HHS Public Access
Author manuscript
Environ Int. Author manuscript; available in PMC 2024 June 26.

Published in final edited form as:
Environ Int. 2024 June ; 188: 108739. doi:10.1016/j.envint.2024.108739.

Associations of street-view greenspace with Parkinson's disease hospitalizations in an open cohort of elderly US Medicare beneficiaries

Jochem O Klompmaker[a,b,*], **Daniel Mork**[c], **Antonella Zanobetti**[a], **Danielle Braun**[d,e], **Steve Hankey**[f], **Jaime E Hart**[g,h], **Perry Hystad**[i], **Marcia Pescador Jimenez**[j], **Francine Laden**[g,h,k], **Andrew Larkin**[i], **Pi-I Debby Lin**[l], **Esra Suel**[m], **Li Yi**[n], **Wenwen Zhang**[o], **Scott W. Delaney**[a,1], **Peter James**[a,n,1]

[a]Department of Environmental Health, Harvard T. H. Chan School of Public Health, Boston, MA, USA

[b]Channing Division of Network Medicine, Department of Medicine, Brigham and Women's Hospital and Harvard Medical School, Boston, MA, USA

[c]Department of Biostatistics, Harvard T.H. Chan School of Public Health, Boston, MA, USA

[d]Department of Biostatistics, Harvard T. H. Chan School of Public Health, Boston, MA 02115, USA

[e]Department of Data Science, Dana-Farber Cancer Institute, Boston, MA 02215, USA

[f]Urban Affairs and Planning (UAP), School of Public and International Affairs, Virginia Polytechnic Institute and State University, Blacksburg, VA, USA

[g]Department of Environmental Health, Harvard T. H. Chan School of Public Health, Boston, MA 02115, USA

[*]Corresponding author at: Department of Environmental Health, Harvard T. H. Chan School of Public Health, Boston, MA, USA. jklompmaker@hsph.harvard.edu (J.O. Klompmaker).
[1]contributed equally as last author.

Appendix A. Supplementary data
Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2024.108739.

CRediT authorship contribution statement
Jochem O Klompmaker: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Daniel Mork:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Antonella Zanobetti:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Danielle Braun:** Writing – review & editing, Resources, Data curation. **Steve Hankey:** Writing – review & editing, Methodology. **Jaime E Hart:** Writing – review & editing, Supervision, Methodology. **Perry Hystad:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Marcia Pescador Jimenez:** Writing – review & editing, Methodology, Conceptualization. **Francine Laden:** Writing – review & editing, Supervision, Methodology. **Andrew Larkin:** Writing – review & editing, Methodology, Conceptualization. **Pi-I Debby Lin:** Writing – review & editing, Methodology. **Esra Suel:** Writing – review & editing, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Li Yi:** Writing – review & editing, Visualization, Methodology. **Wenwen Zhang:** Writing – review & editing, Methodology, Conceptualization. **Scott W. Delaney:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Peter James:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

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

[h]Channing Division of Network Medicine, Department of Medicine, Brigham and Women's Hospital and Harvard Medical School, Boston, MA 02115, USA

[i]College of Public Health and Human Sciences, Oregon State University, Corvallis, OR, USA

[j]Department of Epidemiology, Boston University School of Public Health, Boston, MA, USA

[k]Department of Epidemiology, Harvard T. H. Chan School of Public Health, Boston, MA 02115, USA

[l]Division of Chronic Disease Research Across the Lifecourse (CoRAL), Department of Population Medicine, Harvard Medical School and Harvard Pilgrim Health Care Institute, Boston, MA, USA

[m]Faculty of the Built Environment, University College London, London, England

[n]Department of Population Medicine, Harvard Medical School and Harvard Pilgrim Health Care Institute, Boston, MA, USA

[o]Edward J Bloustein School of Planning and Public Policy, Rutgers, The State University of New Jersey, New Brunswick, NJ, USA

Abstract

Introduction: Protective associations of greenspace with Parkinson's disease (PD) have been observed in some studies. Visual exposure to greenspace seems to be important for some of the proposed pathways underlying these associations. However, most studies use overhead-view measures (e.g., satellite imagery, land-classification data) that do not capture street-view greenspace and cannot distinguish between specific greenspace types. We aimed to evaluate associations of street-view greenspace measures with hospitalizations with a PD diagnosis code (PD-involved hospitalization).

Methods: We created an open cohort of about 45.6 million Medicare fee-for-service beneficiaries aged 65 + years living in core based statistical areas (i.e. non-rural areas) in the contiguous US (2007–2016). We obtained 350 million Google Street View images across the US and applied deep learning algorithms to identify percentages of specific greenspace features in each image, including trees, grass, and other green features (i.e., plants, flowers, fields). We assessed yearly average street-view greenspace features for each ZIP code. A Cox-equivalent re-parameterized Poisson model adjusted for potential confounders (i.e. age, race/ethnicity, socioeconomic status) was used to evaluate associations with first PD-involved hospitalization.

Results: There were 506,899 first PD-involved hospitalizations over 254,917,192 person-years of follow-up. We found a hazard ratio (95% confidence interval) of 0.96 (0.95, 0.96) per interquartile range (IQR) increase for trees and a HR of 0.97 (0.96, 0.97) per IQR increase for other green features. In contrast, we found a HR of 1.06 (1.04, 1.07) per IQR increase for grass. Associations of trees were generally stronger for low-income (i.e. Medicaid eligible) individuals, Black individuals, and in areas with a lower median household income and a higher population density.

Conclusion: Increasing exposure to trees and other green features may reduce PD-involved hospitalizations, while increasing exposure to grass may increase hospitalizations. The protective associations may be stronger for marginalized individuals and individuals living in densely populated areas.

Keywords

Street-View Greenspace; Built Environment; Visual Exposure; Neurological Disorders; Parkinson's Disease

1. Introduction

Exposure to greenspace may protect against several adverse health outcomes, such as cardiovascular disease and mortality (Fong et al., 2018; Twohig-Bennett and Jones, 2018). Some studies have also found protective associations with neurological disorders, including Parkinson's Disease (PD) (Yu et al., 2021; Yuchi et al., 2020; Klompmaker et al., 2022; Jung et al., 2022; Zhu et al., 2023). Several pathways could explain these associations: greenspace can help to reduce stress and restore attention; it provides a setting for physical activity and social interactions; and may reduce exposure to harmful environmental exposures (e.g., air pollution, noise) (Fong et al., 2018; Markevych et al., 2017). These mechanisms could in turn reduce PD risks (Wang et al., 2018; Fang et al., 2018; Kasdagli et al., 2019).

Visual exposure to greenspace is hypothesized to be important for some of the proposed pathways underlying the health effects of greenspace, such as stress reduction and attention restoration (Larkin and Hystad, 2018). However, prior epidemiologic studies that examined associations of greenspace with PD have relied on satellite imagery or land-classification data to assess greenspace (Yu et al., 2021; Yuchi et al., 2020; Klompmaker et al., 2022; Jung et al., 2022; Zhu et al., 2023). A major limitation of these indicators is that they are overhead-view measures and likely differ from people's visual greenspace perception, i.e., the most common view people have of greenspace is from a street-view perspective (Larkin and Hystad, 2018). Overhead- and street-view measures may differently capture greenery, such as vertical greenspace (e.g., trees) obscuring buildings or the other way around and façade greenery, especially in dense built environments (Helbich et al., 2021). In addition, most overhead-view measures do not differentiate between types of greenspace. Conversely, street-view images capture visual exposures at street-level, similar to how individuals experience the environment, and can be used to detect specific greenspace features such as grass, trees, and plants. Hence, measuring greenspace from a street-view perspective may better capture an individual's visual greenspace exposure and could help to reveal relevant greenspace features that may influence PD.

We previously reported protective associations of satellite- and land-classification data-based nature exposures (greenness, park cover, and blue space) with hospitalization with a PD diagnosis code (hereafter referred to as PD-involved hospitalization) in a cohort of Medicare beneficiaries (Klompmaker et al., 2022). For this study, we assessed greenspace exposure based on Google Street View (GSV) images. We obtained approximately 350 million street-view images across all core based statistical areas (CBSAs) in the contiguous US and applied deep learning algorithms to segment specific greenspace features. CBSAs refer to micropolitan and metropolitan statistical areas that contain a large population or urban area (Office of Management and Budget. Federal Register ::, 2020). Our aim was to evaluate associations of specific street-view greenspace features with first PD-involved hospitalization in a cohort of about 45.6 million Medicare beneficiaries (2007–2016).

2. Methods

2.1. Study population

We created an open cohort including all fee-for-service (FFS) Medicare beneficiaries 65 + years living in ZIP codes in CBSAs in the contiguous US from January 1, 2007, through December 31, 2016. Medicare is the US government's near-universal health insurance program for individuals 65 + years. In 2010, about 78 % of all US residents (~240 million individuals) lived in CBSAs (US Census Bureau, 2023). For all beneficiaries, we obtained data on sex, age, race/ethnicity (White, Black, Other), Medicaid eligibility (a proxy for low income), and ZIP code of residence. Information on race/ethnicity in Medicare was primarily obtained from the US Social Security Administration (Filice and Joynt, 2017). Information on ZIP code of residence was annually updated. For each Medicare FFS beneficiary, follow-up started on January 1, 2007, or January of the year after first Medicare enrollment between 2008–2016, whichever was earlier. We followed each beneficiary until first hospitalization, or until they were censored (e.g., left FFS, emigrated), reached the end of the follow-up time (December 31, 2016), or died, whichever occurred first.

2.2. Outcome definition

Our outcome of interest was first hospital admission with any discharge diagnosis code of PD ("PD-involved hospitalization"; International Classification of Disease, Ninth Edition (ICD-9): 332.0 332.1; ICD-10: G20, G21.11, G21.19, and G21.8). We excluded beneficiaries known to have had their first PD hospitalization before the start of the follow-up period (i.e. 2000–2006). Hospitalization with any discharge diagnosis code of PD differs from PD onset. PD does not require hospitalization for diagnosis or treatment; hospitalization likely occurs at more advanced disease stages and potential associations should be interpreted as a measure of accelerated or slower disease progression or increased or decreased susceptibility (Klompmaker et al., 2022).

2.3. Exposure assessment

We created a 100 m street network grid for all CBSAs in the contiguous US. Next, we obtained all GSV images from 2007 through 2020 within each street network grid. We opted to source the images from Google's platform due to its relative consistency and prior completion of quality checks by Google. We exclusively utilized images captured by Google's street view cars to ensure a uniform standard of camera quality and positioning across all images, which is crucial for maintaining data integrity and facilitating accurate analysis. The majority of the GSV images (~78 %) were collected from April-October. For each image location, we used four GSV images with different orientations to capture horizontal street-level vision. To process all GSV images, we applied the pyramid scene parsing network (PSPNet), a deep learning approach pre-trained on the ADE20K dataset (Zhao et al., 2017). The ADE20K dataset is a dataset that contains 150 pre-defined classes of objects and parts of objects (Table S1) and is described in detail elsewhere (Zhou et al., 2017; Bolei et al., 2017). PSPNet utilizes a convolutional neural network (Long et al., 2015; Hu et al., 2015; Nogueira et al., 2017) and also incorporated local (i.e., nearby pixels) and global (i.e., full image) contextual cues to make the final pixel-level predictions more reliable. PSPnet has a good model performance with an overall pixel accuracy of 80.88 % (Zhao et al., 2017).

Using the PSPNet, we segmented the following greenspace features down to the pixel level: trees, palm trees, grass, plants, fields, and flowers. We calculated percent coverage scores for each feature (e.g., % pixels of trees in an image). Examples of GSV images with different coverage scores are shown in Fig. 1. For each year, we averaged the percent coverage scores of images to a 100 m resolution raster for the contiguous US. If a cell within a CBSA had no value in a specific year (e. g., because GSV vehicles did not drive in that cell in that year), we used the cell value closest in time if available (about 45 % of the cells were from the corresponding follow-up year ± 1 year and about 72 % of the cells were from the corresponding follow-up year ± 3 years). Illustrative maps for Detroit, MI; Nashville, TN; and Portland, OR are shown in Figure S1. For each greenspace feature, we calculated the mean value across all GSV images in each ZIP code for each year using Google Earth Engine (Gorelick et al., 2017). For this study, we focused on 1) trees (tree + palm tree), 2) other green (plant + field + flower), 3) grass, and 4) total green (trees + grass + other green). Maps of ZIP code-level trees, other green and grass in ZIP codes in CBSA in the contiguous US are shown in Figure S2. The average (standard deviation (SD)) area of ZIP codes within CBSAs (in 2016) is about 214 km^2 (567 km^2) and the average (SD) number of GSV grid cells per ZIP code is about 1,085 (1,116).

2.4. Covariates

We created ZIP code-level socioeconomic status (SES) indicators from the US Census and American Community Survey, similar to those used in our previous study (Klompmaker et al., 2022). We linked ZIP code-level percent Hispanic, percent Black, population density, median home value, median household income, percent of the population with less than a high school degree, percent below the poverty level, and percent of owner-occupied housing units. In addition, we derived county-level smoking status from the nationwide Behavioral Risk Factor Surveillance System (BRFSS). We also linked US census regions (n = 4) and divisions (n = 9) to be able to account for regional differences.

We obtained daily maximum temperature, relative humidity, total precipitation data (4 km spatial resolution) from the Gridded Surface Meteorological dataset for every year (Abatzoglou, 2013). Daily nitrogen dioxide (NO_2) and fine particulate matter ($PM_{2.5}$) concentrations (1 km spatial resolution) based on spatiotemporal ensemble models for every year were also linked (Di et al., 2019; Di et al., 2019). For each ZIP code for each year, we estimated the ZIP code-level annual average maximum temperature, relative humidity, total precipitation, $PM_{2.5}$, and NO_2.

We also linked overhead-view nature exposures (greenness, park cover and blue space) that we have used previously (Klompmaker et al., 2022). Greenness was estimated for every year of follow-up using the Normalized Difference Vegetation Index (NDVI) based on satellite images from Landsat 7 and Landsat 8 (June 1 − August 31, 30 m spatial resolution).

Before estimating ZIP code-level NDVI, negative NDVI values were set to zero as they correspond to water. Park cover is based on cross-sectional data from the USGS Protected Areas Database of the US (PAD-US) V2.1. For each ZIP code for each year, we calculated the mean NDVI and park cover. Blue space was based on the Joint Research Centre's Global Surface Water Dataset (30 m spatial resolution) (Pekel et al., 2016). In line with our previous study, (Klompmaker et al., 2022) we calculated the mean blue space cover of ZIP codes with a 1000 m buffer, as ZIP codes areas do not always include adjacent water bodies.

2.5. Statistical analyses

We used a Cox-equivalent re-parameterized Poisson approach (Shi et al., 2020) to examine associations of street-view greenspace with PD-involved hospitalization. For each follow-up year, we aggregated all beneficiaries by 2-year age categories at study entry, sex, race/ethnicity (White, Black, Other), Medicaid eligibility, calendar year and ZIP code of residence. For each aggregated cell, we also counted the corresponding number of PD-involved hospitalizations and person-time. We assigned annual ZIP code-level exposures and potential confounders to the corresponding ZIP codes and calendar years based on the ZIP code of each beneficiary's residence. To examine associations, we used Poisson models with count of PD-involved hospitalization as the dependent variable and total person-time of beneficiaries as the offset. This approach is mathematically equivalent to a time-varying Cox proportional hazard model under an Anderson-Gill representation. An *m*-out-*n* bootstrap method (sampling a smaller number (*m*) out of the original sample size (*n*)) (Bickel et al., 1997) using ZIP code units was applied to calculate statistically robust confidence intervals (CIs). This method is used to account for within ZIP code unit observations across years, and is described in detail elsewhere (Shi et al., 2020). We excluded beneficiaries living in ZIP codes with less than 1 % area coverage (street view pixels / ZIP code area) or less than 100 pixels in total (~2.4 % of beneficiaries) as the limited number of images within these ZIP codes is unlikely to accurately capture or represent the average GSV greenspace exposure.

Our minimally-adjusted model included calendar year, census region, an offset for total person-time and strata for all possible combinations of age, sex, race, Medicaid eligibility, and follow-up year to allow for flexible strata-specific baseline rates. Our fully-adjusted model was additionally adjusted for the ZIP code-level SES indicators and smoking status as described above. In our models, we included percent coverage of street-view trees, grass and other green simultaneously, and total green individually. We used natural splines to examine the shape of the exposure–response curves. We performed stratified analyses by sex, age, race/ethnicity, Medicaid eligibility, and race/ethnicity-by-Medicaid eligibility terms. We focused on White (the largest racial group in the US) and Black beneficiaries because Black Americans comprise the second largest racial or ethnic group of Medicare beneficiaries and are uniquely burdened by structural racism (Bailey et al., 2017; Beech et al., 2021). We acknowledge that all non-White racialized groups in the US are marginalized in distinct ways, however, research on other subpopulations enrolled in Medicare is complicated by substantial misclassification of other racial and ethnic identities in the data (Jarrín et al., 2020). Further, we performed stratified analyses by tertiles of ZIP code-level median household income, population density, NO_2, $PM_{2.5}$ and annual average temperature.

For sensitivity analyses, we additionally adjusted our main model for air pollution ($PM_{2.5}$ and NO_2); for meteorological indicators (annual average temperature, relative humidity and precipitation); for overhead-view nature measures (NDVI, park cover and blue space cover (binary indicator: <1% vs. ≥ 1 %)); and for US census division instead of US census region. We also ran single-exposure models for trees, other green and grass. Hazard ratios (HRs) for trees, grass, other green and total green are expressed per IQR increase.

We used R version 4.2.2 software (R Project for Statistical Computing) on the Harvard Faculty of Arts and Science Secure Environment cluster supported by Harvard University. This study was approved by the Human Subjects Committee of the Harvard TH Chan School of Public Health and was exempt from informed consent requirements as a study of existing administrative data. The use of GSV images for this study was approved by the data provider.

3. Results

In our cohort of 45,607,879 Medicare beneficiaries, we found 506,899 first PD-involved hospitalizations in 254,917,192 person years. Most of the beneficiaries were White, between 65–74 years of age at study entry, and not eligible for Medicaid (Table 1). The median and interquartile range (IQR) was larger for trees than for grass and other green exposures (Table S2). Trees, grass and other green were weakly correlated (Spearman rho: −0.12 – 0.29, Figure S3), while total green was strongly correlated with trees (0.89) and grass (0.61).

We observed approximately linear associations between all street-view greenspace exposures and PD-involved hospitalization (Figure S4). In the minimally-adjusted model, we observed negative associations of trees and other green as well as of total green with PD-involved hospitalization (Table 2). In the fully-adjusted model, we found a HR (95 %CI) of 0.95 (0.94, 0.96) per IQR increase for trees, a HR of 0.97 (0.96, 0.97) per IQR increase for other green and a HR of 0.98 (0.96, 0.99) per IQR increase for total green. Conversely, grass was positively associated with PD-involved hospitalization (HR: 1.06 (1.04, 1.07) per IQR increase). Associations of trees, other green, and grass were generally similar in models additionally adjusted for air pollution, climate indicators, and overhead-view nature measures; in models adjusted for division instead of region; and in single-exposure models (Table S3).

In general, effect modification by race/ethnicity showed that the protective associations of trees, other green, and total green were stronger for Black individuals than for White individuals (Fig. 2, numeric results in Table S4). Associations of trees (protective) and of grass (harmful) were stronger for Medicaid-eligible (i.e., low income) individuals than for individuals not eligible for Medicaid. In subgroups defined simultaneously by Medicaid eligibility and race/ethnicity, we found stronger protective associations of trees and other green for high income Black, low income Black, and low income White individuals than for high income White individuals. No clear patterns of effect modification by age and sex were observed (Table S4). Associations of trees were stronger in areas with lower median household income, higher population density, and higher NO_2 concentrations (Fig.

3, numeric results in Table S5). The harmful associations of grass were weaker or absent in areas with lower population density and lower NO_2 concentrations.

4. Discussion

Using 350 million street-view images, a deep learning algorithm to identify greenspace features, and a cohort of 45.6 million Medicare beneficiaries, we observed that some greenspace features may be protective for PD-involved hospitalizations, while others may not be. Specifically, we observed protective associations of street-view trees and other green, but harmful associations with grass. Total green, a combination of trees, grass and other green, was also protectively associated with PD-involved hospitalization. Associations of trees were generally stronger for marginalized individuals and individuals living in densely populated areas.

We are not aware of any prior study that has examined associations of street-view greenspace with PD-involved hospitalizations. We previously reported protective associations of NDVI and park cover with PD-involved hospitalization in a cohort of Medicare beneficiaries from 2000 to 2016 (Klompmaker et al., 2022). Studies in Canada, China and South Korea showed protective associations of NDVI with PD incidence, consistent with our findings for PD-involved hopsitalization (Yu et al., 2021; Yuchi et al., 2020; Jung et al., 2022; Zhu et al., 2023). We found protective associations of trees and other green, and harmful associations of grass, indicating differential associations of greenspace features on PD-involved hospitalization that would have been obscured by coarse vegetation indices like NDVI. Associations of total green were slightly weaker than associations with trees, which is likely because total green combines trees, other green (both protective) and grass (harmful). We found no clear indications that lower air pollution levels explained the protective associations of trees and other green. This could be due to the adjustment for population density (an indicator strongly correlated with NO_2) in the fully-adjusted models, or because of the weak correlations of street-view trees with air pollution." There are several other potential pathways; greenspace may relieve stress and anxiety and create a setting for physical activity and social interactions (Fong et al., 2018; Markevych et al., 2017). Studies reported that improved mental, physical and social health could affect PD (Wang et al., 2018; Fang et al., 2018; Tickle-Degnen et al., 2021). The differential associations between grass and trees and other green could be due to various reasons. The harmful associations with grass may be related to pesticide application. In prior research, a *meta*-analysis showed that long-term exposure to pesticides is positively associated with PD risk (Yan et al., 2018). ZIP codes with a high percentage of grass may contain agricultural or private land where pesticides are used or may be close to agricultural land. Grass may also lead to higher pollen concentrations, which could affect the immune system and increase PD hospitalization risk (Awaya and Kuroiwa, 2022). In addition, grass may be linked to more urban sprawl, private yards, and less walkable environments and thereby negatively affecting PD. Trees are generally perceived as calming (Mullaney et al., 2015) and may also represent more biodiverse areas.

Stratified analyses indicated that the protective associations were stronger for marginalized individuals (Medicaid eligible beneficiaries, Black beneficiaries, beneficiaries living in ZIP code with a lower median household income). These findings are consistent with the “equigenesis” theory that posits that greenspace can decrease health disparities by SES, because greenspace-health associations are stronger in lower SES individuals (Mitchell and Popham, 2008; Rigolon et al., 2021). A review also reported stronger protective associations of public greenspace for racial/ethnic minorities than for White individuals (Rigolon et al., 2021). The stronger associations could be due to structural racism, social exclusion, or less material wealth that puts more stress on marginalized individuals. This may make them more susceptible to the benefits of greenspace because of its stress-reducing and attention-restoration capacity or because greenspaces are freely accessible and can be used for physical/social activities. In addition, associations might be stronger because marginalized individuals may spend more time in their direct neighborhood than other individuals. We previously reported stronger associations of NDVI with PD-involved hospitalization among marginalized individuals (Klompmaker et al., 2022). This study suggests that these stronger protective associations of greenspace for marginalized individuals are driven by trees and other green, while associations of grass may increase health disparities.

Associations with trees were strongest in areas with higher population density and NO_2 concentrations. These findings are consistent with a review that reported stronger associations of greenspace with health outcomes in more urban areas (Browning et al., 2022). This could be because urban dwellers experience more attentional demands and stressors than rural dwellers (Krabbendam et al., 2021; Lederbogen et al., 2011). Further, greenspace in urban areas is more likely to be developed for access and use and therefore provides better opportunities for physical activity, social interactions, stress reduction, and attention restoration than greenspace in non-urban areas (Browning et al., 2022). We also note that differences in associations between environmental and SES strata could be due to differences in symptom awareness, providers recognition and documentation of PD, and health care seeking behaviors (Mantri et al., 2019).

A major strength of this study is that greenspace exposure was based on 350 million street-view images covering all CBSA across the contiguous US from 2007 to 2020. Using a deep learning approach, we were able to differentiate between specific greenspace features and evaluate their independent associations. This provides valuable information and can help policy makers and urban planners to create specific health-beneficial interventions. Correlations of street-view greenspace features with the commonly used NDVI and park cover were low to moderate, and associations remained after adjustment for these overhead-view greenspace measures. This finding indicates that GSV greenspace features represent different aspects of the natural environment. Other studies also showed protective associations of street-view greenspace with other health outcomes (Wang et al., 2019; Helbich et al., 2019; Nguyen et al., 2021; Xiao et al., 2021). Because visual exposure seems to be important for stress reduction, attention restoration, and other potential pathways, street-view greenspace might better capture potential health benefits than overhead-view greenspace measures. However, we note that we used street-view images only from streets and therefore did not capture greenspace within parks or areas where cars cannot drive. GSV images were taken in different months, but we have no reason to believe that there is any systematic bias to how or when images were collected that might influence the observed findings. If GSV values were not available in a specific year, we used GSV values closest in time if available, and assumed that greenspaces did not change rapidly over time. We believe that this is a reasonable assumption. We have not included information about the quality and perception of greenspaces, the amount of time individuals spend in their ZIP codes, or other street view-level urban indicators that may affect health.

Our study has several strengths and some limitations. Our cohort included about 45.6 million Medicare beneficiaries living in CBSAs in the contiguous US. The study population is a fairly representative sample of individuals aged 65 + years in CBSAs in the contiguous US. However, our results may not be generalizable to rural populations. We did not have information on the exact residence of each Medicare beneficiary and therefore assessed ZIP code exposures. The race/ethnicity indicator that we used was based on administrative data and may not accurately capture the complexity of racial and ethnic identity (Jarrín et al., 2020; Josey et al., 2023). In addition, we had limited information on individual-level SES and no information on individual-level lifestyle factors, however, we adjusted multiple ZIP code-level SES indicators and performed several sensitivity analyses. We did not take into consideration the competing risk posed by death. We also note that residential self-selection could explain observed associations between greenspace and greenspace. However, studies indicated that greenspace residential self-selection was not a major source of bias in other US populations (James et al., 2015; Gailey, 2022). PD does not require hospitalization for diagnosis or treatment; hospitalization likely occurs at more advanced disease stages. Hence, associations should be interpreted as accelerated/slower PD progression. We could not test whether the protective associations were due to differences in potential mechanisms of physical activity, social interactions, or reduced stress.

5. Conclusions

This study shows that exposure to street-view measured trees and other green may be protective for PD-involved hospitalization, while exposure to grass may be harmful. The protective associations were generally stronger for marginalized individuals and individuals living in densely populated areas. Increasing trees and other green coverage may help to prevent PD-involved hospitalization.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgements

This study was supported by National Institute of Environmental Health Sciences (R01 ES028033, R01 ES034373, and P30 ES000002), the National Heart, Lung and Blood Institute (R01 HL150119), the National Institute on Aging (R01 AG066793), and Biogen (working through the Harvard Chan-NIEHS Center for Environmental Health under P30 ES000002). The funders had no role in the study design and conduct of the study; collection, management, analysis, and interpretation of the data; preparation, review, or approval of the manuscript; and decision to submit the manuscript for publication.

Data availability

The data that has been used is confidential.

References

Abatzoglou JT, 2013. Development of gridded surface meteorological data for ecological applications and modelling. Int. J. Climatol 33 (1), 121–131. 10.1002/joc.3413.

Awaya A, Kuroiwa Y, 2022. Relationship between annual airborne pollen levels and occurrence of parkinson disease, amyotrophic lateral sclerosis, myasthenia gravis, multiple sclerosis, spinocerebellar degeneration, huntington's disease, shy-drager syndrome, moyamoya disease. Med. Clin. Sci. Curr. Arch. About 4 (4).

Bailey ZD, Krieger N, Agénor M, Graves J, Linos N, Bassett MT, 2017. Structural racism and health inequities in the USA: evidence and interventions. Lancet 389 (10077), 1453–1463. 10.1016/S0140-6736(17)30569-X. [PubMed: 28402827]

Beech BM, Ford C, Thorpe RJ, Bruce MA, Norris KC, 2021. Poverty, racism, and the public health crisis in America. Front Public Heal. 9, 699049 10.3389/FPUBH.2021.699049/BIBTEX.

Bickel PJ, Gotze F, van Zwet WR, 1997. Resampling fewer than n observations: gains, losses and remedies for losses. Stat Sin. 7, 1–31. 10.1007/978-1-4614-1314-1_17.

Bolei Z, Hang Z, Puig X, Fidler S, Barriuso A, Torralba A. ADE20K Dataset. Computer Vision and Pattern Recognition (CVPR). Published 2017. Accessed October 16, 2023. https://groups.csail.mit.edu/vision/datasets/ADE20K/.

Browning MHEM, Rigolon A, McAnirlin O, Yoon H (Violet), 2022. Where greenspace matters most: a systematic review of urbanicity, greenspace, and physical health. Landsc Urban Plan. 217, 104233 10.1016/J.LANDURBPLAN.2021.104233.

Di Q, Amini H, Shi L, et al. , 2019. Assessing NO 2 concentration and model uncertainty with high spatiotemporal resolution across the contiguous united states using ensemble model averaging. ACS Publ. 54 (3), 1372–1384. 10.1021/acs.est.9b03358.

Di Q, Amini H, Shi L, et al. , 2019. An ensemble-based model of PM2.5 concentration across the contiguous United States with high spatiotemporal resolution. Environ. Int 130, 104909 10.1016/j.envint.2019.104909.

Fang X, Han D, Cheng Q, et al. , 2018. Association of levels of physical activity with risk of parkinson disease: s systematic review and meta-analysis. JAMA Netw. Open 1 (5), e182421–e. 10.1001/JAMANETWORKOPEN.2018.2421.

Filice CE, Joynt KE, 2017. Examining race and ethnicity information in medicare administrative data. Med. Care 55 (12), e170–e176. 10.1097/MLR.0000000000000608. [PubMed: 29135782]

Fong KC, Hart JE, James P, 2018. A review of epidemiologic studies on greenness and health: updated literature through 2017. Curr. Environ. Heal Reports. 5 (1), 77–87. 10.1007/s40572-018-0179-y.

Gailey S, 2022. Moving to greener pastures: health selection into neighborhood green space among a highly mobile and diverse population in California. Soc Sci Med. 315 10.1016/j.socscimed.2022.115411.

Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D, Moore R, 2017. Google Earth Engine: planetary-scale geospatial analysis for everyone. Remote Sens Environ. 202, 18–27. 10.1016/j.rse.2017.06.031.

Helbich M, Yao Y, Liu Y, Zhang J, Liu P, Wang R, 2019. Using deep learning to examine street view green and blue spaces and their associations with geriatric depression in Beijing China. Environ. Int 126, 107–117. 10.1016/j.envint.2019.02.013. [PubMed: 30797100]

Helbich M, Poppe R, Oberski D, van Emmichoven MZ, Schram R, 2021. Can't see the wood for the trees? an assessment of street view- and satellite-derived greenness measures in relation to mental health. Landsc Urban Plan. 214 (104181) 10.1016/j.landurbplan.2021.104181.

Hu F, Xia G-S, Hu J, et al. , 2015. Transferring deep convolutional neural networks for the scene classification of high-resolution remote sensing imagery. Remote Sens. 7 (11), 14680–14707. 10.3390/RS71114680.

James P, Hart JE, Arcaya MC, Feskanich D, Laden F, Subramanian SV, 2015. Neighborhood self-selection: the role of pre-move health factors on the built and socioeconomic environment. Int. J. Environ. Res. Public Heal. 12 (10), 12489–12504. 10.3390/ijerph121012489.

Jarrín OF, Nyandege AN, Grafova IB, Dong X, Lin H, 2020. Validity of race and ethnicity codes in medicare administrative data compared to gold-standard self-reported race collected during routine home health care visits. Med. Care 58 (1), e1. [PubMed: 31688554]

Josey KP, Delaney SW, Wu X, et al. , 2023. Air pollution and mortality at the intersection of race and social class. N. Engl. J. Med 388 (15), 1396–1404. 10.1056/NEJMSA2300523/SUPPL_FILE/NEJMSA2300523_DATA-SHARING.PDF. [PubMed: 36961127]

Jung J, Park JY, Myung W, Lee JY, Ko H, Lee H, 2022. Association between residential greenness and incidence of Parkinson's disease: a population-based cohort study in South Korea. Int. J. Environ. Res. Public Health. 19 (6), 3491. 10.3390/IJERPH19063491/S1. [PubMed: 35329176]

Kasdagli MI, Katsouyanni K, Dimakopoulou K, Samoli E, 2019. Air pollution and Parkinson's disease: a systematic review and meta-analysis up to 2018. Int. J. Hyg. Environ. Health 222 (3), 402–409. 10.1016/J.IJHEH.2018.12.006. [PubMed: 30606679]

Klompmaker JO, Laden F, Browning MHEM, et al. , 2022. Associations of greenness, parks, and blue space with neurodegenerative disease hospitalizations among older US adults. JAMA Netw. Open 5 (12), e2247664–e. 10.1001/JAMANETWORKOPEN.2022.47664.

Krabbendam L, Van Vugt M, Conus P, et al. , 2021. Understanding urbanicity: How interdisciplinary methods help to unravel the effects of the city on mental health. Psychol Med. 51 (7), 1099–1110. 10.1017/S0033291720000355. [PubMed: 32156322]

Larkin A, Hystad P, 2018. Evaluating street view exposure measures of visible green space for health research. J. Expo. Sci. Environ. Epidemiol 29 (4), 447–456. 10.1038/s41370-018-0017-1. [PubMed: 29352209]

Lederbogen F, Kirsch P, Haddad L, et al. , 2011. City living and urban upbringing affect neural social stress processing in humans. Nat. 474 (7352), 498–501. 10.1038/nature10190.

Long J, Shelhamer E, Darrell T, 2015. Fully convolutional networks for semantic segmentation. Published Online 3431–3440.

Mantri S, Fullard ME, Beck J, Willis AW, 2019. State-level prevalence, health service use, and spending vary widely among Medicare beneficiaries with Parkinson disease. Npj Park Dis. 5 (1), 1–9. 10.1038/s41531-019-0074-8.

Markevych I, Schoierer J, Hartig T, et al. , 2017. Exploring pathways linking greenspace to health: theoretical and methodological guidance. Environ. Res 158, 301–317. 10.1016/J.ENVRES.2017.06.028. [PubMed: 28672128]

Mitchell R, Popham F, 2008. Effect of exposure to natural environment on health inequalities: an observational population study. Lancet 372 (9650), 1655–1660. 10.1016/S0140-6736(08)61689-X. [PubMed: 18994663]

Mullaney J, Lucke T, Trueman SJ, 2015. A review of benefits and challenges in growing street trees in paved urban environments. Landsc Urban Plan. 134, 157–166. 10.1016/J.LANDURBPLAN.2014.10.013.

Nguyen TT, Nguyen QC, Rubinsky AD, et al. , 2021. Google street view-derived neighborhood characteristics in california associated with coronary heart disease, hypertension, diabetes. Int. J. Environ. Res. Public Health. 18, 10428. [PubMed: 34639726]

Nogueira K, Penatti OAB, dos Santos JA, 2017. Towards better exploiting convolutional neural networks for remote sensing scene classification. Pattern Recognit. 61, 539–556. 10.1016/J.PATCOG.2016.07.001.

Office of Management and Budget. Federal Register :: 2020 Standards for Delineating Core Based Statistical Areas. Published 2021. Accessed November 8, 2023. https://www.federalregister.gov/documents/2021/07/16/2021-15159/2020-standards-for-delineating-core-based-statistical-areas.

Pekel JF, Cottam A, Gorelick N, Belward AS, 2016. High-resolution mapping of global surface water and its long-term changes. Nature 540 (7633), 418–422. 10.1038/nature20584. [PubMed: 27926733]

Rigolon A, Browning MHEM, McAnirlin O, Yoon H, 2021. Green space and health equity: a systematic review on the potential of green space to reduce health disparities. Int. J. Environ. Res. Public Health 18 (5), 1–29. 10.3390/ijerph18052563.

Shi L, Wu X, Danesh Yazdi M, et al. , 2020. Long-term effects of PM2·5 on neurological disorders in the American medicare population: a longitudinal cohort study. Lancet Planet Heal. 4 (12), e557–e565. 10.1016/s2542-5196(20)30227-8.

Tickle-Degnen L, Stevenson MT, Gunnery SD, et al. , 2021. Profile of social self-management practices in daily life with Parkinson's disease is associated with symptom severity and health quality of life. Disabil Rehabil. 43 (22), 3212–3224. 10.1080/09638288.2020.1741035. [PubMed: 32233702]

Twohig-Bennett C, Jones A, 2018. The health benefits of the great outdoors: a systematic review and meta-analysis of greenspace exposure and health outcomes. Environ. Res 166, 628–637. 10.1016/j.envres.2018.06.030. [PubMed: 29982151]

US Census Bureau. Metropolitan and Micropolitan Statistical Areas Population Totals and Components of Change: 2010–2019. Published 2023. Accessed November 8, 2023. https://www.census.gov/data/tables/time-series/demo/popest/2010s-total-metro-and-micro-statistical-areas.html.

Wang R, Helbich M, Yao Y, et al. , 2019. Urban greenery and mental wellbeing in adults: cross-sectional mediation analyses on multiple pathways across different greenery measures. Environ. Res 176 (108535) 10.1016/j.envres.2019.108535.

Wang S, Mao S, Xiang D, Fang C, 2018. Association between depression and the subsequent risk of Parkinson's disease: a meta-analysis. Prog. Neuro-Psychopharmacology Biol. Psychiatry 86, 186–192. 10.1016/J.PNPBP.2018.05.025.

Xiao X, Wang R, Knibbs LD, et al. , 2021. Street view greenness is associated with lower risk of obesity in adults: findings from the 33 Chinese community health study. Environ. Res 200 (111434) 10.1016/j.envres.2021.111434.

Yan D, Zhang Y, Liu L, Shi N, Yan H, 2018. Pesticide exposure and risk of Parkinson's disease: dose-response meta-analysis of observational studies. Regul. Toxicol. Pharmacol 96, 57–63. 10.1016/j.yrtph.2018.05.005. [PubMed: 29729297]

Yu Z, Wei F, Zhang X, et al. , 2021. Air pollution, surrounding green, road proximity and Parkinson's disease: a prospective cohort study. Environ. Res 197, 111170 10.1016/J.ENVRES.2021.111170.

Yuchi W, Sbihi H, Davies H, Tamburic L, Brauer M, 2020. Road proximity, air pollution, noise, green space and neurologic disease incidence: a population-based cohort study. Environ. Heal A Glob Access Sci. Source 19 (1), 1–15. 10.1186/S12940-020-0565-4/FIGURES/1.

Zhao H, Shi J, Qi X, Wang X, Jia J. Pyramid Scene Parsing Network. Published online 2017:2881–2890. Accessed September 28, 2023. https://github.com/hszhao/PSPNet.

Zhou B, Zhao H, Puig X, Fidler S, Barriuso A, Torralba A. Scene Parsing Through ADE20K Dataset. Published online 2017:633–641. Accessed October 16, 2023. http://groups.csail.mit.edu/vision/datasets/ADE20K/.

Zhu Z, Yang Z, Yu L, et al. , 2023. Residential greenness, air pollution and incident neurodegenerative disease: a cohort study in China. Sci. Total Environ. 878, 163173 10.1016/J.SCITOTENV.2023.163173.

Fig. 1. GSV images with different coverage scores for trees, grass and other green.

a a For trees Q1: <12.5 %; Q2: 12.5 %−19.4 %; Q3: 19.4 %−26.2 %; Q4: 26.2 %<. For grass Q1: <4.5 %; Q2: 4.5 %−8.9 %; Q3: 8.9 %−11.9 %; Q4: 11.9 %<. For other green Q1: <1.3 %; Q2: 1.3 %−2.0 %; Q3: 2.0 %−3.5 %; Q4: 3.5 %<. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

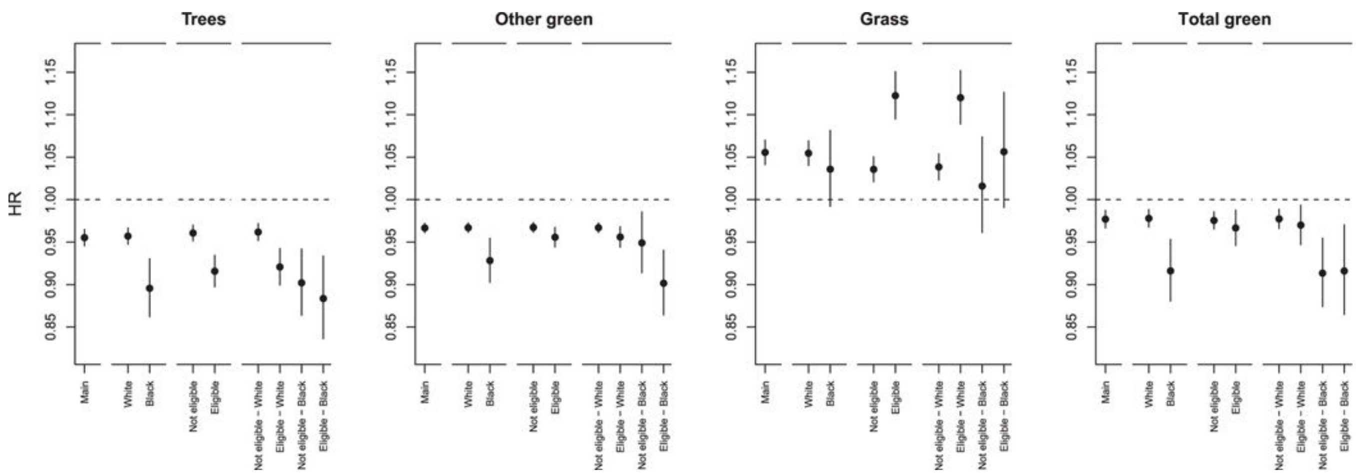

Fig. 2. Associations of ZIP code-level GSV-derived greenspace measures with PD-involved hospitalization stratified by Medicaid eligibility and race/ethnicity.

[a] [a] The models included Trees, Other green, Grass simultaneously and Total green individually. The models included calendar year, region, ZIP code-level percent Hispanic, percent Black, population density, median home value, median household income, percent of the population with less than a high school degree, percent below the poverty level, percent of owner-occupied housing units, county-level smoking status, an offset for total person-time and strata for all possible combinations of sex, race, Medicaid Eligibility, age at study entry (2-year categories), and follow-up year. Effect modification models did not include a strata for the specific effect modifier. Associations are expressed per IQR increase of the full cohort (IQR Trees = 13.7 %, IQR Other green = 2.3 %, IQR Grass = 7.4 %, IQR Total green = 15.9 %).

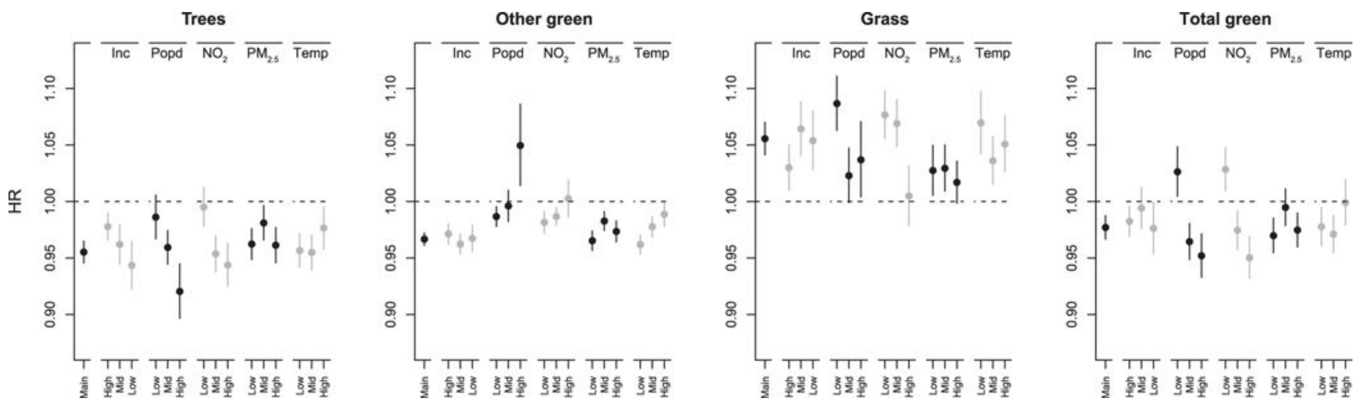

Fig. 3. Associations of ZIP code-level GSV-derived greenspace measures with PD-involved hospitalization stratified by ZIP code-level neighborhood and environmental indicators.

[a, b][a] The models included Trees, Other green and Grass simultaneously and Total green individually. The models included calendar year, region, ZIP code-level percent Hispanic, percent Black, population density, median home value, median household income, percent of the population with less than a high school degree, percent below the poverty level, percent of owner-occupied housing units, county-level smoking status, an offset for total person-time and strata for all possible combinations of sex, race, Medicaid Eligibility, age at study entry (2-year categories), and follow-up year. For effect modification by ZIP code-level median household income, models did not include ZIP code-level median home value, median household income, percent of the population with less than a high school degree, percent below the poverty level, percent of owner-occupied housing units. For effect modification by ZIP code-level population density, models did not include ZIP code-level population density. Associations are expressed per IQR increase of the full cohort (IQR Trees = 13.7 %, IQR Other green = 2.3 %, IQR Grass = 7.4 %, IQR Total green = 15.9 %).[b] Inc = ZIP code-level median household income, Popd = ZIP code-level population density, NO_2 = ZIP code-level NO_2, $PM_{2.5}$ = ZIP code-level $PM_{2.5}$, Temp = ZIP code-level temperature.

Table 1

Descriptive statistics of the full study population and by tree categories [a].

Individual-level variables (at study entry)	Full cohort N (% or pyrs [b])	Trees Q1 N (% or pyrs [b])	Trees Q2 N (% or pyrs [b])	Trees Q3 N (% or pyrs [b])
Sex				
Male	20,515,179 (45.0)	6,129,575 (45.9)	7,497,902 (44.5)	6,887,702 (44.7)
Female	25,092,700 (55.0)	7,224,240 (54.1)	9,360,195 (55.5)	8,508,265 (55.3)
Age				
65–74 years	32,356,955 (70.9)	9,593,437 (71.8)	11,859,521 (70.3)	10,903,997 (70.8)
75–84 years	9,419,694 (20.7)	2,671,502 (20.0)	3,558,792 (21.1)	3,189,400 (20.7)
85 + years	3,831,230 (8.4)	1,088,876 (8.2)	1,439,784 (8.5)	1,302,570 (8.5)
Race/ethnicity				
White	38,070,881 (83.5)	10,642,095 (79.7)	14,030,625 (83.2)	13,398,161 (87.0)
Black	4,018,028 (8.8)	962,037 (7.2)	1,768,992 (10.5)	1,286,999 (8.4)
Other	3,518,970 (7.7)	1,749,683 (13.1)	1,058,480 (6.3)	710,807 (4.6)
Medicaid eligibility				
Ineligible	38,860,594 (85.2)	10,800,643 (80.9)	14,467,998 (85.8)	13,591,953 (88.3)
Eligible	6,747,285 (14.8)	2,553,172 (19.1)	2,390,099 (14.2)	1,804,014 (11.7)
Region				
Midwest	10,279,607 (22.5)	2,775,028 (20.8)	5,001,333 (29.7)	2,503,246 (16.3)
Northeast	9,027,370 (19.8)	1,301,453 (9.7)	2,934,139 (17.4)	4,791,778 (31.1)
South	17,456,677 (38.3)	3,644,368 (27.3)	6,816,887 (40.4)	6,995,422 (45.4)
West	8,844,225 (19.4)	5,632,966 (42.2)	2,105,738 (12.5)	1,105,521 (7.2)
ZIP code-level aggregated variables	**Median (IQR)**	**Median (IQR)**	**Median (IQR)**	**Median (IQR)**
% below the poverty level	8.2 (7.7)	9.4 (9.6)	8.5 (7.0)	7.0 (6.6)
Population density (persons/mile^2)	803.8 (3155.3)	889.7 (4422.8)	1423.0 (3690.9)	455.8 (1828.6)
Median home value ($10,000)	16.6 (16.8)	16.4 (16.4)	15.8 (13.8)	18.5 (19.7)
% Black	4.6 (14.4)	3.1 (9.8)	6.5 (17.7)	4.8 (16)
Median household income ($10,000)	51.0 (26.9)	49.5 (23.0)	49.3 (23.9)	55.4 (34.8)
% owner-occupied housing units	69.8 (22.6)	66.7 (26.1)	67.1 (22.2)	75.1 (18.1)
% Hispanic	6.5 (15.8)	16.4 (35.4)	6.4 (12.7)	3.8 (6.3)
% with less than a high school degree	20.2 (17.5)	22.4 (21.8)	20.9 (15.7)	17.6 (16.1)
% ever smoked	45.5 (8.7)	43.4 (9.2)	46.0 (8.2)	46.7 (7.7)
$PM_{2.5}$ (μg/m^3)	8.9 (2.9)	8.8 (3.3)	9.1 (2.8)	8.7 (2.8)
NO_2 (ppb)	15.3 (11.8)	16.2 (13.2)	15.9 (11.5)	13.7 (10.9)
Annual temperature (°C)	19.7 (8.2)	22.2 (8.6)	19.3 (7.9)	18.7 (7.0)
Annual relative humidity	86.3 (7.9)	83.7 (13.5)	86.8 (7.2)	87.2 (5.9)
Annual precipitation (mm, daily total)	2.9 (1.3)	2.0 (2.2)	3.0 (1.0)	3.2 (0.9)
NDVI summer	0.40 (0.17)	0.34 (0.29)	0.51 (0.21)	0.62 (0.14)
% Park cover	8.0 (15.5)	6.5 (15.7)	7.8 (13.2)	9.6 (17.4)
% Blue space cover (1000 m buffer)	0.6 (3.4)	0.3 (2.5)	0.7 (4.2)	0.8 (3.4)

[a]Trees Q1: < 14.8 %; Q2: 14.8 % – 23.8 %, Q3 23.8 %<.

[b]pyrs = person years.

Table 2

Associations of ZIP code-level GSV-derived greenspace measures with PD-involved hospitalization. [a].

Exposure (IQR)	PD-involved hospitalization (cases = 506,899, pyrs [b] = 254,917,192)	
	Minimally-adjusted Model	Fully-adjusted Model
	HR (95 % CI)	HR (95 % CI)
Trees (13.7 %)	0.96 (0.95, 0.97)	0.96 (0.95, 0.96)
Other green (2.3 %)	0.96 (0.95, 0.96)	0.97 (0.96, 0.97)
Grass (7.4 %)	1.02 (1.01, 1.03)	1.06 (1.04, 1.07)
Total green (15.9 %)	0.97 (0.96, 0.98)	0.98 (0.97, 0.99)

[a] The minimally- and fully-adjusted models included Trees, Other green and Grass simultaneously and Total green individually. The minimally-adjusted model included calendar year, region, an offset for total person-time and strata for all possible combinations of sex, race, Medicaid Eligibility, age at study entry (2-year categories), and follow-up year. The fully-adjusted model was additionally adjusted for ZIP code-level percent Hispanic, percent Black, population density, median home value, median household income, percent of the population with less than a high school degree, percent below the poverty level, percent of owner-occupied housing units and county-level smoking status. Associations are expressed per IQR increase.

[b] pyrs = person years.