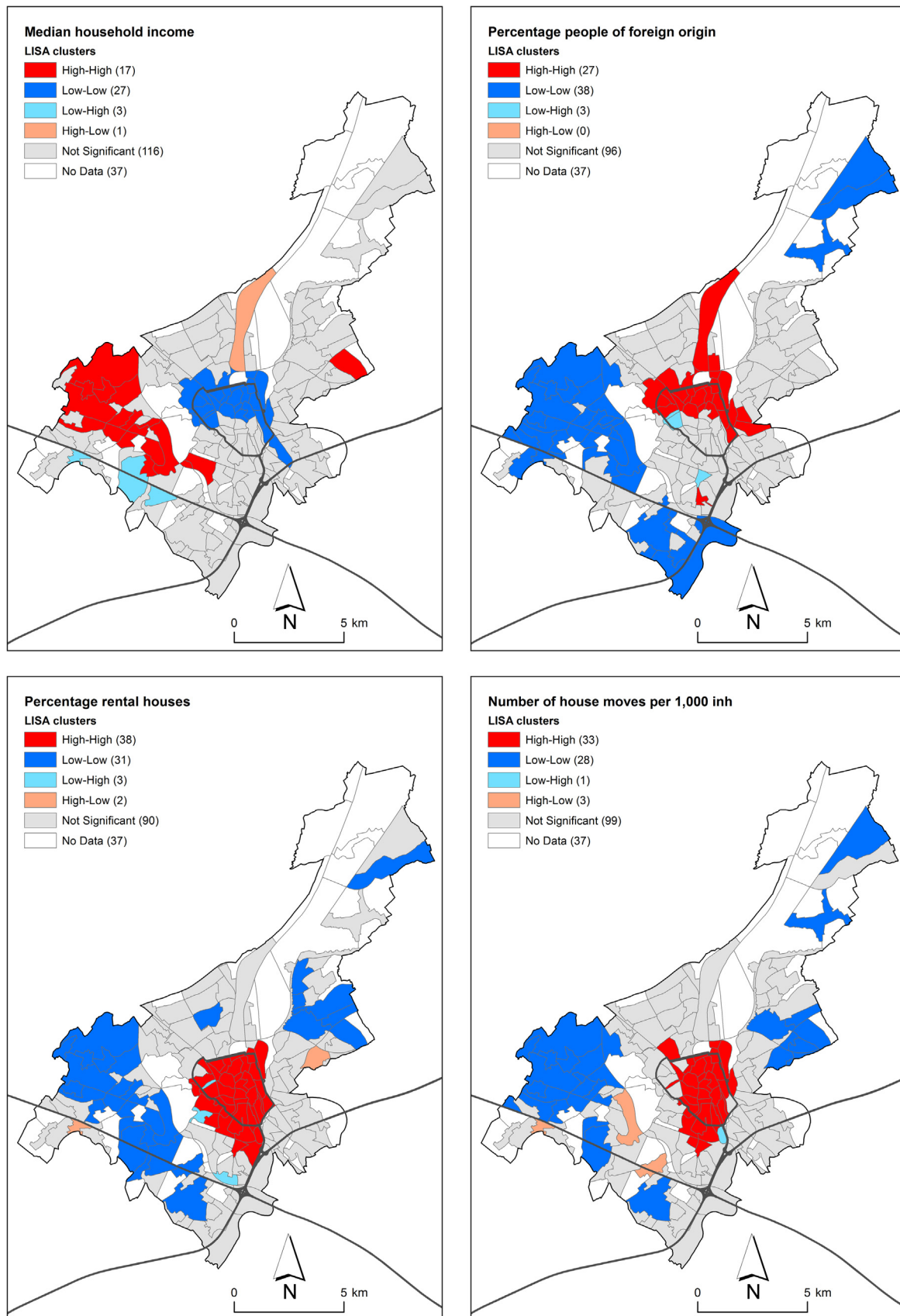


Fig. 5. Local Moran's I cluster and outlier analysis for median household income, percentage people of foreign origin, percentage of rental houses and the relative number of house moves (p -value < 0.05) (highways and urban ring road added for spatial reference).

Table 3
Correlations of covariates and environmental impact indicators (N = 164) (* correlation significant at the 0.01 level; ** correlation significant at the 0.05 level).

	Annual mean NO ₂ concentration (µg/m ³)	Annual mean L _{den} total (dB(A))
Median household income (€)	-0.451**	-0.067
Unemployment pressure (%)	0.481**	0.019
% people of foreign origin	0.463**	-0.017
% people of EU15 origin	0.298**	0.062
% people of EU13 origin	0.351**	-0.030
% people of Turkish/Maghreb origin	0.290**	-0.126
% people of other origin	0.512**	0.159*
% rental houses	0.552**	0.116
Number of house moves per 1,000 inh.	0.607**	0.141

not significant (F(4,159) = 1.81, p = 0.13), showing that noise exposure is much more equally spread across the city.

The spatial dependency tests for all OLS regression models showed significant spatial autocorrelation of the residuals in terms of the Moran's I value. This is no surprise given the significant spatial autocorrelation of both dependent variables, reported earlier. According to the higher values for the Lagrange Multiplier and Robust Lagrange Multiplier tests, spatial lag models (SL_AIR_1 and SL_AIR_2) were developed for explaining residential exposure to air pollution and spatial error models (SE_NOISE_1 and SE_NOISE_2) were developed for explaining residential exposure to noise. Again, the residuals of the models for residential exposure to noise follow a normal distribution, unlike the residuals for residential exposure to air pollution (not shown in table). Since the violation of the normality assumption is not severe, our sample is quite large, and we are mainly interested in predicting the average values for each coefficient (and not the prediction intervals), we consider the models acceptable for the aim of our study.

All four models have a substantially higher predictive power in the form of R². However, it is best to use the Akaike Information Criteria (AIC) to compare the relative quality of spatial regression models with OLS regression models. For all variable combinations the spatial regression model has a better relative quality, but the improvement is larger for the air pollution models. The AIC scores of the models with two and four covariates are almost similar, so both have a comparable quality.

Taking spatial autocorrelation into account, percentage of people of foreign origin is no significant predictor anymore. However, income is a

Table 4
Multiple OLS and spatial lag regression models for explaining NO₂ concentration (µg/m³) (N = 164) (*p < 0.05; **p < 0.01) (AIC = Akaike Information Criterion; LM = Lagrange Multiplier; RLM = Robust Lagrange Multiplier).

	OLS_AIR_1		SL_AIR_1		OLS_AIR_2		SL_AIR_2	
	β (SE)	p	B (SE)	p	B (SE)	p	B (SE)	p
Constant	30.65 (3.18)	0.000**	8.42 (2.09)	0.000**	19.96 (3.71)	0.000**	7.83 (2.43)	0.001**
Rho			0.80 (0.04)	0.000**			0.76 (0.05)	0.000**
Median household income (1,000 €)	-0.24 (0.11)	0.024*	-0.14 (0.06)	0.020*	0.00 (0.11)	0.989	-0.11 (0.07)	0.122
% people of foreign origin	0.08 (0.03)	0.007**	0.00 (0.02)	0.917	0.03 (0.03)	0.327	-0.01 (0.02)	0.568
% rental houses					0.05 (0.03)	0.060	0.00 (0.02)	0.925
Number of house moves per 1,000 inh.					0.02 (0.00)	0.000**	0.01 (0.00)	0.007**
R ²	0.24		0.76		0.41		0.77	
F statistic	25.26**				27.25**			
AIC	959.84		803.02		922.99		798.73	
Moran's I (error)	0.66**		-0.04		0.57**		-0.05	
LM (lag)	173.61**				133.54**			
LM (error)	153.90**				116.29**			
RLM (lag)	19.74**				18.17**			
RLM (error)	0.03				0.92			

significant predictor in both spatial regression models with two covariates (β = -0.14, p = 0.02* in the air pollution model; β = -0.17, p = 0.04* in the noise model). According to the spatial regression models, this means that a € 1,000 increase in median household per sector brings a decrease of 0.14 µg/m³ NO₂ concentration and of 0.17 dB(A) L_{den} total. While for noise none of the covariate coefficients is significant in the model with four covariates, this is not the case for the air pollution model. In this model the number of house moves per 1000 inhabitants is still a highly significant, though weak predictor.

In summary, it seems the two spatial regression models with two covariates have a similar outcome, with only income remaining a significant predictor after correcting for spatial autocorrelation. For air pollution, the number of house moves per sector is a robust predictor in the non-spatial and spatial models and gives important contextual information. Since the inclusion of the spatial autoregressive parameter in the spatial regression models works particularly well in predicting clustered values, coefficients only stay substantial and significant if they help explain the dependent variable where it is less clustered (i.e. the outliers and the non-significant statistical sectors in Fig. 4). The association between a higher/lower percentage of foreign origin and a higher/lower residential exposure to air pollution thus seems to be a rather localized phenomenon.

Discussion

The results of our traditional data analysis suggest some environmental inequalities in Ghent. In general, people in more deprived neighborhoods, with lower incomes, more unemployment, a higher percentage of foreign origin people (of both European and non-European background), a higher percentage of rental houses and a higher residential mobility, were more exposed to air pollution. A multiple OLS regression model showed that the number of house moves and the percentage of rental housing per statistical sector are the most important predictors. After including these variables in the model, the contribution of household income had no explanatory power anymore, proving the role of the housing market in explaining the higher exposure of lower-income neighborhoods. As for residential exposure to noise, only neighborhoods with a higher percentage of people of other foreign origin (non-EU and non-Turkish-Maghreb) had a significantly higher exposure. A multiple OLS regression model did not have a significant predictive power, which means noise is much more equally spread across different socioeconomic and housing variables.

However, after correcting the regression models for spatial autocorrelation, other results were found. Median household income proved to be a significant predictor for both environmental indicators. For air pollution, this means that the association between the variable of

Table 5

Multiple OLS and spatial error regression models for explaining L_{den} total (dB(A)) (N = 164) ($^*p < 0.05$; $^{**}p < 0.01$) (AIC = Akaike Information Criterion; LM = Lagrange Multiplier; RLM = Robust Lagrange Multiplier).

	OLS_NOISE_1		SE_NOISE_1		OLS_NOISE_2		SE_NOISE_2	
	β (SE)	p	B (SE)	p	B (SE)	p	B (SE)	p
Constant	62.29 (2.78)	0.000**	62.74 (2.44)	0.000**	59.00 (3.62)	0.000**	61.67 (3.50)	0.000**
Lambda			0.54 (0.08)	0.000**			0.54 (0.08)	0.000**
Median household income (1,000 €)	-0.14 (0.09)	0.121	-0.17 (0.08)	0.035*	-0.07 (0.11)	0.522	-0.16 (0.10)	0.117
% people of foreign origin	-0.03 (0.03)	0.190	-0.04 (0.03)	0.186	-0.05 (0.03)	0.059	-0.04 (0.03)	0.111
% rental houses					0.01 (0.03)	0.572	0.00 (0.03)	0.861
Number of house moves per 1,000 inh.					0.01 (0.00)	0.126	0.00 (0.00)	0.121
R ²	0.02		0.26		0.04		0.27	
F statistic	1.24				1.81			
AIC	916.05		880.81		915.27		882.40	
Moran's I (error)	0.35**		0.00		0.32**		0.00	
LM (lag)	42.18**				37.28**			
LM (error)	42.64**				37.61**			
RLM (lag)	0.03				0.08			
RLM (error)	0.50				0.41			

foreign origin and air pollution exposure is a localized phenomenon, which especially holds true for the spatial cluster of low air pollution, a suburban area on the southwestern outskirts of the city, with significantly less people of foreign origin. Since this association disappears after correcting for spatial autocorrelation, it does not hold true for the whole urban territory. Instead, household income turns out to be the only variable with robust predictive power across the whole urban territory. Since we found the same outcome in the spatial regression models for noise exposure but not in the OLS models, it means the clusters of high and low noise exposure values do not correspond well to clusters of high or low values of the socioeconomic and housing covariates. However, across the urban territory there is a robust inverse relation between median household income and residential noise exposure. This surprising finding confirms the need to account for spatial autocorrelation in environmental inequality studies.

In the spatial regression models with four covariates, the effect of median household income does not decrease much but loses its significance. Instead, for the air pollution model, the number of house moves remains a robust predictor, providing interesting ideas about the context of unequal exposure.

The global association of income and foreign origin with a higher exposure to air pollution is consistent with most of the European research results (Brainard et al., 2002; Briggs et al., 2008; Chaix et al., 2006; Fecht et al., 2015; Goodman et al., 2011; Jephcote & Chen, 2012). Following the advice of Havard et al. (2009), we corrected for spatial autocorrelation. In line with their findings, this led to better models but weaker coefficients, with particularly the effect of income remaining substantial and robust. The association of income with noise exposure, which we only found in the spatial regression models, adds to the limited and rather mixed evidence base of unequal exposure to noise. Our results are in line with a few other studies that found a weak association between noise exposure and socioeconomic position under specific circumstances (Brainard et al., 2004; Fyhri & Klæboe, 2006; Kruize et al., 2007). However, these studies did not correct for spatial autocorrelation.

The robust relation between household income and exposure to air pollution and noise across the entire urban area provides an important environmental justice argument. It follows that a general reduction of air pollution and noise across the entire urban area of Ghent would benefit more deprived neighborhoods the most. Moreover, as exposure is considered to interact with vulnerability, producing a "triple jeopardy", it has a bigger effect on poor people's health than on the average population (e.g. O'Neill et al., 2003; Walker, 2012), providing an additional environmental justice argument to tackle pollution at the urban level.

While housing variables were not associated with noise exposure,

they helped explain the global socioeconomic inequalities in exposure to air pollution. The higher exposure of renters to air pollution confirms the studies of Lam and Chung (2012), Grineski et al. (2007) and Chakraborty (2009). Contrasting Grineski et al.'s results, adding the percentage of rental houses to the model also substantially reduced the effect of income in our models, which could be explained by the strong association between socioeconomic vulnerability and renting in Belgium (Winters & Heylen, 2014). However, the most important housing variable in our models appeared to be the number of house moves per 1000 inhabitants, both in the non-spatial and the spatial model explaining air pollution exposure. This means that neighborhoods with a high residential mobility are significantly higher exposed to air pollution, also after correcting for spatial autocorrelation. Based on the results we cannot say whether the residential mobility is higher because of the higher air pollution exposure (and lower environmental quality) but it is an interesting coincidence which can be interpreted in a positive and negative way. On the positive side, it means that neighborhoods where a lot of people live only temporarily bear the highest exposure to air pollution. Some people might even deliberately live in a more polluted neighborhood for a while, are aware of the health consequences and will move to a less polluted neighborhood after some years. On the negative side, there will always be people who do not (or cannot) move out of these neighborhoods, and are subject to prolonged exposure to air pollution. This goes together with a generally lower sense of place attachment in neighborhoods with more rental housing and a higher residential mobility. A previous study in a noise-polluted neighborhood in Ghent found that renters who arrived more recently in the neighborhood placed lower demands on their residential environment, reported less annoyance and were less concerned about health effects (Verbeek, 2018). It is also known that homeowners tend to be more active politically on local environmental issues (Pastor, Morello-Frosch, & Sadd, 2005). This makes it a politically unrewarding strategy for a city council to focus on these areas. Because of these complex pathways, more in-depth research is needed to judge on the fairness of such a situation and whether it deserves particular policy attention.

While this study gives robust and significant results, adding to the evidence base on environmental inequalities, the data and methods also have some limitations. First, the air pollution and noise data are the result of modeling processes, starting from relatively few measurements, emission data and road traffic statistics. While the results were validated by tests on the field, the models remain an estimate of the real situation. Second, the analysis used indicators for exposure around the residential address, rather than individual exposure to air pollution or noise during the day. This spatio-temporal exposure gets more attention in recent years, since measuring equipment is getting cheaper and more convenient to use (Steinle, Reis, & Sabel, 2013). However, at the

moment in Belgium no large-scale data sets are available that take spatio-temporal exposure into account. Third, the performed analysis is cross-sectional and not longitudinal. This means no statements about causal relations can be made. The analysis points to inequalities, but does not tell how these were produced. However, the results provide an interesting starting point for longitudinal investigation based on qualitative approaches. Fourth, there is room for further exploration with more advanced statistical methods. Other spatial regression models can be applied, such as geographically weighted regression (Jephtote & Chen, 2012), which accounts for different localized relations between variables. Finally, while the simultaneous analysis of exposure to air pollution and noise with the same methodology is a strength of our analysis, the two environmental indicators were still modeled separately. There exist several interesting attempts that assessed the cumulative effect of air pollution and noise (Carrier, Apparicio, Séguin, & Crouse, 2016), examined the trade-off between accessibility and (traffic-related) air pollution (da Schio, Boussauw, & Sansen, 2018) or combined a range of nuisances and urban amenities in one environmental equity indicator (Carrier, Apparicio, Kestens, et al., 2016; Pearce et al., 2010). In this vein, the data in our analysis could form the basis for a wider environmental equity analysis for Ghent. However, it remains an open question how different environmental benefits and burdens can be combined in a single indicator, since a simple additive method, e.g. based on quantile scores, does not account for differences in impact or interaction effects.

The results add to the empirical evidence base on environmental justice and promote further discussions on the fairness of environmental impact distribution. Following Pearce and Kingham (2008, p. 991), we need to “move beyond simple regional ‘bottom line’ approaches that are focused on addressing aggregated environmental exposures, towards strategies that recognise the intraurban variability in pollution levels, prioritising remedial action for communities bearing the highest exposures”. However, assessing inequalities in the spatial and social distribution of environmental impacts is just the first step in an environmental justice analysis. Only by approaching inequalities from a pluralistic, interpretative, bottom-up and people-driven perspective, next to the top-down mapping of inequalities, environmental justice claims can be substantiated and possible trajectories for future development and improvement of the situation can be devised (Davoudi & Brooks, 2014; Walker, 2012). Although a possible explanation of inequalities is the interplay between personal preferences, personal behavior and forces operating in the public and private housing markets, also government departments can play a role. There is foremost a need to consider whether biases against certain social groups exist within the evident mechanisms driving changes in land use patterns, urbanization and development of transport corridors (Brainard et al., 2004). For example, if urban development takes place in the outer parts of the urban area, these neighborhoods will be safer from traffic and less polluted than the urban average, while inadvertently contributing to an increased overall amount of traffic and air pollution for residents living closer to downtown (Næss, 2013). In the same stance, the Ghent Mobility Plan (City of Ghent, 2015), which tries to decrease the traffic volume in as many streets as possible but inevitably increases traffic volume in some other, might be (inadvertently) biased towards specific population groups. Reporting on environmental inequalities through geospatial data analysis can be a vital element in increasing awareness about the inherent environmentally unjust mechanisms built in our current urban and spatial policies and help us understand the complexity of urban environmental pollution.

Disclosure statement

No potential conflict of interest was reported by the author.

Ethics approval

Ethics approval was not obtained since no data collected from human subjects were used in the research.

Declarations of interest

None.

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References

- AIB-Vinçotte Environment nv and GIM nv (2014). Strategische geluidsbelastingskaarten Antwerpen & Gent 2de ronde - Eindrapport (Strategic Noise Maps Antwerp & Ghent 2nd round - Final Report).
- Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, 19(6), 716–723.
- Anselin, L. (1995). Local Indicators of Spatial Association—LISA. *Geographical Analysis*, 27(2), 93–115.
- Anselin, L., & Bera, A. K. (1998). Spatial dependence in linear regression models with an introduction to spatial econometrics. In A. Ullah (Ed.), *Handbook of applied economic statistics* (pp. 237–289). Boca Raton, FL: CRC Press.
- ATMOSYS (2013). Annual air quality map service. Retrieved from: <http://www.atmosys.eu/faces/services-annual-maps.jsp>.
- Baden, B. M., Noonan, D. S., & Turaga, R. M. R. (2007). Scales of justice: Is there a geographic bias in environmental equity analysis? *Journal of Environmental Planning and Management*, 50(2), 163–185.
- Basner, M., Babisch, W., Davis, A., Brink, M., Clark, C., Janssen, S., & Stansfeld, S. (2014). Auditory and non-auditory effects of noise on health. *The Lancet*, 383(9925), 1325–1332.
- Bell, M. L., & Ebisu, K. (2012). Environmental inequality in exposures to airborne particulate matter components in the United States. *Environmental Health Perspectives*, 120(12), 1699–1704.
- Bocquier, A., Cortaredona, S., Boutin, C., David, A., Bigot, A., Chaix, B., ... Verger, P. (2013). Small-area analysis of social inequalities in residential exposure to road traffic noise in Marseilles, France. *The European Journal of Public Health*, 23(4), 540–546.
- Brainard, J. S., Jones, A. P., Bateman, I. J., & Lovett, A. A. (2004). Exposure to environmental urban noise pollution in Birmingham, UK. *Urban Studies*, 41(13), 2581–2600.
- Brainard, J. S., Jones, A. P., Bateman, I. J., Lovett, A. A., & Fallon, P. J. (2002). Modelling environmental equity: Access to air quality in Birmingham, England. *Environment and Planning A*, 34(4), 695–716.
- Briggs, D., Abellan, J. J., & Fecht, D. (2008). Environmental inequity in England: Small area associations between socio-economic status and environmental pollution. *Social Science Medicine*, 67(10), 1612–1629.
- Brulle, R. J., & Pellow, D. N. (2006). Environmental justice: Human health and environmental inequalities. *Annual Review of Public Health*, 27, 103–124.
- Carrier, M., Apparicio, P., Kestens, Y., Séguin, A.-M., Pham, H., Crouse, D., & Siemiatycki, J. (2016). Application of a global environmental equity index in Montreal: Diagnostic and further implications. *Annals of the American Association of Geographers*, 106(6), 1268–1285.
- Carrier, M., Apparicio, P., & Séguin, A.-M. (2016). Road traffic noise in Montreal and environmental equity: What is the situation for the most vulnerable population groups? *Journal of Transport Geography*, 51, 1–8.
- Carrier, M., Apparicio, P., Séguin, A.-M., & Crouse, D. (2016). The cumulative effect of nuisances from road transportation in residential sectors on the Island of Montreal – Identification of the most exposed groups and areas. *Transportation Research Part D: Transport and Environment*, 46, 11–25.
- Chaix, B., Gustafsson, S., Jerrett, M., Kristersson, H., Lithman, T., Boalt, Å., & Merlo, J. (2006). Children's exposure to nitrogen dioxide in Sweden: Investigating environmental injustice in an egalitarian country. *Journal of Epidemiology and Community Health*, 60(3), 234–241.
- Chakraborty, J. (2009). Automobiles, air toxics, and adverse health risks: Environmental inequities in Tampa Bay, Florida. *Annals of the Association of American Geographers*, 99(4), 674–697.
- City of Ghent (2010). *Lokaal Luchtkwaliteitsplan Gent 2010–2015 (Ghent Local Air Quality Plan 2010–2015)*. Gent: City of Ghent.
- City of Ghent (2014). *Stedelijk Actieplan Geluid 2014–2019 (Ghent Local Noise Action Plan 2014–2019)*. Gent: City of Ghent.
- City of Ghent (2015). *Mobiliteitsplan Gent: Strategische mobiliteitsvisie (Ghent Mobility Plan: Strategic vision on mobility)*. Gent: City of Ghent.

- Clark, L. P., Millet, D. B., & Marshall, J. D. (2014). National patterns in environmental injustice and inequality: Outdoor NO₂ air pollution in the United States. *PLoS One*, 9(4), e94431.
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. New Jersey: Lawrence Erlbaum Associates.
- Crouse, D. L., Ross, N. A., & Goldberg, M. S. (2009). Double burden of deprivation and high concentrations of ambient air pollution at the neighbourhood scale in Montreal, Canada. *Social Science Medicine*, 69(6), 971–981.
- da Schio, N., Boussauw, K., & Sansen, J. (2018). Accessibility versus air pollution: A geography of externalities in the Brussels agglomeration. *Cities*.
- Dale, L. M., Goudreau, S., Perron, S., Ragettli, M. S., Hatzopoulou, M., & Smargiassi, A. (2015). Socioeconomic status and environmental noise exposure in Montreal, Canada. *BMC Public Health*, 15(1), 205.
- Dannenberg, A. L., Frumkin, H., Jackson, R. J., Abrams, R. F., Malizia, E., Wendel, A., ... Cannuscio, C. (2012). *Making healthy places: Designing and building for health, well-being, and sustainability*. Island Press.
- Davoudi, S., & Brooks, E. (2014). When does unequal become unfair? Judging claims of environmental injustice. *Environment and Planning A*, 46(11), 2686–2702.
- Deguen, S., & Zmirou-Navier, D. (2010). Social inequalities resulting from health risks related to ambient air quality—A European review. *European Journal of Public Health*, 20(1), 27–35.
- Dormann, C. F., McPherson, J. M., Araújo, M. B., Bivand, R., Bolliger, J., Carl, G., ... Wilson, R. (2007). Methods to account for spatial autocorrelation in the analysis of species distributional data: a review. *Ecography*, 30(5), 609–628.
- Fecht, D., Fischer, P., Fortunato, L., Hoek, G., de Hoogh, K., Marra, M., ... Hansell, A. (2015). Associations between air pollution and socioeconomic characteristics, ethnicity and age profile of neighbourhoods in England and the Netherlands. *Environmental Pollution*, 198, 201–210.
- Frumkin, H. (2003). Healthy places: Exploring the evidence. *American Journal of Public Health*, 93(9), 1451–1456.
- Fyhri, A., & Klæboe, R. (2006). Direct, indirect influences of income on road traffic noise annoyance. *Journal of Environmental Psychology*, 26(1), 27–37.
- Goodman, A., Wilkinson, P., Stafford, M., & Tonne, C. (2011). Characterising socio-economic inequalities in exposure to air pollution: A comparison of socio-economic markers and scales of measurement. *Health Place*, 17(3), 767–774.
- Grineski, S., Bolin, B., & Boone, C. (2007). Criteria air pollution and marginalized populations: Environmental inequity in metropolitan phoenix, Arizona*. *Social Science Quarterly*, 88(2), 535–554.
- Hajat, A., Hsia, C., & O'Neill, M. S. (2015). Socioeconomic disparities and air pollution exposure: a global review. *Current Environmental Health Reports*, 2(4), 440–450.
- Hänninen, O., Knol, A. B., Jantunen, M., Lim, T.-A., Conrad, A., Rappolder, M., ... Mekel, O. C. L. (2014). Environmental burden of disease in Europe: Assessing nine risk factors in six countries. *Environmental Health Perspectives*, 122(5), 439–446.
- Havard, S., Deguen, S., Zmirou-Navier, D., Schillinger, C., & Bard, D. (2009). Traffic-related air pollution and socioeconomic status: A spatial autocorrelation study to assess environmental equity on a small-area scale. *Epidemiology*, 20(2), 223–230.
- Havard, S., Reich, B. J., Bean, K., & Chaix, B. (2011). Social inequalities in residential exposure to road traffic noise: An environmental justice analysis based on the RECORD Cohort Study. *Occupational and Environmental Medicine*, 68(5), 366–374.
- Health Effects Institute (2010). *Traffic-related air pollution: A critical review of the literature on emissions, exposure, and health effects (Special Report 17)*. Boston, MA: Health Effects Institute.
- Jackson, R. J. (2003). The impact of the built environment on health: An emerging field. *American Journal of Public Health*, 93(9), 1382–1384.
- Jephcote, C., & Chen, H. (2012). Environmental injustices of children's exposure to air pollution from road-transport within the model British multicultural city of Leicester: 2000–09. *Science of The Total Environment*, 414, 140–151.
- Kingham, S., Pearce, J., & Zawar-Reza, P. (2007). Driven to injustice? Environmental justice and vehicle pollution in Christchurch, New Zealand. *Transportation Research Part D: Transport and Environment*, 12(4), 254–263.
- Kohlhuber, M., Mielck, A., Weiland, S. K., & Bolte, G. (2006). Social inequality in perceived environmental exposures in relation to housing conditions in Germany. *Environmental Research*, 101, 246–255.
- Kruize, H., Driessen, P. P. J., Glasbergen, P., & van Egmond, K. (2007). Environmental equity and the role of public policy: Experiences in the Rijnmond region. *Environmental Management*, 40(4), 578–595.
- Lam, K.-c. & Chung, Y.-t T. (2012). Exposure of urban populations to road traffic noise in Hong Kong. *Transportation Research Part D: Transport and Environment*, 17(6), 466–472.
- Laurent, O., Bard, D., Filleul, L., & Segala, C. (2007). Effect of socioeconomic status on the relationship between atmospheric pollution and mortality. *Journal of Epidemiology and Community Health*, 61(8), 665–675.
- Lefebvre, W., Degrawe, B., Beckx, C., Vanhulsel, M., Kochan, B., Bellemans, T., ... Dhondt, S. (2013). Presentation and evaluation of an integrated model chain to respond to traffic- and health-related policy questions. *Environmental Modelling Software*, 40(0), 160–170.
- Mitchell, G., & Dorling, D. (2003). An environmental justice analysis of British air quality. *Environment and Planning A*, 35(5), 909–929.
- Næss, P. (2013). Urban form, sustainability and health: The case of greater Oslo. *European Planning Studies*, 1–20.
- Nega, T. H., Chihara, L., Smith, K., & Jayaraman, M. (2013). Traffic noise and inequality in the twin cities, Minnesota. *Human and Ecological Risk Assessment*, 19(3), 601–619.
- O'Neill, M. S., Jerrett, M., Kawachi, I., Levy, J. I., Cohen, A. J., Gouveia, N., ... Schwartz, J. (2003). Health, wealth, and air pollution: Advancing theory and methods. *Environmental Health Perspectives*, 111(16), 1861–1870.
- Padilla, C. M., Kihal-Talantikite, W., Vieira, V. M., Rossello, P., Nir, G. L., Zmirou-Navier, D., & Deguen, S. (2014). Air quality and social deprivation in four French metropolitan areas—a localized spatio-temporal environmental inequality analysis. *Environmental Research*, 134, 315–324.
- Pastor, M., Morello-Frosch, R., & Sadd, J. L. (2005). The air is always cleaner on the other side: Race, space, and ambient air toxics exposures in California. *Journal of Urban Affairs*, 27(2), 127–148.
- Pearce, J., & Kingham, S. (2008). Environmental inequalities in New Zealand: A national study of air pollution and environmental justice. *Geoforum*, 39(2), 980–993.
- Pearce, J., Richardson, E. A., Mitchell, R. J., & Shortt, N. K. (2010). Environmental justice and health: The implications of the socio-spatial distribution of multiple environmental deprivation for health inequalities in the United Kingdom. *Transactions of the Institute of British Geographers*, 35(4), 522–539.
- Riedel, N., Scheiner, J., Müller, G., & Köckler, H. (2014). Assessing the relationship between objective and subjective indicators of residential exposure to road traffic noise in the context of environmental justice. *Journal Of Environmental Planning and Management*, 57(9), 1398–1421.
- Schweitzer, L., & Valenzuela, A. (2004). Environmental injustice and transportation: The claims and the evidence. *Journal of Planning Literature*, 18(4), 383–398.
- Steinle, S., Reis, S., & Sabel, C. E. (2013). Quantifying human exposure to air pollution—Moving from static monitoring to spatio-temporally resolved personal exposure assessment. *Science of The Total Environment*, 443, 184–193.
- Su, J. G., Larson, T., Gould, T., Cohen, M., & Buzzelli, M. (2010). Transboundary air pollution and environmental justice: Vancouver and Seattle compared. *GeoJournal*, 75(6), 595–608.
- Suades-González, E., Gascon, M., Guxens, M., & Sunyer, J. (2015). Air pollution and neuropsychological development: A review of the latest evidence. *Endocrinology*, 156(10), 3473–3482.
- Verbeek, T. (2018). The relation between objective and subjective exposure to traffic noise around two suburban highway viaducts in Ghent: Lessons for urban environmental policy. *Local Environment*, 23(4), 448–467.
- Walker, G. (2012). *Environmental justice: Concepts, evidence and politics*. London: Routledge.
- WG-AEN (2007). *Good Practice Guide for Strategic Noise Mapping and the Production of Associated Data on Noise Exposure*.
- WHO (1999). *Guidelines for community noise*. Geneva: WHO.
- Winters, S., & Heylen, K. (2014). How housing outcomes vary between the Belgian regions. *Journal of Housing and the Built Environment*, 29(3), 541–556.