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Reduction in socioeconomic inequalities in self-reported mental health conditions with increasing greenspace exposure

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1. Introduction

Depression and other mental health conditions are consistently among the top ten contributors to the global public health burden (Patel et al., 2018). Between 1990 and 2019, the number of disability-adjusted life-years due to mental disorders world-wide increased from 80.8 million to 125.3 million (GBD 2019 Mental Disorders Collaborators, 2022). This mental health burden is not experienced equally between social groups, with lower-income and other marginalized groups often bearing a disproportionately high burden (Ridley et al., 2020). These inequalities may be explained by unjust systems of disadvantage with respect to race, gender identity, ethnicity, income, or numerous other traits (whether real or assigned), in the form of access to economic and geographic resources, privilege, and sociopolitical power, among others (McLeod et al., 2021).

Northridge et al. (2003)and Diez-Roux and Mair (Diez Roux and Mair, 2010) described how poor access to quality neighborhood social and built environments contributes to health inequalities. Structural marginalization, which cause segregation by race and class and associated neighborhood disinvestment, lead to reduced access to quality social and physical environments for marginalized groups, causing negative impacts on health behaviors, stress and other physiological pathways, which can have undue impact on the health and well-being of these groups (Diez Roux and Mair, 2010).

Interventions to reduce health inequalities have traditionally been clinically focused. However, a social determinants of health approach includes interventions to reduce health inequalities by affecting upstream factors; for example, by improving access to quality jobs (Naik et al., 2019), healthy food, or immunizations (Thomson et al., 2018). Addressing geographic determinants of health can reduce health inequalities by benefitting marginalized populations, including through the provision of quality housing, clean water and sanitation (Bambra et al., 2010).

There is also increasing evidence that quality neighborhood amenities, including well-maintained parks and greenspace, have important impacts on physical and mental health (Twohig-Bennett and Jones, 2018). While there are potential negative consequences of greening programs, such as gentrification, which may have harmful mental health consequences particularly for long-term neighborhood residents (Cole et al., 2017), there is also strong evidence that, if appropriately implemented, neighborhood greening programs can improve mental health (including reducing stress) across various sociodemographic groups (Kondo et al., 2018; South et al., 2018). There are numerous pathways by which greenspace might improve mental health, via restorative effects, such as reducing physiological stress, improving our ability to focus, and improving mood (Markevych et al., 2017).

Improved access to greenspace, as a type of public amenity, may also reduce health inequalities (Rigolon et al., 2021). The idea that amenities (such as green neighborhood environments) could disproportionately improve the health of disadvantaged populations, relative to more advantaged ones, has been termed “equigenesis” (Mitchell, 2013; Mitchell and Popham, 2008). Indeed, socially and economically disadvantaged populations may benefit disproportionately from exposure and access to quality greenspace, such as trees and parks; these benefits may be especially important in neighborhoods or communities where clinical services and recreational amenities are not accessible or affordable.

While a growing literature documents links between neighborhood greenspace and mental health outcomes, only a few studies (McEachan et al., 2016; van den Berg et al., 2016; Mitchell et al., 2015) have considered associations with mental health inequalities. In addition, to date, most research on the equigenic potential of greenspace has been conducted using objective measures of availability, density, or

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proximity. Few studies have investigated whether perceived access to greenspace is associated with reduced health inequalities (Rigolon et al., 2021). This is an important gap because objective measures may not accurately represent or capture exposure, and accurate measurement of greenspace access or exposure may have important implications for detecting any health effect (Knobel et al., 2021), and particularly an equigenic one (Rigolon et al., 2021; Koh et al., 2022). In addition, greenspace perception may differ across sociodemographic groups, and capturing perception is important in terms of understanding the equigenic potential of green spaces.

To address these knowledge gaps, we used data from the Southeastern Pennsylvania Household Health Survey to explore whether objectively measured tree canopy, an important target type of greenspace for greening interventions, and perceived park access, were associated with narrower inequalities in mental health in the five-county metropolitan region including and surrounding Philadelphia, USA.

2. Methods

2.1. Context and data

Philadelphia, PA (pop. 1,576,251 in 2021) is the sixth largest city by population in the US, though it has one of the lowest median incomes of large cities. While once a thriving center for industry, with a large supply of single-family homes for ownership, processes including but not limited deindustrialization, redlining, suburban expansion, and White flight caused a decline in resources and population, and exacerbated racial residential segregation in Philadelphia and other cities across the US (Massey and Denton, 2019). Social inequalities are extreme in Philadelphia; while some residents and neighborhoods have good access to health and health services, others do not. These social inequities may explain vast racial and ethnic inequities in health and well-being. For example, life expectancy ranges from 64 (Black males) to 80 (Asian males) (City of Philadelphia Department of Public Health, 2021). Philadelphia is also a city in which many important greening programs are occurring. For example, in year 2009 the city of Philadelphia established Greenworks and declared a goal of increasing city-wide tree canopy to 30% by year 2025 (City of Philadelphia, 2009). Philadelphia is therefore an ideal place to ask whether access to public amenities such as greenspace may reduce health inequalities.

Our primary dataset consisted of pooled individual-level responses from the 2015 and 2018 waves of the Public Health Management Corporation's (PHMC) Southeastern Pennsylvania Household Health Survey (SEPAHHS; http://research.phmc.org/). PHMC conducts a survey in English and Spanish of adults (aged 18+) residing in the five counties within the Philadelphia metropolitan area (Bucks, Chester, Delaware, Philadelphia and Montgomery counties; see Fig. 1) every two to three years. The survey includes questions on a range of health topics such as health status, behaviors, and access to healthcare. The survey is conducted using random-digit dialing to obtain representative, cross-sectional samples of the non-institutionalized adult population in the study area.

We aggregated responses from the 2015 and 2018 administrations of the SEPAHHS which were conducted December 2014 through March 2015 and August 2018 through January 2019, respectively. Respondents of the surveys were unique; no respondents from 2015 were also included in the 2018 sample. The samples were drawn from all telephone households in SEPA as well as cell phone users. Development of samples required partially stratifying the study area into 54 service areas. This ensured that geographic subareas with smaller populations attained a minimum sample of at least 105 households. The methodology for identifying these 54 areas, which combine clusters of ZIP Codes, was developed through a collaborative process by PHMC and members of the local community. Respondent residential addresses were recorded and geocoded.

PHMC generated response rates for the 2018 HHS using the American Association for Public Opinion Research standard definitions. Overall response rates were the following: 2015 (11.7% for cell phones and 6.8% for landlines), 2018 (7.8% for cell phones and 6.3% for landlines). Weights for the 2015 and 2018 surveys were developed using Claritas (http://claritas.com), based on U.S. Census data (race, age, sex, ethnicity, household size and income) from 2010 to 2018, respectively.

There were 13,490 eligible respondents from the 2015 and 2018 wave surveys. After excluding 1889 respondents with missing data on

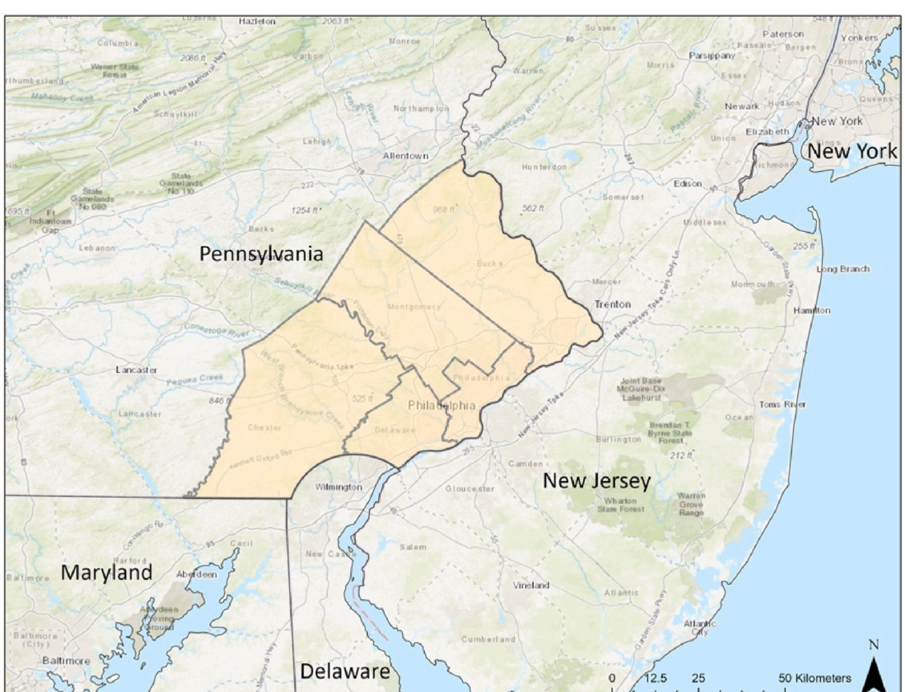

Fig. 1. Map of the 5-county study area.

mental health, income, education, employment, race/ethnicity, or a geocoded address, the analysis included 11,601 respondents.

Data on mental health was derived from the answer to the following question: Have you ever been diagnosed with a mental health condition? Answers were coded as either No or Yes. For each respondent, we also obtained survey responses to questions regarding gender identity, age, race/ethnicity, household income (which we classified as above or below 200% of the federal poverty level (FPL); the FPL was $24,240 USD for a family of four in 2015), highest level of educational achievement, and employment status.

We obtained both individual- and neighborhood-level sociodemographic variables. At the individual level, we classified age into categories (18–34, 35–49, 50–64, 65+), and the other variables into binary categories, including gender identity (man, woman), race/ethnicity (Non-Hispanic White and Non-White, including Hispanic) educational achievement (high school graduate or above, non-high school graduate), and employment status (part- or full-time employed, or not employed including "retired" or "homemaker"). We combined non-White and Hispanic racial/ethnic categories because in Philadelphia, these designations are indicators of relatively poorer health and lower access to resources (City of Philadelphia, 2019). We also consider race/ethnicity to be a social construct, and included this variable as a proxy for the potential experience of racism (Jones, 2001), which may affect mental health (Bailey et al., 2017), as well as greenspace exposures, access, or availability through structures and systems, such as racial residential segregation (Wen et al., 2013). At the neighborhood level, we included a measure of population density (per square kilometer) from the 2011–2015 American Community Survey of the US Census, and a neighborhood sociodemographic index variable constructed from a principal factor analysis of standardized z-scores of housing, education, occupation, and income/wealth data (Roux et al., 2001).

We derived data on self-reported access to a local park from the SEPHHS question: "Is there a park or outdoor space in your neighborhood that you are comfortable visiting? Survey responses in 2015 included: "Yes" and "No." In 2018, responses included: "Yes, there is a park or outdoor space in your neighborhood you feel comfortable visiting; " "No, there is no park in your neighborhood" and "No, there is a park in your neighborhood but you are not comfortable visiting it." Because we only had yes/no responses available for 2015 data, we combined the two negative answers from 2018 into a single response, to build a binary Yes/No variable.

We used very high resolution land cover assessment data to quantify tree canopy coverage near participants' homes. We selected tree canopy cover as the objective measure of greenspace because of its policy relevance due to preponderance of city-wide tree planting initiatives, including Philadelphia's Philly Tree Plan (City of Philadelphia, 2021), and because of evidence from past research that tree canopy is more predictive of positive health outcomes, compared to other types of greenspace (Reid et al., 2017; Janssen and Rosu, 2015). We derived proportion tree canopy cover ("tree cover") within 250, 500, and 1000 m of respondent's geocoded addresses using the Chesapeake Bay Conservancy's 2013/2014 1-m resolution land cover dataset derived from Light Detection and Ranging (LiDAR) data and aerial imagery (Chesapeake Bay Conservancy, 2013). Tree canopy cover is one of 12 land cover classes contained in this dataset, and it is operationalized as a proportion ranging from 0 to 1.

2.2. Statistical analysis

We first calculated descriptive statistics of our data including cross-tabulations by quantile of tree canopy exposure within 250m and by perceived park access. The primary independent variables in our analysis were poverty status, race/ethnicity, education, or employment status. The primary dependent variable in our analysis was mental health status. We fit a series of generalized linear models (GLMs) of the Poisson family with robust standard errors (Zou, 2004) and survey weights to estimate associations between each of the sociodemographic variables (independent variables, each entered individually) with a diagnosed mental health condition (dependent variable). We used modified Poisson regression approach with a robust error variance because it is an accepted method of modeling binomial data, and allowed us to overcome convergence issues when applying a log-binomial distribution (Zou, 2004).

We coded the sociodemographic variables categorically, with the reference categories specified as follows: poverty (income above 200% FPL), race/ethnicity (non-Hispanic White), gender identity (man), age (ages 18–34), education (high school diploma or above), and employment (employed).

Next, we ran eight separate bivariate models to test for unadjusted association between mental health, and each of the four socioeconomic indicators, and four greenspace exposure variables. Finally, to determine whether there was an equigenic effect of green spaces, we ran models that included the greenspace variables (proportion tree canopy or perceived park access) as a covariate, and a two-way interaction between the greenspace exposure variable and the sociodemographic variable. We ran four models for each sociodemographic variable, each one including a different greenspace variable. We coded the greenspace variables as linear terms. These models adjusted for the sociodemographic variables, in addition to survey wave, neighborhood population density, and neighborhood sociodemographic index score. Tests of correlation did not suggest multicollinearity among covariates (correlation coefficient<0.54). We report coefficient estimates as prevalence ratios and 95% confidence intervals. For interaction term effects, we used $p < 0.20$ to indicate statistical significance due to the reduction in power for these terms (Aiken et al., 1991). We present both main effects and interaction coefficients. We also used linear combinations of coefficients (e.g., poverty + poverty x tree canopy cover) to calculate prevalence ratios for each exposure (e.g., being below vs above 200% of the federal poverty line) across levels of tree canopy cover for graphical display. We performed all statistical analyses in Stata v15 (StataCorp, College Station, TX).

3. Results

Sociodemographic characteristics of all respondents are shown in Table 1. Sixty-nine percent of respondents were non-Hispanic White, 61% identified as women, 69% had graduated from high school, 55% were employed, 73% had income above 200% of the FPL, and 83% did not have a mental health condition diagnosis. At respondent home locations, average population density was 3725 people per square kilometer, and deprivation index was 0.33.

Respondent characteristics, by tertile of tree cover exposure, are also shown in Table 1. Based on statistical tests of difference, respondents living under low tree cover (less than 21.3% within 250m) were more likely to be non-White, young, without a high school diploma, not employed, with income below the 200% FPL, and with a diagnosed mental health condition. They also lived in denser neighborhoods with higher socioeconomic deprivation. Most respondents reported comfortable access to a neighborhood park. However, close to 30% of respondents that were non-White, age 65+, without a high school diploma, not employed, or below the 200% FPL reported no access to neighborhood parks. These demographic characteristics match citywide demographics closely, except that respondents who reported no access to neighborhood parks suffered less unemployment (29% versus 45% citywide) but higher poverty status below the 200% FPL (33% versus 27% citywide).

Bivariate analyses, in which we tested for simple associations between each of the sociodemographic and greenspace variables and health, separately, showed that lower education, unemployment, and poverty were associated with higher prevalence of mental health condition diagnosis than comparison groups (see Table 2). By contrast, non-White race/ethnicity was associated with lower prevalence of mental

Table 1
Characteristics of all SEPAHHS 2015 & 2018 study respondents and by tertile of tree cover (n=11,601) (N (%)), with results from statistical tests of difference.[a].

	All Participants	Proportion Tree Cover within 250m			Park Access	
		≤ 21.3%	21.3–40.1%	40.1–100%	No	Yes
Race/Ethnicity-Non-Hispanic White	8027 (69)	1849 (23)	2778 (35)	3400 (42)	1579 (20)	6448 (80)
Race/Ethnicity-Non-White	3574 (31)	2099 (59)	952 (27)	523 (15)***	729 (30)	1739 (70)***
Gender Identity-Woman	7110 (61)	2528 (36)	2274 (32)	2308 (32)	1792 (25)	5318 (75)
Gender Identity-Man	4491 (39)	1420 (32)	1456 (32)	1615 (36)	834 (19)	3657 (81)
Age: 18-34	1172 (10)	484 (41)	400 (34)	288 (25)	201 (17)	971 (83)
Age: 35-49	3034 (26)	987 (33)	985 (32)	1062 (35)	519 (17)	2515 (83)
Age: 50-64	4080 (35)	1349 (33)	1281 (31)	1450 (36)	897 (22)	3183 (78)
Age: 65+	3315 (29)	1128 (34)	1064 (32)	1123 (34)***	1009 (30)	2306 (70)***
Education-High school Grad or Above	7955 (69)	2155 (27)	2592 (33)	3208 (40)	1508 (19)	6447 (81)
Education-Non-High School Grad	3646 (31)	1793 (49)	1138 (31)	715 (20)***	1118 (31)	2528 (69)***
Employment-Full or Part-Time	6428 (55)	1867 (29)	2135 (33)	2426 (38)	1100 (17)	5328 (83)
Employment-Not Employed	5173 (45)	2081 (40)	1595 (31)	1497 (29)***	1526 (29)	3647 (71)***
Poverty Status-Above 200% FPL[b]	8439 (73)	2221 (26)	2810 (33)	3408 (40)	1586 (19)	6853 (81)***
Poverty Status-Below 200% FPL	3162 (27)	1727 (55)	920 (29)	515 (16)***	1040 (33)	2122 (67)
Population density[c] (mean (SD))	3.73 (4.16)	7.37 (4.85)	2.76 (2.74)	1.32 (1.46)	4.27 (4.16)	3.57 (4.15)
Neighborhood sociodemographic index (mean (SD))	2.05 (5.86)	−2.11 (5.42)	2.12 (4.61)	6.01 (4.31)	0.00 (6.05)	2.58 (5.69)
Mental Health Condition Diagnosis						
No	9618 (83)	3159 (33)	3100 (32)	3359 (35)	2113 (22)	7505 (78)
Yes	1983 (17)	789 (40)	630 (32)	564 (28)***	513 (26)	1470 (74)***

[a] Statistical significance indicated as *p<0.05, **p<0.01, ***p<0.001 based on tests of difference between sociodemographic categories for tree canopy cover (Adjusted Wald F-test) and park access (Chi-Square test).
[b] FPL: Federal Poverty Level.
[c] Per 1000 people per square kilometer.

Table 2
Prevalence ratios (PR) and 95% confidence intervals for unadjusted bivariate associations between mental health diagnosis and sociodemographic and greenspace measures, among respondents of the SEPAHHS 2015 & 2018 waves.

Variable	PR	95% CI
Race/Ethnicity: non-White[1]	0.84	(0.73 0.95)
Education: without high school diploma[2]	1.42	(1.26 1.60)
Employment: not employed[3]	2.10	(1.87 2.37)
Poverty: below 200% FPL [4]	1.76	(1.57 1.98)
Proportion tree cover within 250m	0.60	(0.43 0.84)
Proportion tree cover within 500m	0.55	(0.39 0.80)
Proportion tree cover within 1000m	0.57	(0.39 0.85)
Perceived park access: Yes[5]	0.84	(0.74 0.96)

Notes: 1) non-White versus non-Hispanic White reference category; 2) without high school diploma versus with high school diploma reference category; 3) not employed versus employed reference category; 4) below 200% federal poverty level (FPL) versus above 200% FPL reference category; 5) perceived park access versus perceived non-access reference category. All coefficients come from separate Poisson regression models with robust standard errors.

health condition diagnosis than non-Hispanic White race/ethnicity. Regarding greenspace exposure, more tree cover at all distances, and perceived park access, was associated with lower prevalence of mental health condition diagnosis.

Table 3 shows the coefficient estimates (prevalence ratios) of the main effects and two-way interaction terms between the demographic variables and each of the greenspace exposures (250, 500 and 1000m) and perceived park access (Models 1 through 4). The main effect for poverty was positive and statistically significant, indicating that respondents living in areas with no tree canopy cover within 250m and that were living in poverty had a 73% higher prevalence (PR=1.73, 95% CI= 1.42, 2.12) of diagnosed mental health condition than respondents not living in poverty. In addition, we found a statistically significant interaction between greenspace exposure at 250m and poverty (PR=0.65, 95% CI=0.37, 1.13, p=0.13), indicating an equigenic effect of tree canopy cover on income-based mental health disparities. While not statistically significant, a similar direction of association was observed for interaction effects between poverty and tree canopy cover at different buffer distances (500m and 1000m) but not with perceived park access, where we did not find a clear equigenic effect. While *main effects* were statistically significant for race/ethnicity, education and employment, there were no statistically significant *interaction effects* between these variables and greenspace exposure. There was no significant interaction effect between poverty, or any of the other sociodemographic variables, and perceived access to parks. Variance inflation factor (VIF) was 5.79 or lower for all models.

Fig. 3 shows the prevalence ratios of mental health diagnosis for the four sociodemographic variables as a function of tree canopy cover at a 250m buffer (see the **Appendix** for equivalent figures showing the 500m and 1000m buffers). The prevalence ratios representing poverty, education, and employment-based disparities (all of them above 1 in our analysis without interaction terms) became closer to the null, suggesting a reduction in the magnitude of the disparity, as % tree canopy cover increases. For example, the prevalence ratio for a mental health diagnosis comparing individuals living below versus above the 200% FPL was 1.60 (95% CI 1.27 to 2.02) for people living in areas with no tree canopy cover and 1.22 (95% CI 0.73 to 2.04) for people living in areas with complete tree canopy cover. Conversely, the prevalence ratio for race/ethnicity (below 1 in our analysis without an interaction term) moved further away from the null and became more negative with increasing tree canopy cover, suggesting an increase in the magnitude of the disparity (higher prevalence in non-whites vs. non-Hispanic whites) as tree coverage increases. For example, the prevalence ratio for a mental health diagnosis comparing non-white vs non-Hispanic White individuals was 0.75 (95% CI 0.54 to 1.04) for people living in areas with no tree canopy cover and 0.24 (95% CI 0.07 to 0.89) for people living in areas with complete tree canopy cover. Patterns were similar with the other buffers (see **Appendix**).

Footnote: displayed are prevalence ratios for mental health diagnosis by poverty (below 200% FPL vs above 200% FPL), education (< High School vs High School or above), race/ethnicity (non-White vs non-Hispanic White), and employment (not employed vs employed) categories across levels of proportion tree canopy cover at a 250m buffer. These were obtained through a linear combination of the main coefficient for each of the exposures and the interaction term between the exposure and tree canopy cover, from a model with each exposure (in separate models), tree canopy cover, their interaction, and adjusted for age and gender identity.

Table 3
Prevalence ratios (PR) and 95% confidence intervals from adjusted models[1] for mental health diagnosis (main effects and two-way interaction terms between greenspace exposure and demographic variable only), among respondents of the SEPAHHS 2015 & 2018 waves.

	Model 1: %Tree cover within 250m			Model 2: %Tree cover within 500m			Model 3: %Tree cover within 1000m			Model 4: Perceived Access[2]		
	PR	95% CI	p-val	PR	95% CI	p-val	PR	95% CI	p-val	PR	95% CI	p-val
Race/Ethnicity[3]	0.64	(0.52 0.80)	<0.001	0.67	(0.53 0.84)	0.001	0.72	(0.56 0.92)	0.009	0.68	(0.54 0.86)	0.001
Greenspace Exposure	1.27	(0.90 1.80)	0.177	1.21	(0.81 1.83)	0.353	1.34	(0.84 2.13)	0.216	0.99	(0.84 1.16)	0.894
*Race/Ethnicity*Greenspace interaction*	0.80	(0.36 1.79)	0.591	0.71	(0.31 1.61)	0.414	0.53	(0.24 1.22)	0.135	0.87	(0.67 1.14)	0.316
Education[4]	1.24	(1.02 1.51)	0.034	1.24	(1.00 1.53)	0.048	1.22	(0.97 1.53)	0.083	1.06	(0.84 1.33)	0.625
Greenspace exposure	1.39	(0.95 2.03)	0.089	1.31	(0.84 2.05)	0.229	1.36	(0.83 2.23)	0.216	0.90	(0.76 1.08)	0.271
*Education*Greenspace interaction*	0.63	(0.35 1.12)	0.113	0.64	(0.35 1.18)	0.151	0.68	(0.36 1.30)	0.248	1.08	(0.84 1.40)	0.546
Employment[5]	2.02	(1.66 2.46)	<0.001	2.08	(1.68 2.57)	<0.001	2.21	(1.76 2.78)	<0.001	1.90	(1.48 2.43)	<0.001
Greenspace exposure	1.46	(0.93 2.29)	0.101	1.42	(0.85 2.38)	0.180	1.63	(0.94 2.83)	0.085	0.96	(0.76 1.21)	0.733
*Employment*Greenspace interaction*	0.68	(0.41 1.14)	0.146	0.63	(0.36 1.11)	0.110	0.53	(0.29 0.97)	0.038	0.96	(0.73 1.26)	0.782
Poverty[6]	1.73	(1.42 2.12)	<0.001	1.69	(1.37 2.10)	<0.001	1.70	(1.35 2.14)	<0.001	1.51	(1.19 1.92)	0.001
Greenspace exposure	1.36	(0.93 2.00)	0.111	1.26	(0.81 1.98)	0.305	1.34	(0.81 2.22)	0.248	0.96	(0.79 1.17)	0.681
*Poverty*Greenspace interaction*	0.65	(0.37 1.13)	0.127	0.71	(0.39 1.28)	0.254	0.71	(0.38 1.33)	0.287	0.96	(0.74 1.24)	0.746

Notes: 1) Each model adjusted for age, gender identity, race/ethnicity, education, employment, poverty, survey wave, population density, and neighborhood sociodemographic index; 2) perceived park access versus perceived non-access reference category; 3) non-White versus non-Hispanic White reference category; 4) without high school diploma versus with high school diploma reference category; 5) not employed versus employed reference category; 6) below 200% federal poverty level versus above 200% federal poverty level reference category.

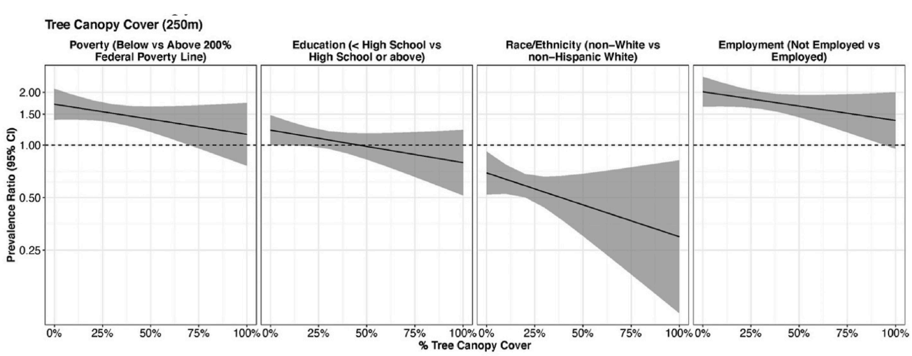

Fig. 3. Prevalence ratios and 95% confidence intervals comparing prevalence of those living with a mental health diagnosis and living below the 200% Federal poverty level versus living above the 200% federal poverty level [reference group, or REF], individuals without a high school education versus those with a high school education or above [REF], non-White versus non-Hispanic White individuals [REF], and not employed vs employed individuals [REF], by levels of tree canopy cover at a 250m buffer.

4. Discussion

In this study, based on a sample of over 11,000 residents of the Philadelphia metropolitan area, results from our interaction regression model indicated that living in areas with higher tree canopy cover (nearby, within 250m of residence) was associated with more narrow income-based inequalities in mental health condition diagnoses. While not statistically significant, increasing tree canopy appeared to reduce the magnitude of race/ethnicity-, education- and employment-based mental health inequalities. However, perceived access to parks was not associated with more narrow inequalities in any of the sociodemographic variables.

While we found a statistically significant interaction term between income (poverty) and greenspace exposure at 250m, the term was not statistically significant at 500m and 1000m. It could be that nearby nature, in particular, is important for lower-income individuals' mental health.

Although our study is cross-sectional and therefore cannot establish causality, our research contributes to a small but growing study of the association between urban nature and mental health inequalities. Our results suggest that greenspace modifies income-based disparities, and similarly Mitchell et al. (2015) reported that good access to green areas was associated with better mental well-being, but only for those with the highest levels of perceived financial strain. Other prior studies have found that greenspace primarily modifies education-based disparities. McEachan et al. (2016) found that higher greenspace exposure was associated with fewer depressive symptoms, but only for respondents with lower education. Van den berg et al. (van den Berg et al., 2016) found that increased reported visits to greenspace was associated with better mental health, also for respondents with lower education. In a study exploring mortality in Latin American cities, researchers found narrower area-level socioeconomic-based disparities in violence-related mortality in cities with higher vegetation density (Moran et al., 2021).

There is also evidence that bluespace exposure (proximity and access to waterbodies) can reduce income-based disparities in mental health (Garrett et al., 2019). While assessing bluespace exposure was beyond the scope of this study, given that the pathways through which greenspaces may benefit both mental health and violence are similar (for example, *restorative* effects (Markevych et al., 2017)), this is consistent with the findings in our study.

Poverty is a serious issue in Philadelphia, the poorest large city in the US. According to the US Census 2015–2019 American Community Survey, 24.3% of the city's population had an income below the FPL (US Census Bureau, 2015). This rate was up to 60% in some neighborhoods. Poverty status, and thereby income, was a strong determinant of inequalities in mental health condition among our respondents. Yet we found that increasing residential tree cover was associated with a significant improvement in prevalence of mental health condition especially for respondents of lower income. This could imply that efforts to maintain and increase the tree canopy in poorer neighborhoods have relatively high returns in terms of resident mental health. Greenspace exposure may impact mental health by improving our ability to cope with stress, by increasing our likelihood of engaging in physical activity, and by supporting our connections with others (Markevych et al., 2017). Greening interventions in Philadelphia have been shown to reduce fear of crime (Branas et al., 2018), which may thereby improve mental health

(Burt et al., 2021). It may also be that greenspaces are more accessible to lower-income individuals than other health promoting features.

Our study is subject to a number of limitations. First, we used a cross-sectional study design and identified temporal relationships between exposures (such as greenspace) and outcomes (such as self-reported mental health diagnoses). This serves as a barrier to establishing causal relationships between variables. Second, it could be that poor mental health causes socioeconomic inequalities, therefore our results are potentially affected by reverse causality. However, to address this risk, we used covariate adjustment, including individual and neighborhood-level characteristics known to influence residential location as predictors. In addition, because we calculated multiplicative rather than additive interaction, the measures of interaction do not reflect biologic interaction.

Third, our study may be subject to issues of mismatched levels of analysis resulting from contrasting associations across individuals but within a single population that is subject to ubiquitous systems (i.e., racism and income-based marginalization within the metropolitan Philadelphia area adult population), rather than making contrasts *across* distinct populations, which is the contrast and level at which these fundamental systems are likely to vary (Riley, 2020).

Fourth, there are multiple limitations to our outcome measure of poor mental health. It is potentially biased because it is self-reported. The question, whether respondents have ever been diagnosed with a mental health condition, is somewhat ambiguous as to whether mental health symptoms or a classified mental health disorder is implied. The timeframe for diagnosis was also not specified. In addition, the requirement of a diagnosis may be influenced by differential access to healthcare, and may only capture the most severe cases. This may explain our finding that there was a higher prevalence of diagnosed mental health in non-Hispanic white vs. Hispanic and Black survey participants.

In addition, our measures of greenspace exposure and access may not accurately or consistently represent true exposure to nature or natural features in a way that matters for mental health. For example, the quality and health of the nearby tree canopy may not be represented in the greenspace exposure (tree canopy cover) metrics. However, compared to a more traditional measure of neighborhood greenness, such as the normalized difference vegetation index (NDVI), the high-resolution land cover data indicating exact locations of tree canopy can be viewed as a more precise estimate of greenspace exposure (Trethewey and Reynolds, 2021). It may also be more health-relevant; a previous study found that percent tree canopy cover and perceived access to greenspace (at the census tract level) was protective against incidence of cardiovascular disease, while overall greenness (NDVI) was not (Knobel et al., 2021). Also, in Philadelphia, PA, we found that census tract level tree canopy coverage was more highly associated with perceived access to parks or open spaces as compared to overall greenness measured with the NDVI (Knobel et al., 2021). Tree canopy is also the type of greenspace for which many cities across the globe, including Philadelphia, have created initiatives. Thus, this is an important measure for focus because of its policy relevance.

Regarding perceived access, the survey asked whether respondents had a neighborhood park or outdoor space they were comfortable visiting. The definition of “park” and “neighborhood” were not given; parks that include vegetation and greenspace were not specified. In addition, the term “comfortable” could be subject to a wide variety of interpretations. Those interpretations may be important to understanding access, and more specific survey question(s) could test each of these interpretations more directly. These uncertainties could also explain why we did not find that perceived access had an equigenic effect.

5. Conclusions

Cities throughout the world are undertaking ambitious initiatives to increase their parks and tree canopies. These initiatives aim to improve sustainability of urban settlements, and are motivated by threats to human and ecological well-being. There is increasing evidence that urban greenspace also provides valuable benefits to the public health and to health equity. Place- and nature-based interventions, such as well-maintained parks and greenspace, may help cities hit not only sustainability targets, but to improve public health, and specifically mental health. Our results indicated that increasing residential tree cover was associated with a significant narrowing of income-based inequalities in the prevalence of mental health conditions. Therefore, efforts to maintain and increase the tree canopy in poorer neighborhoods could have relatively high return in terms of resident mental health equity.

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Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2022.102908.

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