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# Association of air pollution and green space with all-cause general practitioner and emergency room visits: A cross-sectional study of young people and adults living in Belgium

Arthur Vranken [a,b], Esmée Bijnens [c,d], Christian Horemans [a], Agnès Leclercq [a], Wies Kestens [a], Güngör Karakaya [a], Ludo Vandenthoren [a], Elke Trimpeneers [e], Charlotte Vanpoucke [e], Frans Fierens [e], Tim Nawrot [f,g], Bianca Cox [h], Luk Bruyneel [a,b,*]

[a] *Independent Health Insurance Funds, Lenniksebaan 788a, 1070, Anderlecht, Belgium*
[b] *Institute for Healthcare Policy, KU Leuven, Kapucijnenvoer 35, Leuven, Belgium*
[c] *Centre for Environmental Sciences, Hasselt University, Agoralaan Building D, 3590, Diepenbeek, Belgium*
[d] *Department of Environmental Sciences, Open University Heerlen, Valkenburgerweg 177, 6419, AT Heerlen, the Netherlands*
[e] *Belgian Interregional Environment Agency, Brussels, Belgium*
[f] *Centre for Environmental Sciences, Hasselt University, Diepenbeek, Belgium*
[g] *Centre for Environment and Health, KU Leuven, Leuven, Belgium*
[h] *VITO Health, Flemish Institute for Technological Research (VITO), Mol, Belgium*

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## ABSTRACT

*Background:* Residing in areas with lower levels of air pollution and higher green space is beneficial to physical and mental health. We investigated associations of $PM_{2.5}$, tree cover and grass cover with in-hours and out-of-hours GP visits and ER visits, for young people and adults. We estimated potential cost savings of GP visits attributable to high $PM_{2.5}$.

*Methods:* We linked individual-level health insurance claims data of 315,123 young people (10–24 years) and 885,988 adults (25–64 years) with census tract-level $PM_{2.5}$, tree cover and grass cover. Deploying negative binomial generalized linear mixed models, we estimated associations between quartile exposures and the three outcome measures.

*Results:* For in-hours and out-of-hours GP visits, among young people as well as adults, statistically significant pairwise differences between quartiles suggested increasing beneficial effects with lower $PM_{2.5}$. The same outcomes were statistically significantly less frequent in quartiles with highest tree cover (>30.00%) compared to quartiles with lower tree cover, but otherwise pairwise differences were not statistically significant. These associations largely persisted in rural and urban areas. Among adults living in urban areas lower grass cover was associated with increased in-hours GP visits and ER visits. Assuming causality, reducing $PM_{2.5}$ levels to the lowest quartile (4.91–7.49 $\mu g/m^3$), among adults, 195,964 in-hours and 74,042 out-of-hours GP visits could be avoided annually. Among young people, 27,457 in-hours and 22,423 out-of-hours GP visits could be avoided annually. Nationally, this amounts to an annual potential cost saving of €43 million (€5.7 million in out-of-pocket payments and €37.2 million in compulsory health insurance).

*Conclusion:* Higher ambient $PM_{2.5}$ and lower tree cover show associations with higher non-urgent and urgent medical care utilization. These findings confirm the importance of reducing air pollution and fostering green zones, and that such policies may contribute positively to economic growth.

## 1. Background and objective

Lower air pollution concentrations and more residential green space have both been associated with lower mortality rates and various health benefits (Nguyen et al., 2021; Orellano et al., 2020). Air pollution, and specifically fine particulate matter ($PM_{2.5}$), is associated with a range of

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* Corresponding author. Independent Health Insurance Funds, Lenniksebaan 788a, 1070, Anderlecht, Belgium.
*E-mail address:* luk.bruyneel@mloz.be (L. Bruyneel).

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adverse health outcomes, like cardiovascular, cerebrovascular, metabolic and respiratory diseases, as well as all-cause mortality, mental health problems, adverse birth outcomes, and hospital admissions (Orellano et al., 2020; Boogaard et al., 2022; WHO Regional Office for Europe, 2013; Abed Al Ahad et al., 2020). Availability of green space on the other hand is linked with a number of mental and physical health benefits, particularly with cardiovascular disease, respiratory conditions, and diabetes (Nguyen et al., 2021; Geneshka et al., 2021). Most of these studies do not differentiate between tree and grass cover, although evidence indicates that trees are more often linked with beneficial health effects (Nguyen et al., 2021). In Belgium, two ecological studies on green space, air pollution and medication sales found forest cover to be associated with decreased cardiovascular medication sales (Aerts et al., 2020a), whereas grassland and garden cover were associated with increased medication sales for childhood asthma (Aerts et al., 2020b), after adjustment for air pollution. Further, people in urban areas seem to be have more benefits of green space compared to rural areas (Browning et al., 2022).

Health care utilization associated with residential air pollution and green space has not been studied as extensively. Higher $PM_{2.5}$ has been associated with a higher number of general practitioner (GP) visits for asthma (Yamazaki et al., 2015) and respiratory conditions (Ashworth et al., 2021), and with emergency room (ER) visits for chronic obstructive pulmonary disease (COPD) and upper respiratory diseases (Szyszkowicz et al., 2018) as well as asthma (Anenberg et al., 2018). In addition, indicators of green space, e.g. tree cover and proximity, are associated with ER visits related to asthma and mental health on census level (Kim and Ahn, 2021; Douglas et al., 2019; Yoo et al., 2022). However, to our knowledge, no studies have investigated the joint associations of air pollution and green space with GP visits.

The objective of this study was to estimate spatial associations of $PM_{2.5}$, tree cover and grass cover with all-cause non-urgent and urgent medical care among young people and adults by means of a population-wide cross-sectional analysis of individual-level health insurance claims data. In contrast to many previous studies, associations with air pollution and green space were assessed jointly, and we allowed for non-linear exposure-response associations. We also assessed effect modification by urbanization. Finally, we estimated the direct costs of air pollution exposure in terms of expenditure on out-of-pocket payments and compulsory health insurance.

## 2. Methods

### 2.1. Study population

The study population comprises members of the Independent Health Insurance Funds. Being one of the seven recognized health insurance funds in Belgium, it represents approximately two million members, or 19% of the Belgian population. Included in our analysis are members with a Belgian residence and living at the same census tract during the study period (January 1, 2019 to December 31, 2019). Our focus is on young people, which cover the age range from 10 to 24 years (applying the definition from the World Health Organization) and adults from 25 to 64 years.

We included 315,123 young people and 885,988 adults living at the same census tract throughout 2019. Outcomes with extreme outcome values (>99.99 percentile) were removed (82 young people and 325 adults), leaving 315,041 young people and 885,663 adults for analysis. These persons lived in 16,103 census tracts and 17,913 census tracts, respectively.

### 2.2. Exposure measures

Average concentrations of $PM_{2.5}$ for 2019 at the level of the census tract are calculated from modelled data provided by the Belgian Interregional Environment Agency (Irceline). Irceline gathers the air pollutant monitoring data from the Belgian regional telemetric air quality networks. Seventy-three monitoring stations continuously measured the concentrations of $PM_{2.5}$ in 2019. The modelled data used in this study originate from ATMO-Street, an integrated model chain that models air quality at high resolution, starting from the monitoring data. More information on the air pollution model is described by Lefebvre et al. (2013). In brief, the integrated model chain consists of an advanced measurement interpolation model, a biGaussian plume model and a canyon model to simulate the street-level concentrations. This integrated model chain is able to assess the air quality at the local (street level) scale, including both regional variability as well as local variation in sources of air pollution. The results of this model chain were evaluated for $NO_2$ since this pollutant is influenced by local emissions. The model was compared against independent weekly averaged measurements at 49 locations in the city of Antwerp, during both a late autumn and a late spring week. It is shown that the model performed well, explaining between 62% and 87% of the spatial variance, with a root mean squared error between 5 and 6 $\mu gm^{-1}$ and small biases.

Green space measures are derived from High Resolution Layers from the Copernicus Land Monitoring Service. Percentages of tree cover and grass cover for each census tract in Belgium in 2018 were computed from Dominant Leaf Type and Grassland 10 × 10 m raster data respectively, using ArcGIS 10.7.1 (Copernicus Land Monitoring Service, 2023).

Measures of air pollution and green space were assessed as categorical predictors. For $PM_{2.5}$, quartiles were constructed for values as follows: min-Q1, Q1-median, median-Q3 and Q3-max, rounded to the nearest half. For grass and tree cover, categories were constructed as follows: min-10%, 10%–20%, 20%–30%, 30%-max, with 10%, 20% and 30% corresponding closely to Q1, the median and Q3, respectively.

### 2.3. Outcome measures

Non-urgent and urgent medical care utilization were measured from routinely collected health care expenditure data. The database contains individual-level administrative and accounting data of medical care provided to a person on a given date. These data include the amount covered by compulsory health insurance and, if applicable, the out-of-pocket payment. Using reimbursement data for the year 2019, three count outcomes were created. Non-urgent medical care utilization was measured by calculating for each member the number of in-hours GP visits. In-hours GP visits include consultations in the GP consulting room or visits by a GP during regular hours. Urgent medical care utilization was measured in two ways. We calculated both the number of out-of-hours GP visits as well as the number of hospital ER visits. Out-of-hours GP visits occur in the evening (after 6p.m.), night (between 9p.m. and 8a.m.) or in the weekend. Even though since December 2011, the patient share of supplementary fees for out-of-hours GP consultations is fully reimbursed for all patients to reduce unnecessary reliance on hospital emergency departments (Farfan-Portet et al., 2012), there might still be substitution between primary care and hospital care to seek urgent medical help. Appendix 1 details the methods for constructing each outcome.

### 2.4. Potential confounders

Individual-level characteristics included in the analysis are age and gender (male, female). These member characteristics are routinely available within the databases of the Independent Health Insurance Funds (Chi et al., 2022a; Aerts et al., 2020c).

At the level of the census tract, we adjusted for urban-rural differences, categorized as having a population density (in the year 2019) of more or less than 600 inhabitants/$km^2$ at the level of the census tract, respectively. We also adjusted for indicators of socioeconomic status (SES) that have previously been used in studies assessing the association between air pollution, green space and medication sales in Belgium: the percentage of foreign-born inhabitants from lower- and middle-income countries, the percentage of unemployment, and the percentage of low educated persons (Chi et al., 2022a; Aerts et al., 2020c). These are derived from the 2011 Belgian census, which was based on linking various national administrative databases. The definition of indicators adhered to Regulation (ec) no 763/2008 of the European Parliament and of the Council of 9 July 2008 on population and housing censuses.

Last, we included administrative arrondissements as a potential source of spatial dependencies. The 43 administrative arrondissements are an administrative level between the municipalities and provinces.

### 2.5. *Statistical analysis*

First, we constructed generalized linear mixed models (GLMM) with a random intercept for census tract to assess the associations of $PM_{2.5}$, grass cover, and tree cover with the three outcomes. GLMM allows modelling and partitioning the covariance structure of the outcomes within and between census tracts, thereby acknowledging that contextual factors may alter the relationship between the measured variables and their population effect. Because the three count outcomes showed a long positive tail to the distribution, we assessed overdispersion by comparing the fit of a GLMM with empty means applying either Poisson or negative binomial conditional distributions (Appendix 2). Based on these findings, we subsequently fitted a negative binomial GLMM for all three outcomes separately, as shown in Equation 1.

$$y_{ic} \sim NB(\mu_{ic}, \alpha)$$

$$\mu_{ic} = exp(\beta_o + x_{1ic}{}'\beta_1 + x_{2c}{}'\beta_2 + x_{3c}\beta_3 + u_c) \tag{1}$$

where $y_{ic}$ is the number of visits by person $i$ in census tract $c$. $NB(u_{ic}, \alpha)$ denotes the negative binomial distribution with mean $u_{ic}$ and dispersion parameter $\alpha$. $x_{1ic}{}'$ represents the individual-level variables (age, gender) and $\beta_1$ their regression coefficients. $x_{2c}{}'$ represents the group-level variables (exposure measures of air pollution and green space, rural-urban differences and indicators of socioeconomic status) for census tract c and $\beta_2$ their regression coefficients. $x_{3c}$ represents arrondissements and $\beta_3$ the corresponding regression coefficients. $u_c$ represents the random intercept term for the c-th census tract, assumed to be normally distributed with mean zero and variance τˆ2.

We started by modelling $PM_{2.5}$, grass cover and tree cover separately. In the main analysis, $PM_{2.5}$, grass cover and tree cover were modelled jointly. All models were constructed for young people and adults separately. The estimation method was Maximum Likelihood with Adaptive Quadrature.

Second, main regression models were stratified by urban-rural differences.

Third, we conducted several sensitivity analyses. As an alternative to GLMM, we fitted marginal models via generalized estimating equations (GEE). Using such population average model, we describe changes in the population mean given changes in air pollution and green space, while accounting for within-census tract nonindependence of observations when deriving the variability estimates of these coefficients (Hubbard et al., 2010). This type of sensitivity analysis included the same set of potential confounders as in GLMM. We also fitted generalized linear models with exposure measures, potential confounders and outcomes at the census tract level. We therefore calculated the average value for all outcomes at the census tract level as well as the average age of study subjects within the census tract and the proportion of males in the census tract. Other potential confounders were the same as in GLMM and GEE.

The least squares means (LS Means, predicted population margins) were calculated for the main model. In GLMM, these represent the median for the outcome by each level of the categorical predictor, adjusted for means of other predictors in the model. We computed LS Means estimates and confidence limits on the inverse linked scale and maintained the proportions that are represented in the original data. We conducted an analysis of all pairwise comparisons between the LS Means. Adjusted confidence intervals for multiple comparisons were computed with the Tukey-Kramer method.

Using the LS Means, we estimated the number of GP visits and direct cost that can be avoided if all census tracts moved to the lowest $PM_{2.5}$ quartile. We calculated the number of visits that can be avoided from living in lowest quartile census tracts, by taking the product of the study population living within other census tracts and the respective LS Means and subtracting from this the product of the study population living within those other census tracts and the LS Means from the lowest quartile census tract. Direct costs were then calculated by taking the product of the number of GP visits that can be avoided with the average out-of-pocket payments and the amount covered by compulsory health insurance. Our focus was on the cost of air pollution on in-hours and out-of-hours GP visits as these associations proved consistent and since air pollution presents a modifiable risk factor that could be targeted through multiple policy measures. Moreover, the cost of ER visits is more difficult to fully estimate.

The data analysis for this paper was generated using SAS software.

## 3. Results

### 3.1. *Descriptives*

In the sample of young people, the mean age was 16.7 (SD = 4.2) years and 49.4% were female. In the sample of adults, the mean age was 45.3 (SD = 11.0) years and 52.1% were female.

Green space and air pollution varied greatly between census tracts as shown in Table 1 and visually depicted in Appendix 3. In rural areas, air pollution levels are lower and green space is more frequent, but variation across census tracts persists. The largest Pearson correlation was observed between grass cover and $PM_{2.5}$ ($r = -0.41$) (Table 1).

The number of in-hours GP visits in 2019 totaled to 656,174 (mean = 2.08) for young people and 2,918,005 (mean = 3.29) for adults. Out-of-hours GP visits totaled to 128,551 (mean = 0.41) for young people and 398,557 (mean = 0.45) for adults. ER visits totaled to 118,470 (mean = 0.38) for young people and 410,799 (mean = 0.46) for adults. Fig. 1 presents the distribution of the outcomes for young people and adults, illustrating the overdispersion for which we applied negative binomial regression.

### 3.2. *Associations of air pollution and green space with GP and ER visits*

Table 2 (young people) and 3 (adults) present findings for the main model with $PM_{2.5}$, tree cover and grass cover modelled jointly.

Compared to census tracts with $PM_{2.5}$ ranging from 4.91 to 7.49 μg/m$^3$, in-hours and out-of-hours GP visits as well as ER visits were statistically significantly higher in census tracts with higher $PM_{2.5}$, among young people as well as among adults, with the exception of ER visits among adults in census tracts with highest $PM_{2.5}$. There were more ER visits among young people, more in-hours GP visits among adults, and more out-of-hours GP visits among adults and young people in census tracts with tree cover lower than 30.00%. Also, in-hours GP visits were more frequent in young people living in census tracts with lowest tree cover, compared to census tracts with highest tree cover. In adults, less grass cover was associated with more in-hours GP visits and ER visits. Also, ER visits were more frequent in young people living in census tracts with lowest grass cover, compared to census tracts with highest grass cover. Tukey-adjusted LS Means differences (Appendix 4) suggest that the associations between $PM_{2.5}$ and in-hours GP visits among young people and adults, and between $PM_{2.5}$ and out-of-hours GP visits among young people and adults, were statistically significant and consistent across multiple quartiles of census-tract level exposure measures. That is, pairwise differences between quartiles suggested increasing beneficial effects with lower $PM_{2.5}$. For example, in adults, in-hours GP visits were more frequent in census tracts with $PM_{2.5}$ ranging between 7.50

**Table 1**
Variation across census tracts and correlation between air pollution and green space.

| | Variation across census tracts | | | | | | | | Pearson correlation coefficients | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | IQR | Min | Q1 | Median | Q3 | Max | $PM_{2.5}$ | Tree cover | Grass cover |
| $PM_{2.5}$, μg/m$^3$ | 9.8 | 2.5 | 4.6 | 4.9 | 7.5 | 10.1 | 12.1 | 14.6 | 1 | | |
| Tree cover, % | 23.2 | 16.9 | 19.2 | 0.0 | 11.2 | 18.9 | 30.4 | 99.5 | −0.21 | 1 | |
| Grass cover, % | 20.0 | 15.4 | 21.9 | 0.0 | 7.6 | 17.5 | 29.4 | 85.0 | −0.41 | −0.12 | 1 |

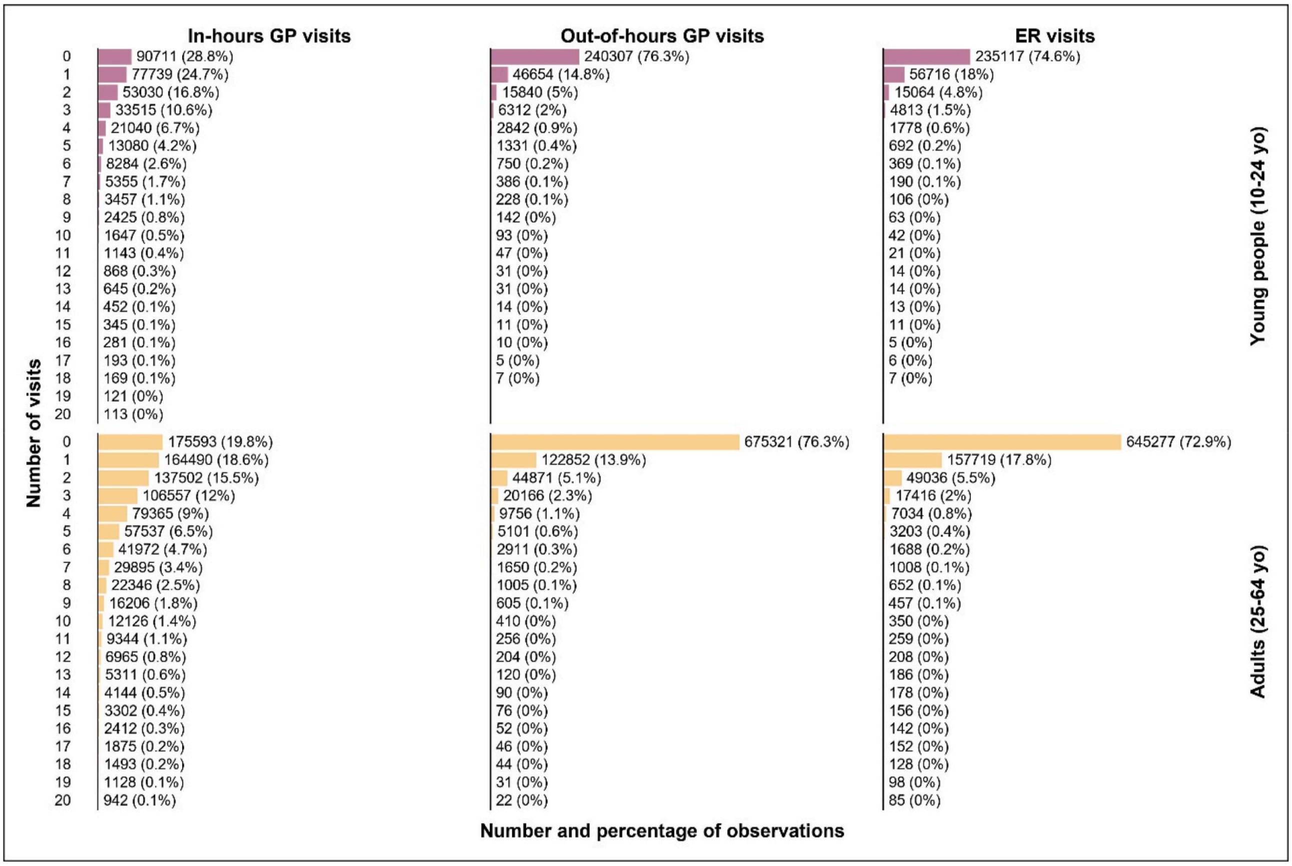

**Fig. 1.** Distribution of the number of in-hours GP visits, out-of-hours GP visits and ER visits for young people and adults. Note: A cut-off at 20 visits was applied for visualization purposes. The maximum number of in-hours GP visits equaled 41 for young people and 68 for adults. The maximum number of out-of-hours GP visits equaled 18 for young people and 25 for adults. The maximum number of ER visits equaled 18 for young people and 25 for adults.

and 9.99 μg/m$^3$, between 10.00 and 11.99 μg/m$^3$, and between 12.00 and 14.64 μg/m$^3$, compared to census tracts with $PM_{2.5}$ ranging from 4.91 to 7.49 μg/m$^3$. In addition, in-hours GP visits were more frequent in census tracts with $PM_{2.5}$ ranging between 10.00 and 11.99 μg/m$^3$ and between 12.00 and 14.64 μg/m$^3$, compared to census tracts with $PM_{2.5}$ ranging between 7.50 and 9.99 μg/m$^3$. And in-hours GP visits were more frequent in census tracts with $PM_{2.5}$ ranging between 12.00 and 14.64 μg/m$^3$, compared to census tracts with $PM_{2.5}$ ranging between 10.00 and 11.99 μg/m$^3$. The LS Means on the inverse linked scale and maintaining the proportions that are represented in the original data facilitate interpretation of the large advantage from living in census tracts with less $PM_{2.5}$. The median number of in-hours GP visits equaled 2.96 in census tracts with $PM_{2.5}$ ranging between 4.91 and 7.49 μg/m$^3$, 3.10 in census tracts with $PM_{2.5}$ ranging between 7.50 and 9.99 μg/m$^3$, 3.20 in census tracts with $PM_{2.5}$ ranging between 10.00 and 11.99 μg/m$^3$, and 3.30 in census tracts with $PM_{2.5}$ ranging between 12.00 and 14.64 μg/m$^3$.

Detailed findings for the other fixed effects included in the main models are displayed in Appendix 4. Medical care utilization was higher among older persons and lower among males (except for ER visits in young people). In-hours GP visits were more frequent in urban areas. ER visits were also more frequent in urban areas, but among adults only. In census tracts with a higher percentage of unemployment and a higher percentage of low educated persons, medical care utilization was higher. The direction and magnitude of the associations with the three outcomes were largely consistent with the findings from exposure measures modelled separately (Appendix 5).

In null models, the variance of the random census tract intercepts was estimated as 0.034 and 0.053 (in-hours GP visits), 0.669 and 0.714 (out-of-hours GP visits) and 0.067 and 0.067 (ER visits), for adults and young people, respectively. In the main models including the exposures jointly, the variance of the random census tract intercepts was estimated as 0.017 and 0.033 (in-hours GP visits), 0.145 and 0.178 (out-of-hours GP visits) and 0.031 and 0.032 (ER visits), for adults and young people, respectively. The low values indicate that the median values from the LS Means correspond very closely with the mean values.

Analyses stratified by urban-rural differences (Appendix 6) showed that in young people the association between $PM_{2.5}$ and in-hours GP visits persisted in urban census tracts. Nevertheless, also for rural census tracts with highest $PM_{2.5}$ an association persisted. A similar conclusion

**Table 2**

Young people – negative binomial generalized linear mixed models estimating the association between air pollution, green space and all-cause non-urgent and urgent medical care utilization.

| | | | In-hours GP visits | | | Out-of-hours GP visits | | | ER visits | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | n census tracts | Study pop. | Est (95% CI) | Crude means | Least square means | Est (95% CI) | Crude means | Least square means | Est (95% CI) | Crude means | Least square means |
| **$PM_{2.5}$, μg/m$^3$** | | | | | | | | | | | |
| 4.91–7.49 | 3653 | 30,670 | Ref | 2.13 | 1.90 | Ref | 0.22 | 0.23 | Ref | 0.38 | 0.33 |
| 7.50–9.99 | 4095 | 85,917 | 0.034 (0.008–0.059) | 2.13 | 1.96 | 0.136 (0.074–0.198) | 0.20 | 0.26 | 0.098 (0.058–0.139) | 0.41 | 0.36 |
| 10.00–11.99 | 3794 | 93,745 | 0.046 (0.009–0.083) | 1.94 | 1.99 | 0.369 (0.285–0.453) | 0.42 | 0.33 | 0.111 (0.055–0.167) | 0.37 | 0.37 |
| 12.00–14.64 | 4561 | 104,709 | 0.092 (0.051–0.133) | 2.16 | 2.08 | 0.372 (0.281–0.463) | 0.62 | 0.33 | 0.118 (0.055–0.181) | 0.35 | 0.37 |
| **Tree cover, %** | | | | | | | | | | | |
| 30.00–99.46 | 4012 | 86,895 | Ref | 1.98 | 1.98 | Ref | 0.33 | 0.29 | Ref | 0.36 | 0.35 |
| 20.00–29.99 | 3491 | 75,074 | 0.015 (−0.001–0.032) | 2.11 | 2.01 | 0.059 (0.024–0.094) | 0.40 | 0.30 | 0.035 (0.010–0.060) | 0.38 | 0.37 |
| 10.00–19.99 | 5282 | 99,431 | 0.012 (−0.004–0.028) | 2.10 | 2.00 | 0.063 (0.029–0.097) | 0.46 | 0.31 | 0.037 (0.013–0.062) | 0.38 | 0.37 |
| 0–9.99 | 3318 | 53,641 | 0.029 (0.010–0.048) | 2.18 | 2.03 | 0.070 (0.030–0.109) | 0.43 | 0.31 | 0.046 (0.017–0.076) | 0.39 | 0.37 |
| **Grass cover, %** | | | | | | | | | | | |
| 30.00–84.98 | 3671 | 39,409 | Ref | 2.03 | 1.99 | Ref | 0.40 | 0.30 | Ref | 0.36 | 0.35 |
| 20.00–29.99 | 3192 | 46,605 | 0.007 (−0.013–0.027) | 2.04 | 2.00 | 0.037 (−0.005–0.079) | 0.47 | 0.31 | 0.031 (−0.001–0.064) | 0.37 | 0.36 |
| 10.00–19.99 | 4034 | 71,255 | 0.010 (−0.009–0.030) | 2.09 | 2.01 | 0.030 (−0.011–0.071) | 0.46 | 0.31 | 0.022 (−0.009–0.053) | 0.37 | 0.36 |
| 0–9.99 | 5206 | 157,769 | 0.007 (−0.013–0.027) | 2.11 | 2.00 | −0.019 (−0.062–0.024) | 0.37 | 0.29 | 0.035 (0.003–0.068) | 0.39 | 0.37 |

Note: Models are for each outcome separately and all measures of air pollution and green space jointly. All models include a random intercept for census tract and fixed effects for age and gender at the individual level, urban-rural differences and indicators of SES (the percentage of foreign-born inhabitants from lower- and middle-income countries, the percentage of unemployment, and the percentage of low educated persons) at the census tract level, and administrative arrondissement. Estimates (Est) represent the difference in the logs of expected counts of the outcomes relative to the reference category (Ref) given the other variables are held constant in the model. Confidence Intervals (CI) for LS Means are not presented since the overlap (or lack thereof) between two confidence intervals does not give sufficient information about whether the difference between the means is significant at the α level. Claims of statistical significance are based on the solution for the fixed-effects parameters. CI that do not contain 0 indicate significant differences. For multiple comparisons of LS Means, we refer to Appendix 4.

can be made for the association between tree cover and in-hours GP visits in adults. For the latter, associations between $PM_{2.5}$ and in-hours GP visits persisted in rural as well as urban areas. The previous observation from the main model that in-hours GP visits were more frequent in young people living in census tracts with lowest tree cover, was confirmed in urban areas. For adults, associations between grass cover and in-hours GP visits consistently persisted in urban areas only. Associations between $PM_{2.5}$ and out-of-hours GP visits persisted across urban and rural areas for both groups of interest. The same can be said for the association between tree cover and out-of-hours GP visits among adults. For young people, this association was less consistent for census tracts with more than 10% tree cover, but consistently observed for urban and rural census tracts with lowest tree cover. For grass cover, the association with out-of-hours GP visits was ambiguous. For ER visits, associations with $PM_{2.5}$ and tree cover persisted among young people living in urban census tracts, whereas for adults consistent associations were only observed with grass cover in urban census tracts.

Estimates from GEE sensitivity analyses (Appendix 7) were generally very close to those from GLMM. Generalized linear models were constructed for census tract-level analyses. These also largely confirmed the associations between exposure measures and in-hours and out-of-hours GP visits in particular.

Finally, we estimated the number of visits and direct cost of in-hours and out-of-hours GP visits that could be avoided if all census tracts moved to the lowest quartile of $PM_{2.5}$ (Fig. 2). Among adults, 195,964 in-hours GP visits and 74,042 out-of-hours visits could be avoided. The number of avoided in-hours GP visits represents a potential saving of €4,249,247 in compulsory insurance and €698,735 in out-of-pocket payments. The number of avoided out-of-hours GP visits represents a potential saving of €2,014,502 in compulsory insurance and €268,466 in out-of-pocket payments. Among young people, 27,457 in-hours GP visits (in urban areas only) and 22,423 out-of-hours visits could be avoided. The number of avoided in-hours GP visits represents a potential saving of €577,952 in compulsory insurance and €97,614 in out-of-pocket payments. The number of avoided out-of-hours GP visits represents a potential saving of €591,842 in compulsory insurance and €82,310 in out-of-pocket payments. Thus, healthcare expenditure of close to €8.6 million (€1,147,125 million in out-of-pocket payments and €7,433,543 million in compulsory health insurance) could be saved annually. Extrapolating this finding to the Belgian population, close to €43 million (€5,735,625 million in out-of-pocket payments and €37,167,715 million in compulsory health insurance) could be saved annually.

## 4. Discussion

### *4.1. Main findings*

In this population-wide study we show that all-cause non-urgent and urgent medical care utilization is higher in areas with increased exposure to air pollution and limited access to tree cover. Higher $PM_{2.5}$ and lower tree cover were statistically significantly associated with increased in-hours and out-of-hours GP visits, among young people as well as adults. Increasing beneficial effects of living in census tracts with lower $PM_{2.5}$ were apparent. Whereas quartiles with highest tree cover (>30.00%) showed lower in-hours and out-of-hours GP visits compared to quartiles with lower tree cover, but otherwise pairwise differences were insignificant. Associations largely persisted in rural and urban areas, although especially for tree cover and in-hours GP visits, associations were more apparent in urban areas. In addition, among adults residing in urban areas, lower grass cover was associated with increased

**Table 3**
Adults – negative binomial generalized linear mixed models estimating the association between air pollution, green space and all-cause non-urgent and urgent medical care utilization.

| | | | In-hours GP visits | | | Out-of-hours GP visits | | | ER visits | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | n census tracts | Study pop. | Est (95% CI) | Crude means | Least square means | Est (95% CI) | Crude means | Least square means | Est (95% CI) | Crude means | Least square means |
| **$PM_{2.5}$, μg/m$^3$** | | | | | | | | | | | |
| 4.91–7.49 | 4494 | 87,874 | Ref | 3.42 | 2.96 | Ref | 0.26 | 0.26 | Ref | 0.47 | 0.43 |
| 7.50–9.99 | 4394 | 241,028 | 0.046 (0.030–0.061) | 3.41 | 3.10 | 0.110 (0.068–0.151) | 0.24 | 0.29 | 0.049 (0.022–0.076) | 0.51 | 0.45 |
| 10.00–11.99 | 4116 | 270,783 | 0.078 (0.056–0.101) | 3.07 | 3.20 | 0.376 (0.317–0.436) | 0.45 | 0.38 | 0.039 (0.000–0.077) | 0.46 | 0.45 |
| 12.00–14.64 | 4909 | 285,978 | 0.108 (0.083–0.134) | 3.37 | 3.30 | 0.387 (0.322–0.453) | 0.68 | 0.38 | 0.038 (−0.005–0.082) | 0.43 | 0.45 |
| **Tree cover, %** | | | | | | | | | | | |
| 30.00–99.46 | 4609 | 232,844 | Ref | 3.17 | 3.10 | Ref | 0.37 | 0.32 | Ref | 0.45 | 0.44 |
| 20.00–29.99 | 3792 | 210,835 | 0.030 (0.020–0.041) | 3.36 | 3.20 | 0.068 (0.041–0.094) | 0.44 | 0.34 | 0.028 (0.011–0.046) | 0.48 | 0.46 |
| 10.00–19.99 | 5776 | 281,333 | 0.034 (0.024–0.044) | 3.34 | 3.21 | 0.091 (0.066–0.116) | 0.51 | 0.35 | 0.019 (0.003–0.036) | 0.46 | 0.45 |
| 0–9.99 | 3736 | 160,651 | 0.034 (0.022–0.045) | 3.32 | 3.21 | 0.091 (0.062–0.120) | 0.47 | 0.35 | 0.009 (−0.012–0.029) | 0.47 | 0.45 |
| **Grass cover, %** | | | | | | | | | | | |
| 30.01–84.98 | 4309 | 103,324 | Ref | 3.25 | 3.07 | Ref | 0.45 | 0.33 | Ref | 0.44 | 0.43 |
| 20.00–29.99 | 3579 | 120,741 | 0.025 (0.013–0.037) | 3.30 | 3.14 | 0.040 (0.010–0.071) | 0.53 | 0.35 | 0.027 (0.005–0.049) | 0.45 | 0.44 |
| 10.00–19.99 | 4425 | 188,378 | 0.046 (0.035–0.058) | 3.39 | 3.21 | 0.054 (0.024–0.084) | 0.51 | 0.35 | 0.044 (0.022–0.065) | 0.46 | 0.45 |
| 0–9.99 | 5600 | 473,220 | 0.040 (0.028–0.053) | 3.26 | 3.19 | 0.010 (−0.021–0.041) | 0.41 | 0.34 | 0.054 (0.032–0.076) | 0.48 | 0.46 |

Note: Models are for each outcome separately and all measures of air pollution and green space jointly. All models include a random intercept for census tract and fixed effects for age and gender at the individual level, urban-rural differences and indicators of SES (the percentage of foreign-born inhabitants from lower- and middle-income countries, the percentage of unemployment, and the percentage of low educated persons) at the census tract level, and administrative arrondissement. Estimates (Est) represent the difference in the logs of expected counts of the outcomes relative to the reference category (Ref) given the other variables are held constant in the model. Confidence Intervals (CI) for LS Means are not presented since the overlap (or lack thereof) between two confidence intervals does not give sufficient information about whether the difference between the means is significant at the α level. Claims of statistical significance are based on the solution for the fixed-effects parameters. CI that do not contain 0 indicate significant differences. For multiple comparisons of LS Means, we refer to Appendix 4.

in-hours GP visits and ER visits.

In our main analyses we constructed generalized linear mixed models with medical care utilization modelled at the individual level and including a random intercept for census tract, the geographical level at which our exposure measures were measured and analyzed. Findings from sensitivity analyses using generalized estimating equations, another framework for analyzing correlated data, and a generalized linear model, with exposure and outcomes measures all at the level of the census tract, largely confirmed the associations observed in the main model.

Assuming causality of the associations estimated from our main model, potential cost savings of in-hours and out-of-hours GP visits attributable to $PM_{2.5}$ exposure were examined. If $PM_{2.5}$ levels were reduced to the lowest quartile in our analysis (4.91–7.49 μg/m$^3$), assuming causality, an estimated amount of €8.6 million could be saved within our study population, which extrapolates to approximately €43 million in the Belgian population. The analysis only includes direct costs of physician fees. In addition to these direct costs, health effects of $PM_{2.5}$ and low green cover may, among others, lead to reductions in output per worker, which can occur through greater absenteeism at work or reduced labor productivity (Bruyneel et al., 2022).

### *4.2. Comparison with previous studies*

Consistent with our findings, a study on spatio-temporal associations of air pollutants with individual-level primary care data showed an association of $PM_{2.5}$ with GP consultations for asthma, COPD and upper respiratory tract infection (Ashworth et al., 2021). Yamazaki et al. (2015) only observed a significant association between $PM_{2.5}$ and out-of-hours GP visits for childhood asthma during winter. In a Canadian case-crossover study, short-term associations of $PM_{2.5}$ with respiratory ER visits were found (Szyszkowicz et al., 2018). Aside from GP and ER visits, associations of $PM_{2.5}$ with hospital admissions and respiratory, cardiovascular and mental health outcomes have been repeatedly reported (Orellano et al., 2020; Boogaard et al., 2022; WHO Regional Office for Europe, 2013; Klompmaker et al., 2019a; Klompmaker et al., 2019b; Alcock et al., 2017; Niu et al., 2021).

Also our findings for green space are in line with results from previous studies on GP or ER visits, although most of these studies did not use individual-level data and mostly focused on a single disease group. A study in Los Angeles County on the level of census tract found that more public parks and open spaces and less exposure to diesel particulate matter were associated with a lower number of ER visits for asthma (Douglas et al., 2019). Especially tree cover, average tree cover patch size and to a lesser extent private green space were inversely associated with asthma ER visits aggregated by census tract in Los Angeles (Kim and Ahn, 2021). In New York City, ER visits related to mental disorders were found to be inversely associated with green space proximity and visibility but only in neighborhoods with high social vulnerability (Yoo et al., 2022). Also other health outcomes (Nguyen et al., 2021; Astell-Burt and Feng, 2020) and medication sales (Aerts et al., 2020b; Chi et al., 2022b) have been found to be associated with tree cover.

Similar to our results, effect modification by urbanization has also been shown in studies on air pollution-related hospitalizations in the US and China (Chen et al., 2022; Zhang et al., 2022). A study among 968 US counties noted that counties with a high degree of urbanization have a higher risk of respiratory and cardiovascular hospitalization associated with $PM_{2.5}$ compared to counties with a low degree of urbanization (Chen et al., 2022). The absence of an association of $PM_{2.5}$ with ER visits in rural areas may be due to differences in the composition of $PM_{2.5}$

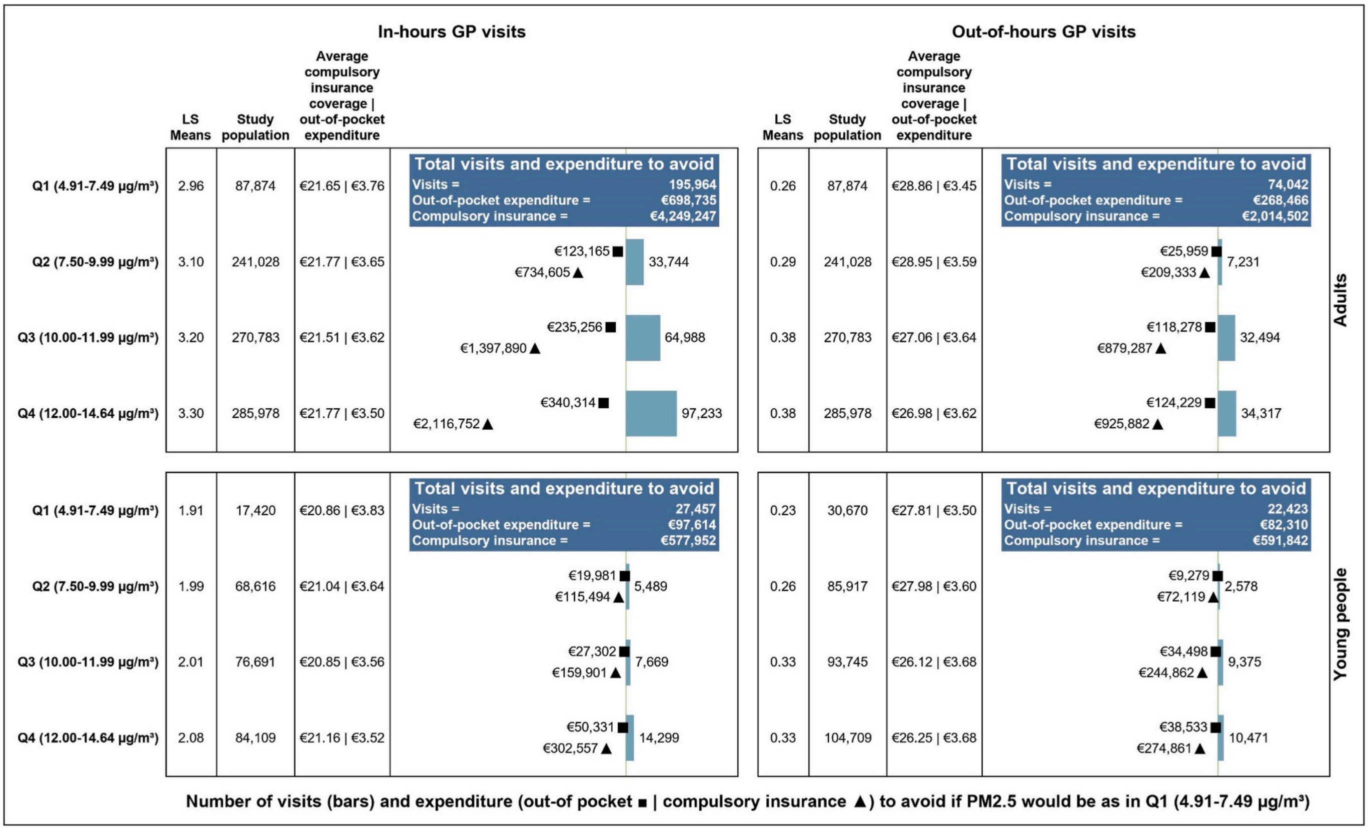

**Fig. 2.** Avoided number and direct cost of in-hours and out-of-hours GP visits if all census tracts moved to the lowest quartile of $PM_{2.5}$. Note: Using the LS Means from the negative binomial generalized linear mixed models, we estimated the number of visits and direct cost of in-hours and out-of-hours GP visits that can be avoided if all census tracts moved to the lowest quartile of $PM_{2.5}$. For the associations between $PM_{2.5}$ and in-hours GP visits and between $PM_{2.5}$ and out-of-hours GP among adults and between $PM_{2.5}$ and in-hours GP visits among young people, the full study population was used. For the association between $PM_{2.5}$ and in-hours GP visits among children, only the study population living in urban areas was used given the largely non-significant association (i.e. for Q3 and Q2 versus Q1) in rural areas. The number of visits that can be avoided from living in lowest quartile census tracts (i.e. lowest annual $PM_{2.5}$) was calculated as follows, e.g. for in-hours GP visits among adults: (LS Means from Q2 (3.10) x study population from Q2 (241,028)) – (LS Means from Q1 (2.96) x study population from Q2 (241,028)) = 33,744. This was multiplied with the average out-of-pocket payments and amount covered by compulsory health insurance to calculate the direct cost.

between urban and rural areas, or interactions with population characteristics and health behaviors that were unaccounted for in the analyses (Chen et al., 2022; Zhang et al., 2022). Our finding of stronger associations for tree cover in urban areas is in line with a recent systematic review of urban-rural differences in associations of green space with physical health (Browning et al., 2022), and with a recent Belgian study on mental health-related prescriptions (Aerts et al., 2022). These differences are hypothesized to be related to the different pathways between green space and health. Urban areas may have more to gain from green space, since it may mitigate or alleviate urban-specific problems like higher exposure to certain harmful pollutants, extreme temperatures, and psychological stressors (Browning et al., 2022).

Our findings of protective effects of green space were more consistent for tree cover than for grass cover. In previous studies, both beneficial and detrimental associations of grass cover with health or healthcare utilization have been reported (Alcock et al., 2017; Astell-Burt and Feng, 2020; Aerts et al., 2020d, 2022; Astell-Burt et al., 2022). Grass cover may not be as beneficial as tree cover because it offers less shade, less reduction of noise and air pollution and less psychological restoration (Reid et al., 2017; Fowler et al., 2002). Grass pollen may also have stronger detrimental effects on asthma and pollen allergies than tree pollen, counteracting potential beneficial associations for young people specifically (Aerts et al., 2020b; Alcock et al., 2017; Todkill et al., 2020; García-Mozo, 2017). The stronger associations of grass cover with ER visits adults living in urban areas compared to those living in rural areas are in line with urban-rural differences reported in the systematic review by Browning et al. (2022).

When comparing young people and adults, results were very similar except for the association of tree cover with in-hours GP visits and grass cover with all types of visits, which were significant only for adults. No previous studies on grass cover and GP visits, stratified by age could be found. However, a previous Belgian study has found higher grass cover to be associated with increased medication sales for childhood asthma specifically (Aerts et al., 2020b).

### 4.3. Causal mechanisms

The associations of air pollution exposure with cardiovascular and respiratory morbidity and mortality are generally attributed to biochemical reactions to pollutants within the body, resulting in oxidative stress and systemic inflammation (WHO Regional Office for Europe, 2013). These pathways have mainly been observed in toxicological studies of short-term exposure in animals and in humans, but are harder to study for long-term exposures (WHO Regional Office for Europe, 2013). In contrast to the biological pathways of health effects of air pollution, the hypothesized effects of green space are mainly due to behavioral and psychological mechanisms (Markevych et al., 2017; Hartig et al., 2014). In an overview by Nieuwenhuijsen et al. (2017), six causal pathways have been identified: increased physical activity, psychological restoration due to reduction of stressors like noise and presence of beautiful scenery and symbolic qualities, increased social cohesion, reduction of harmful exposures like air pollution and extreme temperatures, increased microbial diversity, and lastly the potential biochemical properties of certain natural compounds. Of these pathways, physical activity and psychological effects seem to produce the largest mediation effects, followed by social cohesion. Some studies have investigated the air filtering capabilities of green space, but air pollution reduction due to green space is usually small (Tallis et al., 2011). Regarding biodiversity and effects of certain natural compounds, evidence is still very limited.

### *4.4. Strengths and limitations*

This is a population-wide study with an individual-level analysis of objective exposure, outcome and covariate metrics. Additional strengths of our study are the inclusion of measurements of both tree cover and grass cover, and stratification for young people versus adults as well as urban versus rural areas allowing for detection of vulnerable subgroups. The use of exposure quantiles in the analysis provided the ability to assess potential non-linearity of the associations. Another strength is the use of all-cause GP visits as outcome, through which less severe consequences of air pollution and lack of green space may be captured compared to traditional outcomes like hospitalization, physician-diagnosed disease incidence and mortality.

Our findings should also be viewed in light of some limitations. First, we conducted a cross-sectional analysis, which does not allow causal interpretation of the findings. While we did include age, sex and various measures of SES, some residual confounding is likely. Potential confounders that we could not account for in our analyses are individual health behaviors and other disease risk factors. On the other hand, some behaviors like physical exercise may also be a mediator in the association between green space and health, in which case it should not simply be added as a covariate, since it would lead to underestimation of the health effects of green space (Nieuwenhuijsen et al., 2017). Associations of air pollution and green space with health outcomes may also be influenced by people's choice to live somewhere. People with health problems may choose to live in urban areas that come with easier access to goods and services, but that are also less green and more polluted, biasing our results towards overestimation of associations. On the other hand, people with health problems may also deliberately choose to live in greener, less polluted areas, in which case our findings would be underestimations of the causal effects.

Second, $PM_{2.5}$, tree cover and grass cover were measured on the level of census tracts. Actual individual exposures may differ from these aggregate measures, because $PM_{2.5}$, tree cover and grass cover may vary within census tracts, and because people may spend a lot of time outside of these sectors for work, studies or other reasons. In addition, beneficial effects of green space may depend on certain specific qualities that could not be taken into account in our study, such as patch size or walkability (Astell-Burt et al., 2022; Rollings et al., 2015).

Third, we did not adjust our analyses for other air pollutants. One reason for this is to avoid problems of multicollinearity. In addition, $NO_2$ does not spread as far from its emission sources, creating a large variability of exposures on a smaller scale within census tracts. As a consequence, including census-tract averages of $NO_2$ may yield imprecise results due to low power and substantial ecological bias (Fierens, 2008; Lefebvre et al., 2019).

### *4.5. Potential policy implications*

This study confirms the need to continue to reduce air pollution with an ambitious plan, which is to implement the WHO guidelines on air quality for 2030. It also supports the importance of green zones for public health and the need to protect or develop these where needed. The public health relevance is further confirmed by the impact on the financial sustainability of compulsory healthcare insurance.

## Credit author statement

**Arthur Vranken**: Conceptualization, Methodology, Writing – original draft. **Esmée Bijnens**: Conceptualization, Methodology, Data Curation, Formal analysis, Writing - Original Draft, Supervision. **Christian Horemans**: Conceptualization, Writing - review and editing. **Agnes Leclercq**: Data Curation, Writing - review and editing. **Wies Kestens**: Data Curation, Writing - review and editing, Formal analysis. **Güngör Karakaya**: Data Curation, Writing - review and editing. **Ludo Vandenthoren**: Data Curation, Writing - review and editing. **Elke Trimpeneers**: Data Curation, Writing - review and editing. **Charlotte Vanpoucke**: Data Curation, Writing - review and editing. **Frans Fierens**: Data Curation, Methodology, Writing - review and editing. **Tim Nawrot**: Conceptualization, Methodology, Writing - review and editing. **Bianca Cox**: Conceptualization, Methodology, Data Curation, Formal analysis, Writing - Original Draft, Supervision. **Luk Bruyneel**: Conceptualization, Methodology, Data Curation, Formal analysis, Visualization, Writing - Original Draft, Supervision.

## 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.

## Data availability

The authors do not have permission to share data.

## Appendices.

### *Appendix 1. Construction of the three count outcomes used in this study*

All three outcomes in our study (the number of in-hours GP visits, the number of out-of-hours GP visits and the number of ER visits) are count data derived from reimbursement data. Within the Belgian nomenclature of health care services, an official list of reimbursable diagnostic and therapeutic procedures, a six-figure code is used to identify health services covered by the compulsory health insurance. The selection of services presented in Table A1 to derive the number of in-hours GP visits and the number of out-of-hours GP visits is based on a national methodology to publish an indicator on the number of GP visits.[11] Each outcome was constructed as the number of occurrences of any of the included six-figure codes.

For the two outcomes on GP visits, we excluded members with six or more contacts in medical homes. Medical homes offer access to a variety of health providers. These structures aim at providing health care regardless of social inequities. The exclusion of such members is consistent with the national methodology.

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[1] See https://ima-aim.be/IMG/pdf/methodologie_patientenbestand_huisartsen_externen-2021.pdf.

**Table A1**
Nomenclature codes to derive the number of in-hours GP visits, the number of out-of-hours GP visits and the number of ER visits

| In-hours GP visits | |
|---|---|
| 101010 | Consultation in the consulting room by a GP on the basis of acquired rights |
| 101032 | Consultation in the consulting room by a general practitioner |
| 101054 | Consultation in the consulting room by a physician, holder of a degree in dentistry (TL) |
| 101076 | Consultation in the consulting room by an accredited general practitioner |
| 103110 | Visit by a general practitioner on the basis of acquired rights |
| 103132 | Visit by a general practitioner |
| 103213 | Visit by a general practitioner on the basis of acquired rights, following the same trip for two entitled persons |
| 103235 | Visit by a general practitioner on the basis of acquired rights, following the same trip for more than two entitled persons |
| 103412 | Visit by a general practitioner, following the same trip for two entitled persons |
| 103434 | Visit by a general practitioner, following the same trip for more than two entitled persons |
| **Out-of-hours GP visits** | |
| 101091 | Standby duty charged for consultations from 7 p.m. to 9 p.m. that take place as part of an organized standby duty |
| 101113 | Standing charge for consultations between 6 p.m. and 9 p.m. reserved for physicians on call as part of an organized standby service |
| 102410 | Surcharge for a consultation in the consulting room by a general practitioner (101032, 101076) if the consultation is held Saturday, Sunday, on a holiday between 8 a.m. and 9 p.m. |
| 102432 | Surcharge for a consultation in the consulting room by a general practitioner (101032, 101076) if the consultation is held at night between 9 p.m. and 8 a.m. |
| 102454 | Surcharge for a consultation in the consulting room by a general practitioner on the basis of acquired rights (101010) if the consultation is held Saturday, Sunday or on a holiday between 8 a.m. and 9 p.m. |
| 102476 | Surcharge for a consultation in the consulting room by a general practitioner on the basis of acquired rights (101010) if the consultation is held at night between 9 p.m. and 8 a.m. |
| 104215 | Visit made by the licensed general practitioner between 6 and 9 p.m. at the sick person's home |
| 104230 | Visit made between 9 p.m. and 8 a.m. by the general practitioner |
| 104252 | Visits made on Saturdays, Sundays or public holidays between 8 a.m. and 9 p.m. by the general practitioner |
| 104296 | Surcharge for a visit following the same trip for several patients by a general practitioner (103412, 103434) when the visit is made Saturday, Sunday or on a holiday between 8 a.m. and 9 p.m. |
| 104311 | Surcharge for a visit following the same trip for several patients by a general practitioner (103412, 103434) when the visit is made between 9 p.m. and 8 a.m. |
| 104333 | Surcharge for a visit following the same trip for several patients by a general practitioner (103412, 103434) when the visit is made between 6 p.m. and 9 p.m. |
| 104510 | Visits made between 6 p.m. and 9 p.m. by a general practitioner on the basis of acquired rights |
| 104532 | Visit made between 9 p.m. and 8 a.m. by a general practitioner on the basis of acquired rights |
| 104554 | Visit made Saturday, Sunday or on a holiday between 8 a.m. and 9 p.m. by a general practitioner on the basis of acquired rights |
| 104591 | Surcharge for a visit following the same trip for several patients by a general practitioner on the basis of acquired rights (103213, 103235) when the visit is made Saturday, Sunday or on a holiday between 8 a.m. and 9 p.m. |
| 104613 | Surcharge for a visit following the same trip for several patients by a general practitioner on the basis of acquired rights (103213, 103235) when the visit is made between 9 p.m. and 8 a.m. |
| 104635 | Surcharge for a visit following the same trip for several patients by a general practitioner on the basis of acquired rights (103213, 103235) when the visit is made between 6 p.m. and 9 p.m. |
| **ER visits** | |
| 590181 | Flat fee for inpatient medical permanency in a recognized specialty emergency care hospital function per admission to an acute service A, C, D, E, G, H, (i), K, L, M or NIC of a general hospital that has a recognized specialty emergency care hospital function |
| 590310 | Flat fee for inpatient medical permanency in a recognized specialty emergency care hospital function per day entitling the maximum flat rate or day hospital flat rate for any of the following benefits from the restricted list or surgical day hospital amount of a general hospital having a recognized specialty emergency care function |
| 590435 | Fee for medical assistance provided by a physician of a recognized specialist emergency care function in the context of an extramural medical intervention of the mobile emergency group and medically-assisted transport of a patient to a hospital other than the hospital to which the recognized specialist emergency care function belongs |
| 590446 | Fees for medical assistance provided by a physician of a recognized function specialized emergency care for a medically accompanied transport of an admitted patient to a hospital other than the hospital of which the recognized function specialized emergency care is a part, with a view to an urgent diagnosis and/or treatment to be carried out |
| 590472 | Fee for medical assistance provided by a physician of a recognized function specialized emergency care, within the framework of an extramural medical intervention of the mobile emergency group for the purpose of a medically accompanied transport to the hospital of which the recognized function specialized emergency care is a part |
| 590516 | Fee for the anamnesis, clinical examination, initial reception and orientation of a patient during an emergency reception in the premises of a recognized function for specialized emergency care, without a referral letter from a general practitioner, by the physician-specialist in emergency medicine or the physician-specialist who holds the special professional title in emergency medicine that ensures its permanence, with written report |
| 590531 | Fee for the anamnesis, clinical examination, initial reception and orientation of a patient during an emergency reception in the premises of a recognized function for specialized emergency care, with referral letter from a general practitioner, by the physician-specialist in emergency medicine or the physician-specialist who holds the special professional title in emergency medicine that ensures its permanence, with written report |
| 590553 | Fee for the anamnesis, clinical examination, initial reception and orientation of a patient during an emergency reception in the premises of a recognized function for specialized emergency care, without a referral letter from a general practitioner, by the accredited physician specialist in emergency medicine or the accredited physician specialist who holds the special professional title in emergency medicine that ensures its permanence, with written report |
| 590575 | Fee for the anamnesis, clinical examination, initial reception and orientation of a patient during an emergency reception in the premises of an accredited specialist emergency care facility, with referral letter from a general practitioner, by the accredited specialist physician in emergency medicine or the accredited specialist physician who holds the special professional title in emergency medicine that ensures its permanence, with written report |
| 590590 | Fee for the anamnesis, clinical examination, initial reception and orientation of a patient during an emergency reception in the premises of an accredited function for specialized emergency care, without a referral letter from a general practitioner, by the physician-specialist who ensures the permanence there, with written report |
| 590612 | Fee for the anamnesis, clinical examination, initial reception and orientation of a patient during an emergency reception at the premises of a recognized specialist emergency care unit, with referral letter from a general practitioner, by the specialist physician in charge of permanency, with written report |
| 590634 | Fee for the anamnesis, clinical examination, initial reception and orientation of a patient during an emergency reception at the premises of a recognized function for specialized emergency care, without referral letter from a general practitioner, by the specialist physician in acute medicine who ensures its permanence, with written report |
| 590656 | Fee for the anamnesis, clinical examination, initial reception and orientation of a patient during an emergency reception in the premises of a recognized function for specialized emergency care, with referral letter from a general practitioner, by the physician-specialist in acute medicine who ensures its permanence, with written report |
| 590671 | Fee for the anamnesis, clinical examination, initial reception and orientation of a patient during an emergency reception at the premises of a recognized function for specialized emergency care, without referral letter from a general practitioner, by the accredited physician-specialist in acute medicine who ensures its permanence, with written report |

(*continued on next page*)

**Table A1** (*continued*)

| In-hours GP visits | |
|---|---|
| 590693 | Fee for the anamnesis, clinical examination, initial reception and orientation of a patient during an emergency reception in the premises of a recognized function for specialized emergency care, with referral letter from a general practitioner, by the accredited physician-specialist in acute medicine who ensures its permanence, with written report |
| 590715 | Fee for the anamnesis, clinical examination, initial reception and orientation of a patient during an emergency reception in the premises of an accredited function for specialized emergency care, without a referral letter from a general practitioner, by the accredited specialist physician in acute medicine who ensures its permanence, with written report |
| 590730 | Fee for the anamnesis, clinical examination, initial reception and orientation of a patient during an emergency reception at the premises of an accredited specialist emergency room, with referral letter from a general practitioner, by the accredited specialist physician who provides on-call care, with written report |
| 590752 | Fee for the anamnesis, clinical examination, initial reception and orientation of a patient during an emergency reception at the premises of an accredited specialist emergency room, without referral letter from a general practitioner, by the accredited specialist physician in charge of permanency, with written report |
| 590774 | Fee for the anamnesis, clinical examination, initial reception and orientation of a patient during an emergency reception at the premises of a recognized function for specialized emergency care, with referral letter from a general practitioner, by the physician holding an acute medicine license who ensures its permanence, with written report |
| 590796 | Fee for the anamnesis, clinical examination, initial reception and orientation of a patient during an emergency reception in the premises of a recognized function for specialized emergency care, without a referral letter from a general practitioner, by the accredited physician holding an acute medicine license who ensures its permanence, with written report |
| 590811 | Fee for the anamnesis, clinical examination, initial reception and orientation of a patient during an emergency reception at the premises of an accredited specialist emergency care facility, with referral letter from a general practitioner, by the accredited physician holding a diploma in acute medicine who ensures its permanence, with written report |
| 590833 | Additional fee for one of the services in the series 590516, 590531, 590553, 590575, 590590, 590612, 590634, 590656, 590671, 590693, 590715, 590730, 590752, 590774, 590796 or 590811 when the service is provided between 9 p.m. and 8 a.m. or Saturday, Sunday or a holiday between 8 a.m. and 9 p.m. |

## *Appendix 2. Assessment of overdispersion in in-hours GP visits, out-of-hours GP visits and ER visits*

Because the three count outcomes showed a long positive tail to the distribution, we assessed overdispersion by comparing the fit of a two-level random intercept (for census tract) model (GLMM) with empty means applying either Poisson or negative binomial conditional distributions. The Pearson $\chi 2$/DF statistic is an index of fit to the conditional distribution. It should be close to 1 for good fit. negative binomial models showed better fit (Table A2).

**Table A2**
Assessment of overdispersion in in-hours GP visits, out-of-hours GP visits and ER visits for young people and adults, by comparing the fit of the two-level random intercept models with empty means applying either Poisson or negative binomial conditional distributions

| | Young people | | Adults | |
|---|---|---|---|---|
| | Pearson $\chi 2$/DF | AIC | Pearson $\chi 2$/DF | AIC |
| **In-hours GP visits** | | | | |
| Poisson | 2.74 | 1512843 | 4.13 | 5481365 |
| Negative binomial | 1.07 | 1291411 | 1.13 | 4270284 |
| **Out-of-hours GP visits** | | | | |
| Poisson | 1.60 | 539789 | 2.24 | 1668337 |
| Negative binomial | 0.99 | 497521 | 1.19 | 1453696 |
| **ER visits** | | | | |
| Poisson | 1.57 | 510317 | 2.54 | 1764577 |
| Negative binomial | 1.03 | 489794 | 1.25 | 1566954 |

## *Appendix 3. Variation in air pollution and green space across census tracts*

Here, we revisit the first part of Table 1 from the main text and present variation across census tracts in air pollution and green space visually (Figures A1 to A3) and by urban-rural differences (Table A3). The latter is informative for subgroup analyses that are conducted later on (Appendix 6).

In the figures below, variation is depicted at the level of the census tract. In the map of Belgium, black outlined geographical areas represent the three regions and white outlined geographical areas represent arrondissements. In the zoom in map of the Brussels-Capital Region, white outlined geographical areas represent census tracts.

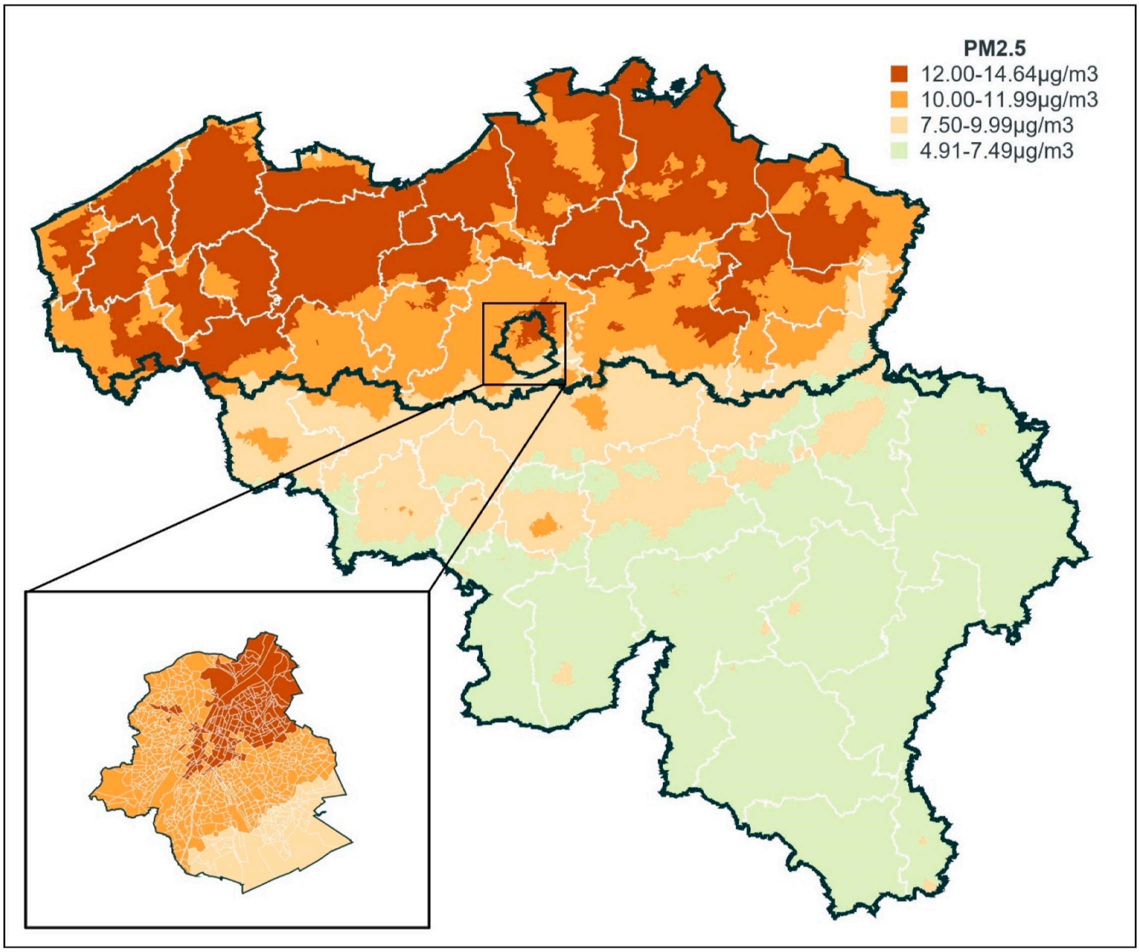

**Fig. A1.** Variation in $PM_{2.5}$ across census tracts

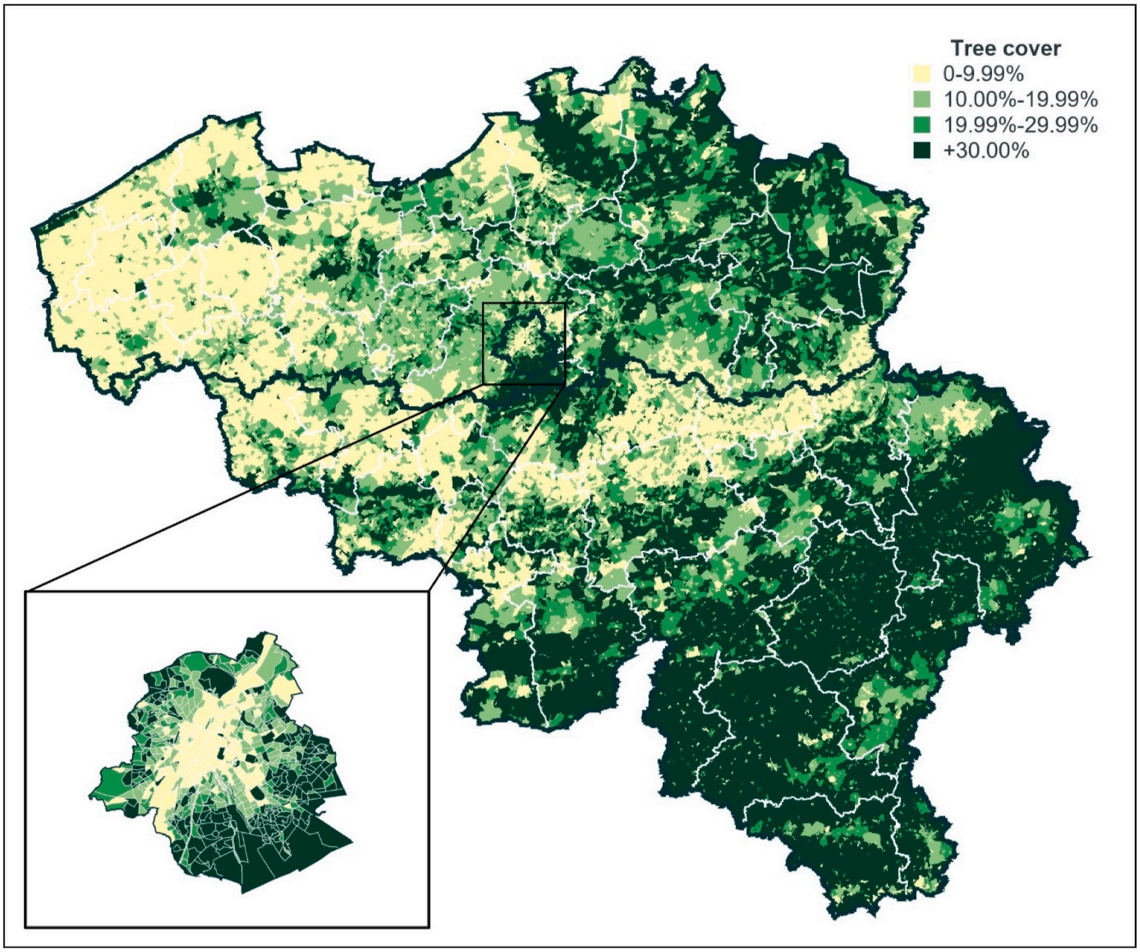

**Fig. A2.** Variation in tree cover across census tracts

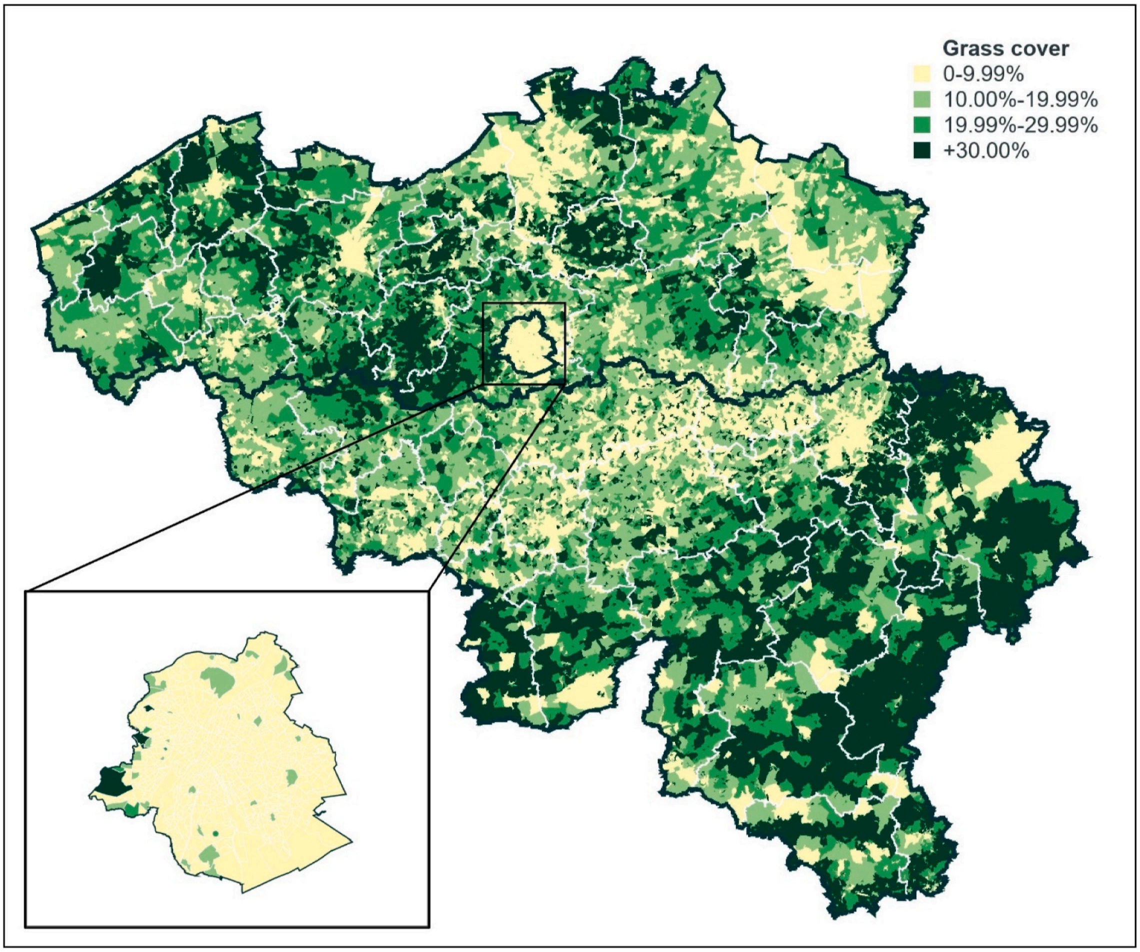

**Fig. A3.** Variation in grass cover across census tracts

**Table A3**
Variation across census tracts between air pollution and green space by urban-rural differences

| Degree of urbanization (number of census tracts) | Variation across census tracts | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | IQR | Min | Q1 | Median | Q3 | Max |
| **Urban (n = 10,469)** | | | | | | | | |
| $PM_{2.5}$, μg/$m^3$ | 10.1 | 2.4 | 4.2 | 4.9 | 8.1 | 10.6 | 12.2 | 14.5 |
| Tree cover, % | 21.0 | 12.3 | 14.9 | 0.0 | 12.3 | 18.6 | 27.2 | 86.1 |
| Grass cover, % | 15.9 | 13.4 | 19.8 | 0.0 | 4.6 | 13.2 | 24.37 | 73.3 |
| **Rural (n = 7469)** | | | | | | | | |
| $PM_{2.5}$, μg/$m^3$ | 9.3 | 2.6 | 5.2 | 4.9 | 6.7 | 9.2 | 11.9 | 14.6 |
| Tree cover, % | 26.3 | 21.4 | 29.2 | 0.0 | 9.3 | 19.8 | 38.5 | 99.5 |
| Grass cover, % | 25.7 | 16.2 | 21.4 | 0.0 | 13.6 | 23.6 | 35.0 | 85.0 |

## *Appendix 4. Estimating the association between air pollution, green space and all-cause non-urgent and urgent medical care: findings for all predictors modelled jointly*

This appendix comes in addition to Tables 2 and 3 presented in the main text.

First, we present findings for the analysis of all pairwise comparisons between the LS Means, for in-hours GP visits (Figure A4), out-of-hours GP visits (Figure A5) and ER visits (Figure A6). Adjusted confidence intervals for multiple comparisons were computed with the Tukey-Kramer method. This explains why confidence intervals are slightly different from those presented in Table 2 ad 3 in the main text.

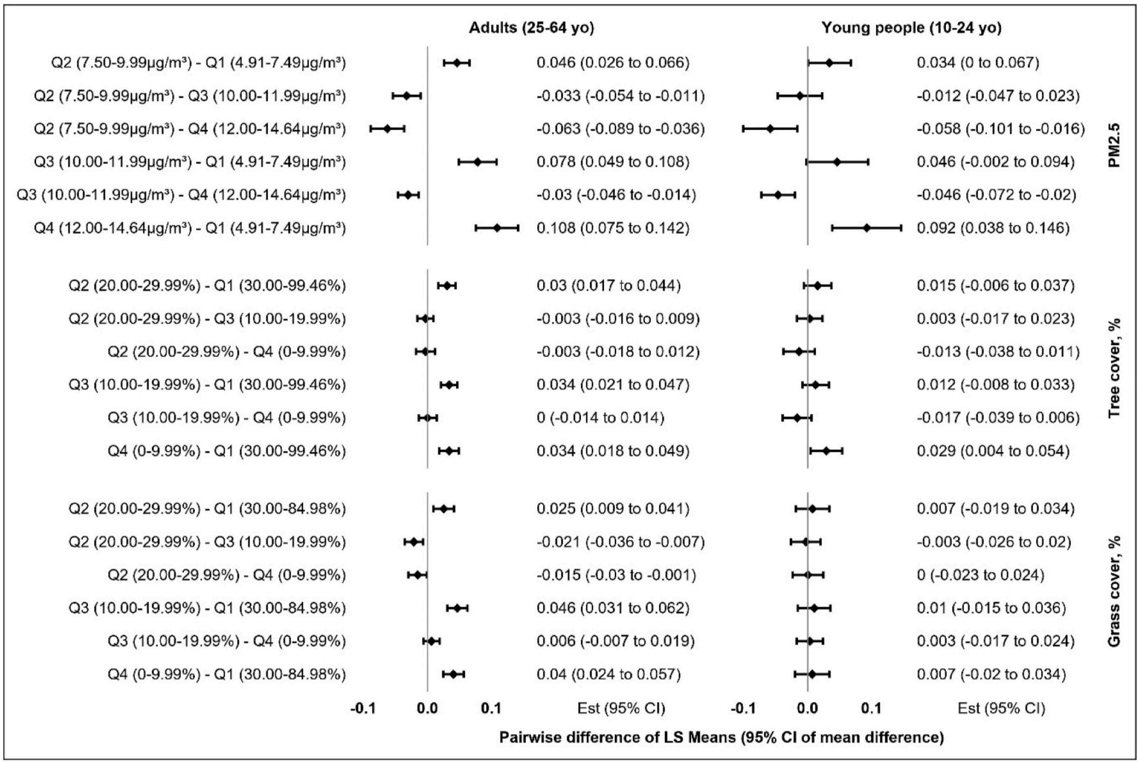

**Fig. A4.** Negative binomial generalized linear mixed models estimating the association between air pollution, green space and in-hours GP visits among adults and young people – multiple comparisons of means (Tukey-adjusted LS Means differences)

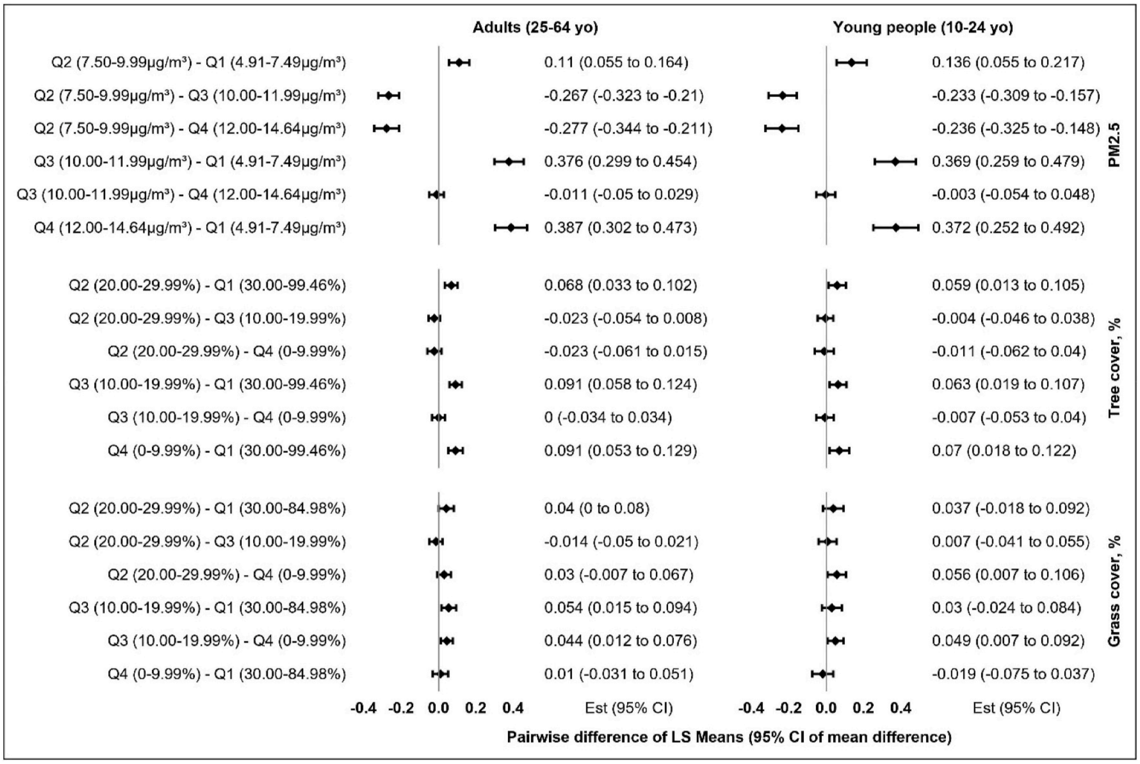

**Fig. A5.** Negative binomial generalized linear mixed models estimating the association between air pollution, green space and out-of-hours GP visits among adults and young people – multiple comparisons of means (Tukey-adjusted LS Means differences)

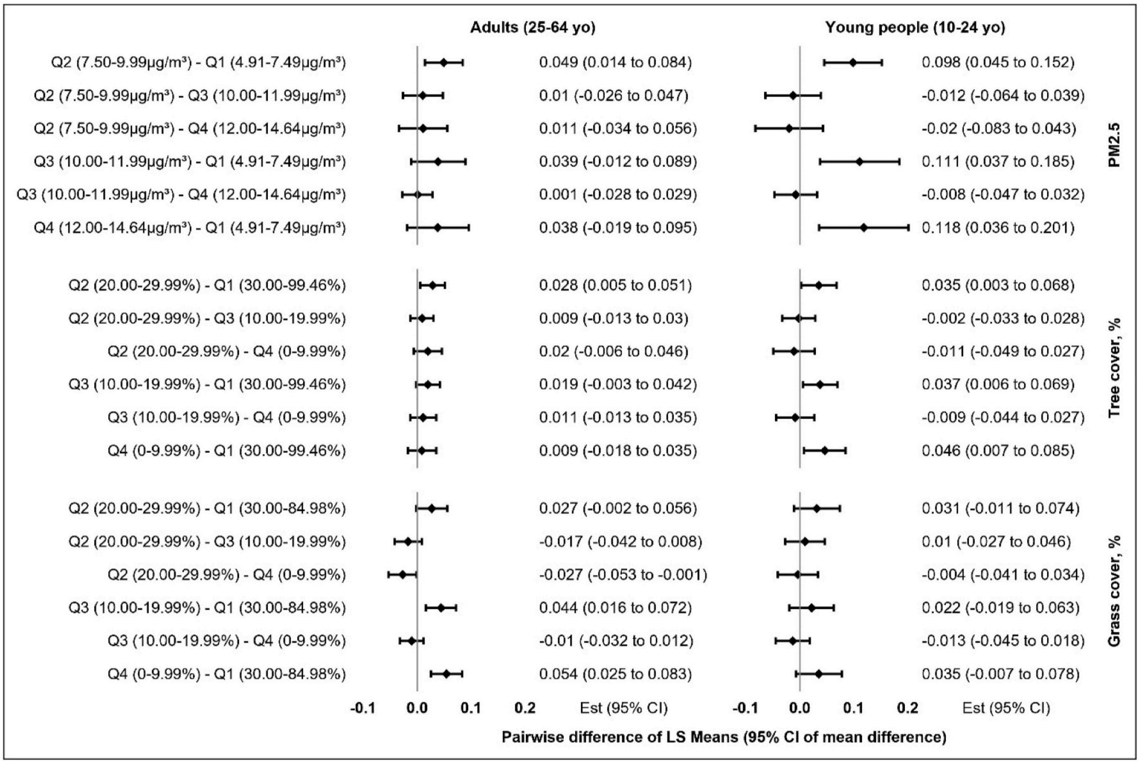

**Fig. A6.** Negative binomial generalized linear mixed models estimating the association between air pollution, green space and ER visits among adults and young people – multiple comparisons of means (Tukey-adjusted LS Means differences)

Second, we present the estimates and P-values for the potential confounders. Models for young people (Table A4) and adults (Table A5) are for each outcome separately. All models include a random intercept for census tract and fixed effects for age and gender at the individual level, urban-rural differences and indicators of SES (the percentage of foreign-born inhabitants from lower- and middle-income countries, the percentage of unemployment, and the percentage of low educated persons) at the census tract level, and administrative arrondissement. Estimates (Est) represent the difference in the logs of expected counts of the outcomes relative to the reference category (Ref) given the other variables are held constant in the model.

**Table A4**
Young people – negative binomial generalized linear mixed models estimating the association between air pollution, green space and all-cause non-urgent and urgent medical care utilization

| | In-hours GP visits | Out-of-hours GP visits | ER visits |
|---|---|---|---|
| | Est (95% CI) | Est (95% CI) | Est (95% CI) |
| **Age** | 0.035 (0.034–0.036) | 0.025 (0.024–0.027) | 0.023 (0.021–0.025) |
| **Gender** | | | |
| Female | Ref | Ref | Ref |
| Male | −0.197 (−0.205 to −0.189) | −0.199 (−0.215 to −0.184) | 0.016 (0.002–0.031) |
| **Rural-urban differences** | | | |
| Rural | Ref | Ref | Ref |
| Urban | 0.028 (0.013–0.042) | −0.001 (−0.028 to 0.031) | 0.014 (−0.0091 to 0.0367) |
| **Percentage of foreign-born inhabitants from lower- and middle-income countries** | 0.0087 (0.0076–0.0099) | 0.0131 (0.0107–0.0154) | −0.0019 (−0.0040 to 0.0002) |
| **Percentage of unemployment** | 0.0091 (0.0076–0.0105) | 0.0048 (0.0016–0.0081) | 0.0087 (0.0065–0.0110) |
| **Percentage of low educated persons** | 0.0087 (0.0076–0.0099) | 0.0131 (0.0107–0.0154) | 0.0093 (0.0075–0.0111) |

**Table A5**
Adults – negative binomial generalized linear mixed models estimating the association between air pollution, green space and all-cause non-urgent and urgent medical care utilization

| | In-hours GP visits | Out-of-hours GP visits | ER visits |
|---|---|---|---|
| | Est (95% CI) | Est (95% CI) | Est (95% CI) |
| **Age** | 0.014 (0.014–0.014) | 0.002 (0.001–0002) | 0.006 (0.005–0.006) |
| **Gender** | | | |
| Female | Ref | Ref | Ref |

(*continued on next page*)

**Table A5** (*continued*)

| | In-hours GP visits | Out-of-hours GP visits | ER visits |
|---|---|---|---|
| | Est (95% CI) | Est (95% CI) | Est (95% CI) |
| Male | −0.293 (−0.298 to −0.289) | −0.162 (−0.171 to −0.152) | −0.097 (−0.106 to −0.088) |
| **Rural-urban differences** | | | |
| Rural | Ref | Ref | Ref |
| Urban | 0.028 (0.020–0.037) | 0.004 (−0.018 to 0.025) | 0.017 (0.002–0.033) |
| **Percentage of foreign-born inhabitants from lower- and middle-income countries** | −0.0005 (−0.0014 to 0.0003) | −0.0097 (−0.0119 to −0.0075) | 0.0093 (0.0080–0.0105) |
| **Percentage of unemployment** | 0.0054 (0.0046–0.0062) | 0.0031 (0.0009–0.0052) | 0.0091 (0.0076–0.0106) |
| **Percentage of low educated persons** | 0.0092 (0.0085–0.0099) | 0.0150 (0.0133–0.0166) | 0.0093 (0.0080–0.0105) |

## *Appendix 5. Estimating the association between air pollution, green space and all-cause non-urgent and urgent medical care: findings for all predictors modelled separately*

Models for young people (Table A6) and adults (Table A7) include a random intercept for census tract and fixed effects for age and gender at the individual level, urban-rural differences and indicators of SES (the percentage of foreign-born inhabitants from lower- and middle-income countries, the percentage of unemployment, and the percentage of low educated persons) at the census tract level, and administrative arrondissement. Estimates (Est) represent the difference in the logs of expected counts of the outcomes relative to the reference category (Ref) given the other variables are held constant in the model.

**Table A6**
Young people – negative binomial generalized linear mixed models estimating the association between air pollution, green space and all-cause non-urgent and urgent medical care utilization

| | In-hours GP visits | Out-of-hours GP visits | ER visits |
|---|---|---|---|
| | Est (95% CI) | Est (95% CI) | Est (95% CI) |
| **$PM_{2.5}$, μg/m$^3$** | | | |
| 4.91–7.49 | Ref | Ref | Ref |
| 7.50–9.99 | 0.034 (0.009–0.060) | 0.121 (0.060–0.183) | 0.099 (0.060–0.140) |
| 10.00–11.99 | 0.047 (0.011–0.083) | 0.356 (0.273–0.440) | 0.120 (0.064–0.176) |
| 12.00–14.64 | 0.094 (0.053–0.135) | 0.361 (0.270–0.452) | 0.132 (0.069–0.194) |
| **Tree cover, %** | | | |
| 30.00–99.46 | Ref | Ref | Ref |
| 20.00–29.99 | 0.015 (−0.001–0.032) | 0.068 (0.033–0.103) | 0.031 (0.007–0.056) |
| 10.00–19.99 | 0.012 (−0.004–0.027) | 0.067 (0.034–0.101) | 0.031 (0.008–0.055) |
| 0–9.99 | 0.033 (0.014–0.051) | 0.066 (0.027–0.106) | 0.040 (0.011–0.069) |
| **Grass cover, %** | | | |
| 30.00–84.98 | Ref | Ref | Ref |
| 20.00–29.99 | 0.007 (−0.013–0.027) | 0.032 (−0.009–0.073) | 0.033 (0.001–0.065) |
| 10.00–19.99 | 0.010 (−0.010–0.029) | 0.023 (−0.018–0.064) | 0.021 (−0.009–0.052) |
| 0–9.99 | 0.005 (−0.015–0.025) | −0.025 (−0.067–0.017) | 0.036 (0.004–0.068) |

**Table A7**
Adults – negative binomial generalized linear mixed models estimating the association between air pollution, green space and all-cause non-urgent and urgent medical care utilization

| | In-hours GP visits | Out-of-hours GP visits | ER visits |
|---|---|---|---|
| | Est (95% CI) | Est (95% CI) | Est (95% CI) |
| **$PM_{2.5}$, μg/m$^3$** | | | |
| 4.91–7.49 | Ref | Ref | Ref |
| 7.50–9.99 | 0.051 (0.036–0.066) | 0.110 (0.068–0.151) | 0.059 (0.003–0.085) |
| 10.00–11.99 | 0.088 (0.066–0.111) | 0.386 (0.327–0.445) | 0.053 (0.015–0.092) |
| 12.00–14.64 | 0.118 (0.093–0.143) | 0.400 (0.335–0.466) | 0.056 (0.013–0.099) |
| **Tree cover, %** | | | |
| 30.00–99.46 | Ref | Ref | Ref |
| 20.00–29.99 | 0.027 (0.017–0.038) | 0.082 (0.056–0.108) | 0.021 (0.003–0.073) |
| 10.00–19.99 | 0.027 (0.017–0.037) | 0.092 (0.067–0.117) | 0.008 (−0.008–0.025) |
| 0–9.99 | 0.027 (0.016–0.039) | 0.086 (0.058–0.115) | 0.001 (−0.019–0.021) |
| **Grass cover, %** | | | |
| 30.00–84.98 | Ref | Ref | Ref |
| 20.00–29.99 | 0.027 (0.015–0.039) | 0.027 (−0.004–0.058) | 0.028 (0.006–0.050) |
| 10.00–19.99 | 0.045 (0.034–0.057) | 0.031 (0.002–0.061) | 0.044 (0.022–0.065) |
| 0–9.99 | 0.037 (0.025–0.049) | −0.009 (−0.040–0.021) | 0.054 (0.032–0.075) |

### *Appendix 6. Estimating the association between air pollution, green space and all-cause non-urgent and urgent medical care: associations by rural-urban differences*

This section presents findings for models estimating the association between air pollution, green space and in-hours GP visits (Figure A7), out-of-hours GP visits (Figure A8) and ER visits (Figure A9), stratified by urban-rural differences. Models are for each outcome separately and all measures of air pollution and green space jointly (cf. the main model presented in the main text). All models include a random intercept for census tract, fixed effects for age and gender at the individual level, indicators of SES (the percentage of foreign-born inhabitants from lower- and middle-income countries, the percentage of unemployment, and the percentage of low educated persons) at the census tract level, and administrative arrondissement. Estimates (Est) represent the difference in the logs of expected counts of the outcomes relative to the reference category (Ref) given the other variables are held constant in the model.

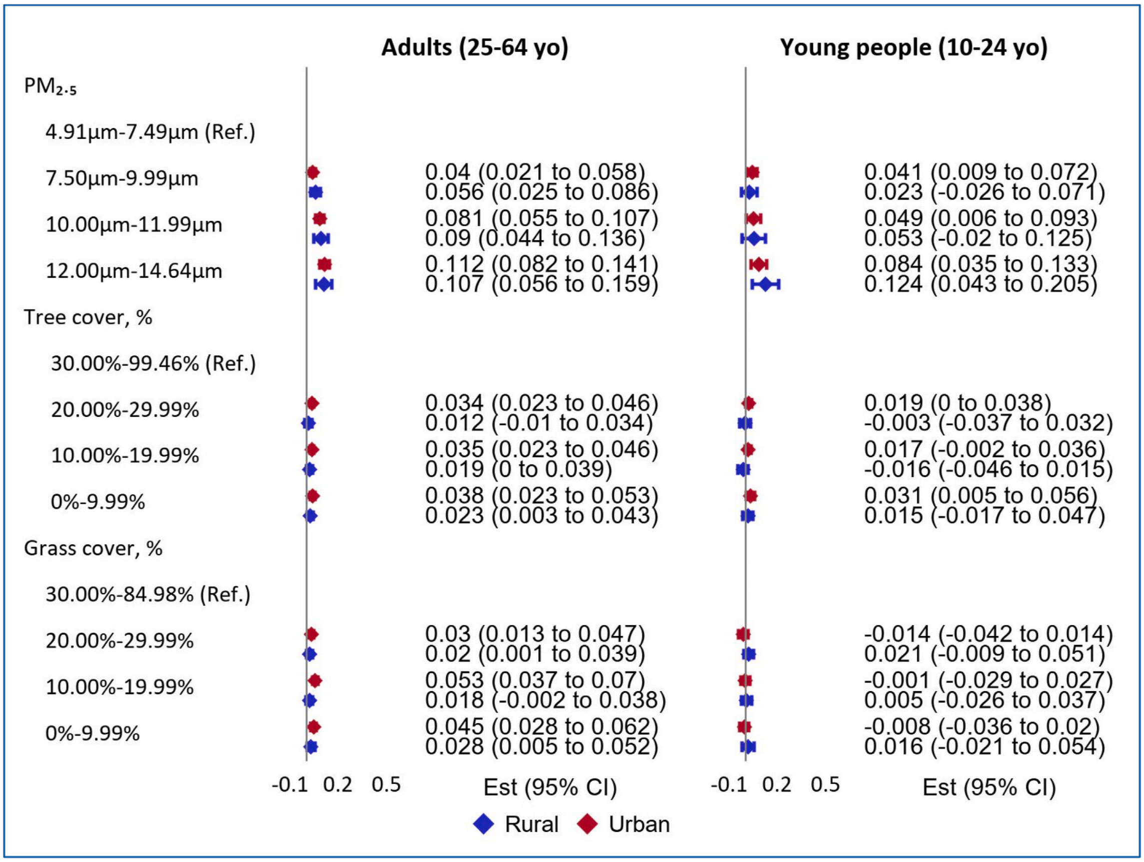

**Fig. A7.** Negative binomial generalized linear mixed models estimating the association between air pollution, green space and in-hours GP visits among adults and young people, by urban-rural differences

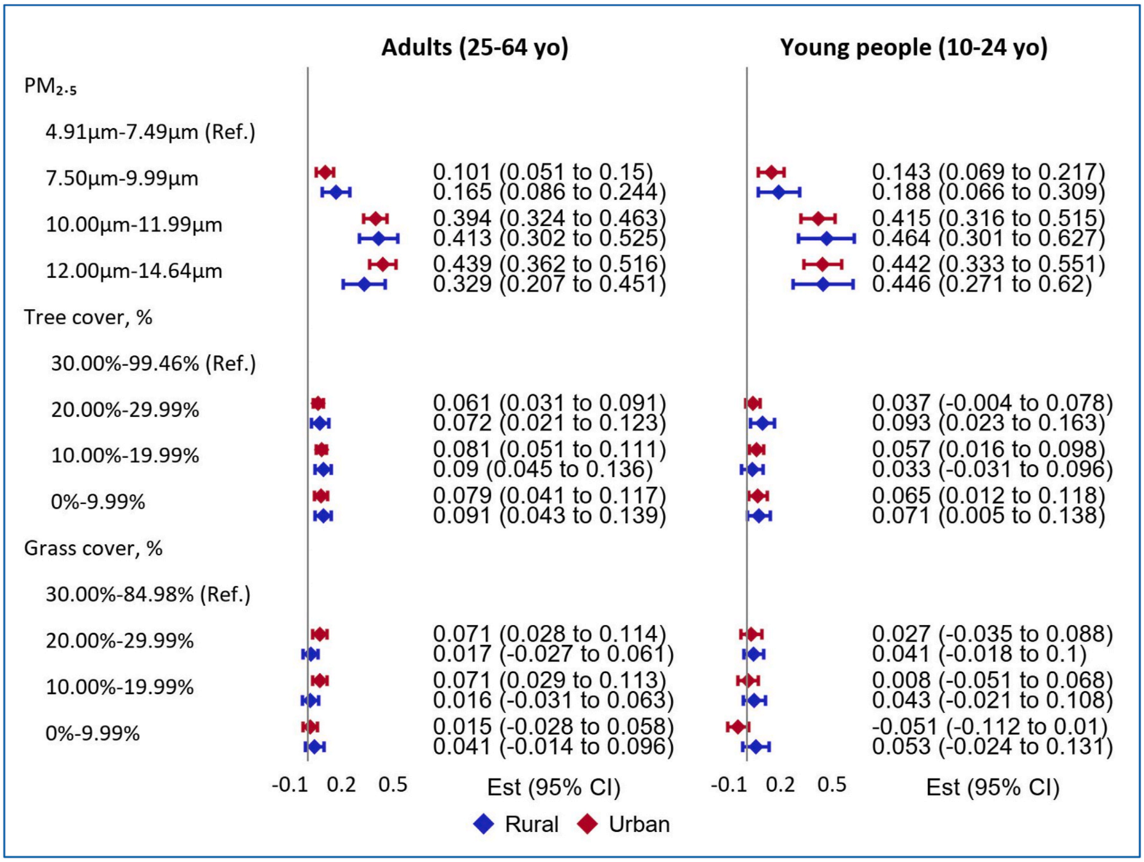

**Fig. A8.** Negative binomial generalized linear mixed models estimating the association between air pollution, green space and out-of-hours GP visits among adults and young people, by urban-rural differences

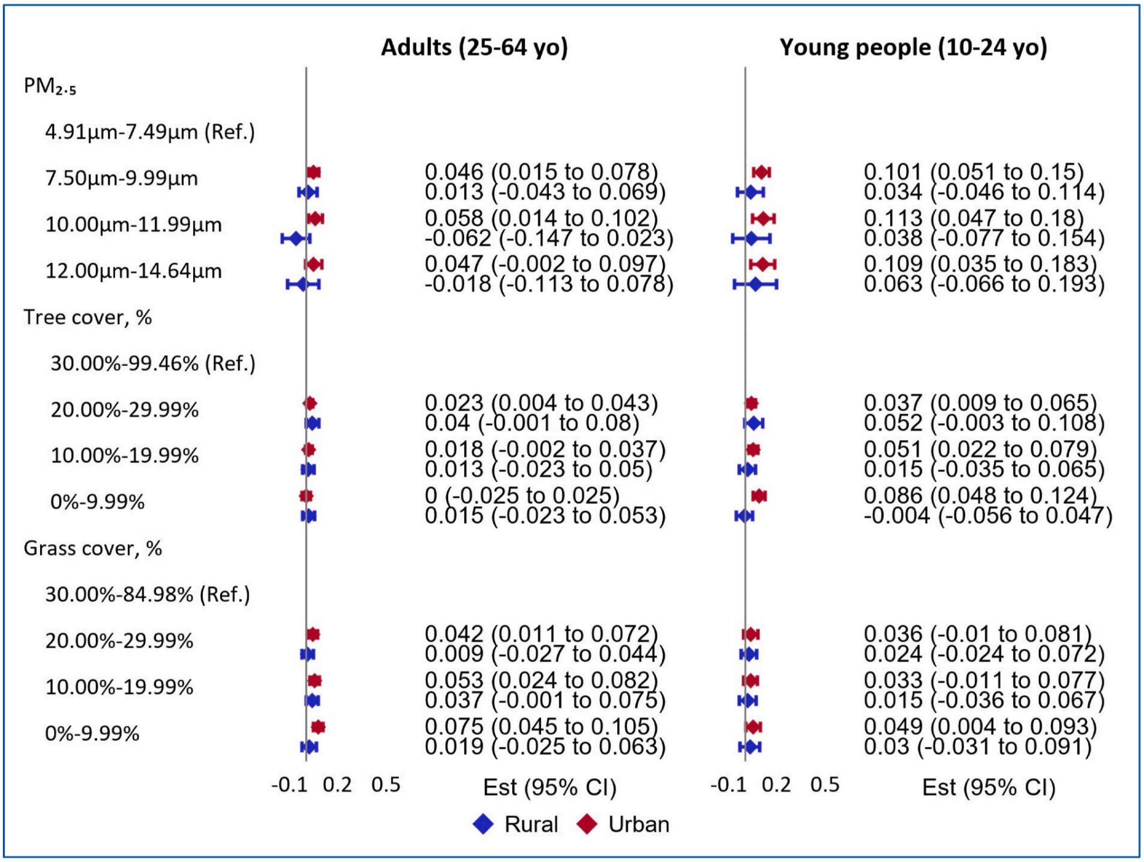

**Fig. A9.** Negative binomial generalized linear mixed models estimating the association between air pollution, green space and ER visits among adults and young people, by urban-rural differences

### *Appendix 7. Sensitivity analyses*

This appendix comes in addition to Tables 2 and 3 presented in the main text. Here, we present the findings for two sensitivity analyses.

First, as an alternative to GLMM, we fitted marginal models via generalized estimating equations (GEE), see Equation (2). Using such population average model, we describe changes in the population mean given changes in air pollution and green space, while accounting for within-census tract nonindependence of observations when deriving the variability estimates of these coefficients (Hubbard et al., 2010). This type of sensitivity analysis included the same set of potential confounders as in the GLMM (main model).

$$y_{ic} \sim NB(\mu_{ic}, \alpha)$$

$$\mu_{ic} = exp(\beta_o + x_{1ic}{}'\beta_1 + x_{2c}{}'\beta_2 + x_{3c}\beta_3) \tag{2}$$

where $y_{ic}$ is the number of visits by person $i$ in census tract $c$. $NB(u_{ic}, \alpha)$ denotes the negative binomial distribution with mean $u_{ic}$ and dispersion parameter $\alpha$. All other parameters have the same meaning as before. Contrary to GLMM, between-census tract variation is not explicitly modelled. Instead, GEE focuses on estimating within-census tract similarity of individuals and adjusts the standard errors to account for this correlation.

Second, we fitted regression models with exposure measures, potential confounders and outcomes at the census tract level. We therefore calculated the average value for all outcomes at the census tract level as well as the average age of study subjects within the census tract and the proportion of males in the census tract. Other potential confounders were the same as in GLMM and GEE. Given the distribution of the outcomes (Figure A10), generalized linear models (GLM) were constructed with a gamma distribution, see Equation (3).

$$y_c \sim G(\mu_c)$$

$$\mu_c = exp(\beta_o + x_{1c}{}'\beta_1 + x_{2c}{}'\beta_2 + x_{3c}\beta_3) \tag{3}$$

where $y_c$ is the average number of visits in census tract $c$. $G(u_c)$ denotes the gamma distribution with mean $u_c$. $x_{1c}{}'$ represents the group-level variables (average age, gender expressed as the percentage of males) and $\beta_1$ their regression coefficients. $x_{2c}{}'$ represents the group-level variables (exposure measures of air pollution and green space, rural-urban differences and indicators of socioeconomic status) for census tract c and $\beta_2$ their regression coefficients. $x_{3c}$ represents arrondissements and the corresponding regression coefficients.

Findings from the GEE and GLM sensitivity analyses confirmed all major consistent associations observed in the main model (GLMM), for both young people (Table A8) and adults (Table A9).

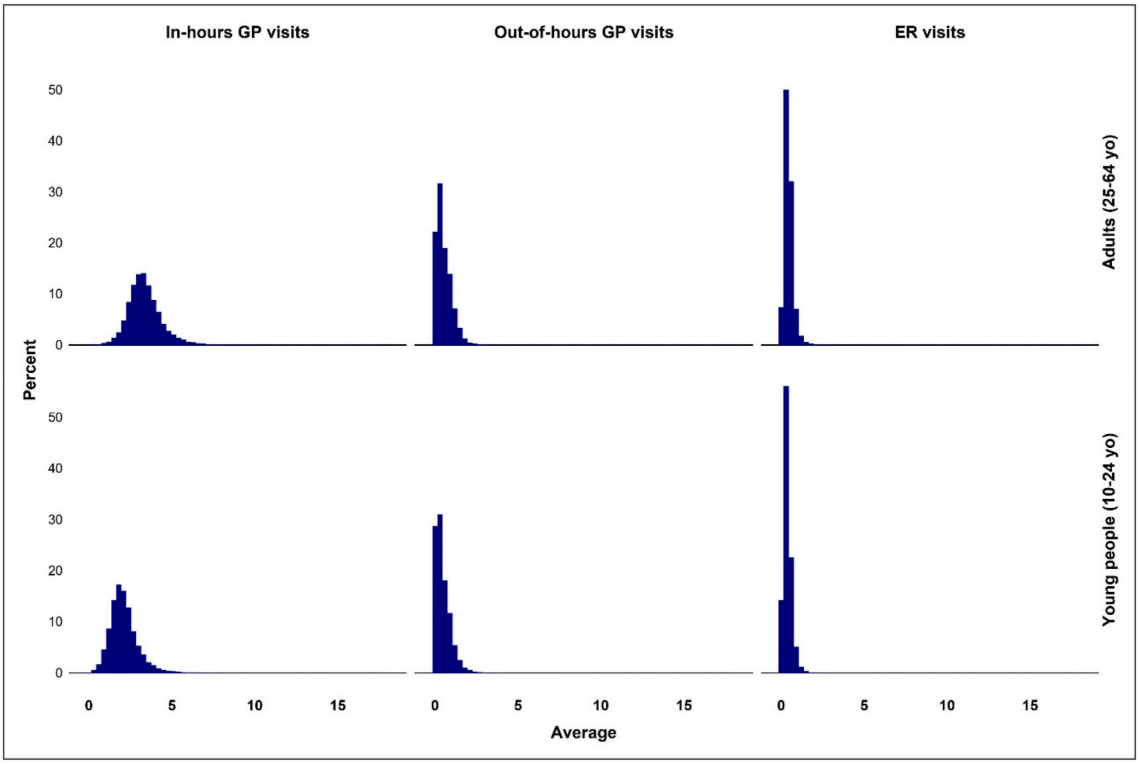

**Fig. A10.** Histogram of the distribution of the census tract-level average number of in-hours GP visits, out-of-hours GP visits and ER visits for young people and adults

**Table A8**
Young people – negative binomial generalized linear mixed models, negative binomial generalized estimating equations, and generalized linear models at the level of the census tract estimating the association between air pollution, green space and all-cause non-urgent and urgent medical care utilization

| | In-hours GP visits, Est (95% CI) | | | Out-of-hours GP visits, Est (95% CI) | | | ER visits, Est (95% CI) | | |
|---|---|---|---|---|---|---|---|---|---|
| | Generalized Linear Mixed Model (Main model) | Generalized Estimating Equations (Sensitivity analysis) | Census tract-level generalized linear model (Sensitivity analysis) | Generalized Linear Mixed Model (Main model) | Generalized Estimating Equations (Sensitivity analysis) | Census tract-level generalized linear model (Sensitivity analysis) | Generalized Linear Mixed Model (Main model) | Generalized Estimating Equations (Sensitivity analysis) | Census tract-level generalized linear model (Sensitivity analysis) |
| **PM$_{2.5}$, μg/m$^3$** | | | | | | | | | |
| 4.91–7.49 | Ref | Ref | Ref | Ref | Ref | Ref | Ref | Ref | Ref |
| 7.50–9.99 | 0.034 (0.008–0.059)* | 0.028 (−0.000–0.056) | 0.041 (0.008–0.074)* | 0.136 (0.074–0.198)* | 0.125 (0.051–0.200)* | −0.042 (−0.102–0.018) | 0.098 (0.058–0.139)* | 0.098 (0.056–0.140)* | 0.055 (0.031–0.080)* |
| 10.00–11.99 | 0.046 (0.009–0.083)* | 0.049 (0.012–0.087)* | 0.036 (−0.015–0.086) | 0.369 (0.285–0.453)* | 0.392 (0.292–0.492)* | 0.115 (0.031–0.200)* | 0.111 (0.055–0.167)* | 0.108 (0.050–0.165)* | 0.076 (0.040–0.113)* |
| 12.00–14.64 | 0.092 (0.051–0.133)* | 0.090 (0.047–0.132)* | 0.076 (0.019–0.132)* | 0.372 (0.281–0.464)* | 0.377 (0.272–0.483)* | 0.127 (0.036–0.220)* | 0.118 (0.055–0.182)* | 0.113 (0.050–0.176)* | 0.089 (0.049–0.130)* |
| **Tree cover, %** | | | | | | | | | |
| 30.00–99.46 | Ref | Ref | Ref | Ref | Ref | Ref | Ref | Ref | Ref |
| 20.00–29.99 | 0.015 (−0.001–0.032) | 0.021 (0.005–0.037)* | −0.000 (−0.024–0.023) | 0.059 (0.024–0.094)* | 0.056 (0.019–0.092)* | 0.043 (0.006–0.079)* | 0.035 (0.010–0.060)* | 0.036 (0.010–0.061)* | 0.036 (0.019–0.052)* |
| 10.00–19.99 | 0.012 (−0.004–0.028) | 0.015 (−0.002–0.032) | −0.007 (−0.029–0.015) | 0.063 (0.029–0.097)* | 0.065 (0.030–0.101)* | 0.063 (0.028–0.097)* | 0.037 (0.013–0.062)* | 0.041 (0.016–0.066)* | 0.026 (0.010–0.042)* |
| 0–9.99 | 0.029 (0.010–0.048)* | 0.033 (0.013–0.054)* | 0.015 (−0.010–0.040) | 0.070 (0.030–0.109)* | 0.068 (0.024–0.112)* | 0.096 (0.056–0.136)* | 0.046 (0.017–0.076)* | 0.045 (0.014–0.076)* | 0.039 (0.021–0.057)* |
| **Grass cover, %** | | | | | | | | | |
| 30.01–84.98 | Ref | Ref | Ref | Ref | Ref | Ref | Ref | Ref | Ref |
| 20.00–29.99 | 0.007 (−0.013–0.027) | 0.004 (−0.016–0.025) | 0.001 (−0.024–0.026) | 0.037 (−0.005–0.079) | 0.054 (0.010–0.097)* | −0.005 (−0.045–0.036) | 0.031 (−0.001–0.064) | 0.032 (−0.001–0.065) | 0.022 (0.004–0.040)* |

(continued on next page)

**Table A8** (*continued*)

| | In-hours GP visits, Est (95% CI) | | | Out-of-hours GP visits, Est (95% CI) | | | ER visits, Est (95% CI) | | |
|---|---|---|---|---|---|---|---|---|---|
| | Generalized Linear Mixed Model (Main model) | Generalized Estimating Equations (Sensitivity analysis) | Census tract-level generalized linear model (Sensitivity analysis) | Generalized Linear Mixed Model (Main model) | Generalized Estimating Equations (Sensitivity analysis) | Census tract-level generalized linear model (Sensitivity analysis) | Generalized Linear Mixed Model (Main model) | Generalized Estimating Equations (Sensitivity analysis) | Census tract-level generalized linear model (Sensitivity analysis) |
| 10.00–19.99 | 0.010 (−0.009–0.030) | 0.008 (−0.013–0.029) | 0.012 (−0.012–0.037) | 0.030 (−0.011–0.071) | 0.025 (−0.019–0.068) | 0.026 (−0.014-0.066) | 0.022 (−0.009–0.053) | 0.024 (−0.009–0.056) | 0.037 (0.020–0.055)* |
| 0–9.99 | 0.007 (−0.013–0.027) | −0.000 (−0.022–0.022) | 0.021 (−0.005–0.047) | −0.019 (−0.062–0.024) | −0.031 (−0.077–0.014) | 0.017 (−0.025–0.059) | 0.035 (0.003–0.067)* | 0.038 (0.005–0.072)* | 0.041 (0.023–0.060)* |

**Table A9**

Adults – negative binomial generalized linear mixed models, negative binomial generalized estimating equations, and generalized linear models at the level of the census tract estimating the association between air pollution, green space and all-cause non-urgent and urgent medical care utilization

| | In-hours GP visits, Est (95% CI) | | | Out-of-hours GP visits, Est (95% CI) | | | ER visits, Est (95% CI) | | |
|---|---|---|---|---|---|---|---|---|---|
| | Generalized Linear Mixed Model (Main model) | Generalized Estimating Equations (Sensitivity analysis) | Census tract-level generalized linear model (Sensitivity analysis) | Generalized Linear Mixed Model (Main model) | Generalized Estimating Equations (Sensitivity analysis) | Census tract-level generalized linear model (Sensitivity analysis) | Generalized Linear Mixed Model (Main model) | Generalized Estimating Equations (Sensitivity analysis) | Census tract-level generalized linear model (Sensitivity analysis) |
| **$PM_{2.5}$, µg/$m^3$** | | | | | | | | | |
| 4.91–7.49 | Ref | Ref | Ref | Ref | Ref | Ref | Ref | Ref | Ref |
| 7.50–9.99 | 0.046 (0.030–0.061)* | 0.037 (0.020–0.054)* | 0.055 (0.031–0.080)* | 0.110 (0.068–0.152)* | 0.108 (0.046–0.156)* | 0.011 (−0.035–0.057) | 0.049 (0.022–0.076)* | 0.050 (0.021–0.079)* | 0.033 (−0.005–0.070) |
| 10.00–11.99 | 0.078 (0.056–0.101)* | 0.071 (0.048–0.094)* | 0.076 (0.040–0.113)* | 0.376 (0.317–0.436)* | 0.346 (0.269–0.423)* | 0.182 (0.117–0.248)* | 0.039 (0.000–0.077)* | 0.047 (0.008–0.086)* | 0.004 (−0.052–0.059) |
| 12.00–14.64 | 0.108 (0.083–0.134)* | 0.107 (0.081–0.134)* | 0.089 (0.049–0.130)* | 0.387 (0.322–0.453)* | 0.336 (0.254–0.418)* | 0.172 (0.100–0.245)* | 0.038 (−0.005–0.082) | 0.047 (0.004–0.090)* | −0.000 (−0.063–0.062) |
| **Tree cover, %** | | | | | | | | | |
| 30.00–99.46 | Ref | Ref | Ref | Ref | Ref | Ref | Ref | Ref | Ref |
| 20.00–29.99 | 0.030 (0.020–0.041)* | 0.028 (0.017–0.040)* | 0.036 (0.019–0.052)* | 0.068 (0.041–0.094)* | 0.068 (0.038–0.097)* | 0.023 (−0.008–0.053) | 0.028 (0.011–0.046)* | 0.028 (0.011–0.045)* | 0.012 (−0.014–0.038) |
| 10.00–19.99 | 0.034 (0.024–0.044)* | 0.034 (0.022–0.045)* | 0.026 (0.010–0.042)* | 0.091 (0.066–0.116)* | 0.084 (0.057–0.111)* | 0.050 (0.021–0.078)* | 0.019 (0.003–0.036)* | 0.018 (0.001–0.034)* | 0.006 (−0.019–0.030) |
| 0–9.99 | 0.034 (0.022–0.045)* | 0.028 (0.014–0.041)* | 0.039 (0.021–0.057)* | 0.091 (0.062–0.120)* | 0.076 (0.042–0.110)* | 0.074 (0.042–0.106)* | 0.009 (−0.012–0.029) | 0.000 (−0.020–0.021) | 0.024 (−0.004–0.051) |
| **Grass cover, %** | | | | | | | | | |
| 30.01–84.98 | Ref | Ref | Ref | Ref | Ref | Ref | Ref | Ref | Ref |
| 20.00–29.99 | 0.025 (0.027–0.047)* | 0.023 (0.010–0.035)* | 0.022 (0.004–0.040)* | 0.040 (0.010–0.071)* | 0.038 (0.001–0.074)* | 0.039 (0.006–0.071)* | 0.027 (0.005–0.049)* | 0.027 (0.003–0.051)* | −0.003 (−0.030–0.025) |
| 10.00–19.99 | 0.046 (0.036–0.055)* | 0.045 (0.032–0.057)* | 0.037 (0.020–0.055)* | 0.054 (0.024–0.084)* | 0.022 (−0.014–0.058) | 0.059 (0.027–0.091)* | 0.044 (0.022–0.065)* | 0.046 (0.023–0.068)* | 0.014 (−0.014–0.041) |
| 0–9.99 | 0.040 (0.041–0.063)* | 0.037 (0.023–0.050)* | 0.041 (0.023–0.060)* | 0.010 (−0.021–0.041) | −0.042 (−0.080 to −0.004)* | 0.050 (0.017–0.084)* | 0.054 (0.032–0.076)* | 0.057 (0.034–0.080)* | 0.051 (0.022–0.079)* |

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