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1 Associations of objective and perceived
2 greenness measures with
3 cardiovascular risk factors in
4 Philadelphia, PA: A spatial analysis

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25 **Abstract:**

26 There is mounting scientific evidence that greenness is associated with improved
27 cardiovascular health. However, few studies have distinguished between vegetation
28 type, measured perceived green space access, or investigated heterogeneity of
29 associations across categories of neighborhood sociodemographic and racial/ethnic
30 composition. We conducted an ecologic spatial analysis of associations of three
31 objective measures of greenness (percent vegetation cover, percent tree canopy cover,
32 and greenness density), and one measure of perceived access to green spaces with
33 census tract level percentages of the adult population who were obese, ever had a high
34 blood pressure diagnosis, and ever had a diabetes diagnosis, in the city of Philadelphia,
35 PA, year 2013. We explored effect modification by census-tract level percent living in
36 poverty and percent non-Hispanic Black categories. We used data from the Southeastern
37 Pennsylvania Household Health Survey (SEPAHH) linked with high-resolution
38 landcover, remotely sensed, and American Community Survey data and estimated
39 associations using spatial lag models. We observed modest protective associations
40 between percent of the adult population reporting perceived access to green spaces and
41 percent with the cardiovascular risk factors, particularly in moderate and high poverty
42 census tracts. Percent tree canopy cover was also protective against the cardiovascular
43 risk factors, particularly in census tracts with low percentages of the population living in
44 poverty and with low percent non-Hispanic Black populations. These results suggest
45 that perceived access to green spaces and objectively measured high tree canopy cover,
46 may protect against cardiovascular disease, but associations may vary across
47 neighborhood sociodemographic categories.

48 **Keywords:**

49 Greenspace; vegetation, urban health, cardiovascular; cardiovascular; trees; NDVI;
50 perceived access; socioeconomic status; race

51 **Highlights:**

52 • Perceived access to green spaces and high percent tree canopy cover were
53 protective against CVD risk factors.

54 • The protective associations between perceived access to green spaces and CVD
55 risk factors were restricted to census tracts with moderate or high percentages of
56 the population living in poverty.
57 • The protective associations between percent tree canopy cover and CVD risk
58 factors were restricted to census tracts with low percent non-Hispanic Black
59 residents and low percentages of population living in poverty.

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67

68 1. Introduction

69 Cardiovascular disease (CVD) is the leading cause of mortality worldwide
70 (Collaborators *et al.*, 2018). Obesity (Body Mass Index > 30), high blood pressure, and
71 diabetes are among the most important risk factors for CVD (Damen *et al.*, 2016).
72 These risk factors are associated with a modern urban lifestyle through different
73 pathways, including living a sedentary life (Medina *et al.*, 2017), poor diet (Becerra-
74 Tomás *et al.*, 2020), exposure to air pollution (Bhatnagar, 2006) and noise (Swinburn *et*
75 *al.*, 2015), and urban sprawl (Chandrabose *et al.*, 2019). Mounting scientific evidence
76 also suggests that increased exposure to urban greenness is associated with reduced risk
77 of being overweight (Müller *et al.*, 2018), of having high blood pressure (Tamosiunas
78 *et al.*, 2014), or of having type 2 diabetes (Müller *et al.*, 2018).

79 This growing evidence base has given rise to interest in the installation, renewal, and
80 use of urban green spaces for population health promotion. Broadly, green infrastructure
81 is a cultural and regulating ecosystem service that falls under the umbrella of “Nature-
82 Based Solutions.” Nature Based Solutions are nature-inspired actions, intended to
83 address urban environmental challenges (Nesshöver *et al.*, 2017; Laforteza & Sanesi,
84 2019; Haase *et al.*, 2014; Kabisch *et al.*, 2017). Green infrastructure is a broad
85 category, and it includes forests, green roofs, urban parks, street trees, and more. There
86 is no consensus on the terminology that should be used to distinguish these different
87 green space typologies, as evidenced by recent literature reviews (Knobel *et al.*, 2019;
88 Taylor & Hochuli, 2017). Here, we use the term greenness to describe any area with
89 vegetation (e.g., grass, tree canopy, parks), and the term "green space" to refer to the
90 subset of vegetated areas that are structured (e.g., parks or gardens). This terminology is
91 consistent with past literature (Taylor & Hochuli, 2017), and the distinction between
92 greenness and green space adds a layer of quality to the greenness concept (Markevych
93 *et al.*, 2017). For example, it distinguishes overgrown abandoned lots from pocket
94 gardens, which may have different associations with human health due to their
95 contrasting quality (Knobel *et al.*, 2020).

96 Thus far, most research on links between greenness and health has estimated exposures
97 using indices that represent overall greenness density, derived from remotely-sensed
98 data. These remotely-sensed measures are easily accessible across all world regions and

99 have a relatively high temporal resolution, allowing for easy use in multi-site,
100 population-based studies. However, because they represent overall greenness density,
101 they fail to discern different types of greenness (e.g., trees vs. grass) (Reid *et al.*, 2017)
102 or measure perceived green space access. Different types of greenness may have
103 different associations with health outcomes. For example, tree canopy has a greater
104 potential to offer shade and improve thermal comfort than grass or shrubs (Armson *et*
105 *al.*, 2012). The potential effect of greenness on air quality may not require that the
106 vegetation to be seen or used, as its presence, alone, could potentially have impacts on
107 health (Nowak *et al.*, 2006). In this case, objective measures, like surrounding
108 greenness, may be more critical and better suited to exploring this potential health-
109 promoting mechanism. On the other hand, for greenness to positively impact physical
110 activity, it must be perceived to be usable, accessible, inclusive, and/or safe (Tabatabaie
111 *et al.*, 2019). Therefore, perceived measures would be a better fit in this case. Perceived
112 and objective measures should not aim to be interchangeable and compared as equals
113 (Leslie *et al.*, 2010). Perceived and objective metrics can, and should, be used as
114 complementary measures (Moore *et al.*, 2008), especially when studying less explored
115 mechanisms and outcomes. We use this approach in the current study.

116 Besides considering overall associations, it is also important to assess the heterogeneity
117 of these relationships across categories of socioeconomic position or racial composition.
118 Indeed, the direction and magnitude of associations may differ across categories of
119 neighborhood sociodemographic composition for various reasons, including potential
120 differential access, utilization, perception, quality, or experience of greenness and green
121 spaces, among others (Wang *et al.*, 2021; De Vries *et al.*, 2020). Previous studies of the
122 differences in relationships between greenness and health have arrived at conflicting
123 conclusions, with some, but not all, suggesting greater benefits for low socioeconomic
124 position populations (Mitchell & Popham, 2008; McEachan *et al.*, 2016; Dadvand *et al.*,
125 2012; Knobel *et al.*, 2020; Browning *et al.*, 2018). In addition to heterogeneity based on
126 socioeconomic deprivation or poverty indicators, greenness may have distinct,
127 differential impacts on cardiovascular health based on neighborhood racial/ethnic
128 composition. Although race/ethnicity is correlated with socioeconomic position, these
129 two constructs may modify associations between greenness and cardiovascular disease
130 in different ways. Structural racism has resulted in the concentration of environmental
131 pollutants, toxic stress, and low access to assets and resources (such as greenness) in

132 racial/ethnic minority areas (Williams et al., 2009; Gee & Payne-Sturges, 2004).
133 Racism may result in differential perception of safety or interaction with greenness and
134 green spaces (Jones, 2000). Nevertheless, few studies, to date, have quantified
135 heterogeneity of greenness-CVD relationships across neighborhood racial/ethnic
136 composition categories.

137 In the present study, we used population-based survey data linked with several
138 geospatial data sets to quantify associations of four different greenness measures
139 (percent vegetation cover, percent tree canopy cover, overall greenness density, and
140 percent of residents reporting perceived access to a park or outdoor space) with three
141 CVD risk factors (obesity, high blood pressure diagnosis, and diabetes diagnosis).
142 Additionally, we explored potential effect modification of these associations by
143 neighborhood percent living in poverty and percent non-Hispanic Black.

144 2. Methods

145 2.1. Study setting and design

146 We conducted a neighborhood-level, ecologic analysis of associations between percent
147 vegetation cover, percent tree canopy cover, overall greenness density (measured with
148 NDVI), and perceived park and outdoor space access with three CVD risk factors:
149 percent of adult residents with obesity, with a high blood pressure/hypertension
150 diagnosis (ever), and with a diabetes diagnosis (ever). We used survey and geospatial
151 data from several sources to conduct this analysis.

152 This study's setting was Philadelphia, PA, the sixth most populated and one of the
153 poorest major cities in the United States (US Census Bureau). The distribution of
154 greenness is heterogeneous across Philadelphia, making it an excellent setting for an
155 analysis that depends on spatial contrasts (Schinasi, *et al.*, 2019).

156 This study's analysis unit was the census tract, and all data were aggregated to 2010
157 census tract boundaries. Census tracts are small subdivisions of a county, defined by the
158 US Census Bureau. They are commonly used in population-based research to
159 approximate neighborhoods. In Philadelphia, census tracts are densely populated. For
160 example, based on data from the American Community Survey (ACS) 2011-2015 five-

161 year estimates, the average population density of a census tract was 7,390 people/km².
162 We included all 377 populated census tracts in Philadelphia in the current analysis.

163 We selected year 2013 as the year for this study to optimize data availability from the
164 different linked data sources. This year was also the median year between two land
165 cover assessments that were conducted for the city of Philadelphia, which we used to
166 estimate the percent of tree canopy and grass/shrub cover (described in detail below).

167 [2.2. Data](#)

168 The Southeastern Pennsylvania Household Health Survey (SEPAHH) is a biennial
169 telephone survey administered by the Public Health Management Corporation and is
170 conducted in five counties of southeastern Pennsylvania (Bucks, Chester, Delaware,
171 Montgomery, and Philadelphia) (PHMC, 2015). For this study, we used data from
172 Philadelphia County only. The survey data are collected through random digit dialing,
173 with oversampling of people ages 60 and over. We used survey data collected from
174 adult residents (ages 18+) in 2012 and 2014/2015; we assigned the average values from
175 these two years as the value for the year 2013. We used survey data to estimate the
176 percent of all residents in a census tract ages 18 years and older reporting perceived
177 park or outdoor space access. The specific question on perceived park or outdoor space
178 access was the following: "Is there a park or other outdoor space in your neighborhood
179 that you are comfortable visiting during the day?". We also used survey data to estimate
180 percentages of adults aged 18 years and older in each census tract who reported ever
181 receiving a diabetes diagnosis, who reported ever having a high blood
182 pressure/hypertension diagnosis, or who were obese. The percent reporting diabetes or
183 high blood pressure diagnosis measures were based on survey questions that asked
184 respondents if they had ever been told by a doctor or medical professional that they had
185 the condition. The percent obese measure was based on self-reported height and weight.
186 In our analyses, we used estimates that were smoothed using Bayesian hierarchical
187 models that simultaneously account for spatial, temporal, and between race/ethnic
188 dependence structures to account for the uncertainty resulting from using survey data to
189 derive census tract-level estimates. The methods used to derive these smoothed
190 estimates have been reported in detail elsewhere (Quick *et al.*, 2020). The exact

191 SEPAHH questions, responses, and coding of the included variables can be found in
192 Table S1.

193 We used images from the Moderate-resolution Imaging Spectroradiometer (MODIS) of
194 NASA's Terra satellite (MOD13Q1, Version 6 product) to derive normalized difference
195 vegetation index (NDVI) estimates (Carroll *et al.*, 2004). These data are generated every
196 16 days at a 250-meter resolution. We used all images available from the year 2013 to
197 calculate the annual mean greenness density value. A larger number of previous studies
198 of links between greenness and cardiovascular disease have used MODIS-derived
199 NDVI data (Yuan *et al.*, 2020). Thus, this measure allows excellent comparison with
200 previously conducted studies that have relied on MODIS captured NDVI data. The
201 NDVI is a quantitative measure of greenness density, ranging in value from -1 to 1, with
202 higher values indicating more photosynthetically active land cover. Its calculation is
203 based on vegetated versus non-vegetated areas' reflectance properties: Healthy
204 vegetation absorbs visible light but reflects near-infrared light, but non-vegetated areas
205 reflect more visible light and less near-infrared light. Negative NDVI values represent
206 water, values close to zero are areas without green (e.g., pavement), and those close to
207 one are the most densely green areas. We used the Raster package's extract function
208 (Hijmans & van Etten, 2012) of the R software (version 3.5.1) to calculate the mean
209 NDVI value in each census tract, for each image capture. We then calculated the mean
210 NDVI for the year of 2013 within each census tract.

211 We used high-resolution (30.5 cm × 30.5 cm) orthophotography and Light Detection
212 and Ranging (LiDAR) based land cover data to calculate percent tree canopy cover and
213 percent vegetation cover within each census tract. These data were based on land cover
214 assessments conducted for the city of Philadelphia, for which each 1-foot pixel was
215 assigned to the following seven mutually exclusive categories: (1) tree canopy, (2)
216 grass/shrub, (3) bare earth, (4) water, (5) buildings, (6) roads, and (7) other paved
217 surfaces. Percents were defined as the total area covered by tree canopy, for tree canopy
218 cover, or tree canopy plus grass/shrub cover, for vegetation cover, divided by the total
219 land area in each census tract (km²). Two land cover assessments were conducted for
220 Philadelphia; one was conducted in 2008 and the other in year 2018 (O'Neil-Dunne &
221 Grove, 2011; O'Neil-Dunne *et al.*, 2013). We derived the 2013 estimates by linearly
222 interpolating the values across the years.

223 Data on census tract-level population density, percent of the population living in
224 poverty, and percent of the population who were non-Hispanic Black were derived from
225 American Community Survey data for years 2011-2015 (US Census Bureau). The
226 threshold for living in poverty is defined by the US Census Bureau and varies based on
227 family size and composition.

228 [2.3. Statistical analysis](#)

229 *Main analysis*

230 We developed spatial lag models to estimate associations of percent tree canopy cover,
231 percent vegetation cover, overall greenness (NDVI), and perceived park or outdoor
232 space access with percentages of the adult population in the census tract who were
233 obese or reported having diagnosed high blood pressure or diabetes. We used spatial lag
234 models to account for potential spatial autocorrelation across census tract boundaries.
235 Neighbors were defined using a first-order Queen contiguity matrix. We ran separate
236 models for each combination of outcome and greenness measure, or twelve separate
237 models in total. Given that we observed nonlinearity in the associations, we modeled the
238 exposures as categorical variables, with the categories based on tertiles (Table 1). We
239 treated the first tertile (low) as the reference category; our estimates represent the
240 average change in the percentage of the census tract's population with the health
241 outcome associated with moving from the first (low) to the second (medium) or the first
242 to the third (high) tertile. We adjusted our models for the percent of the census tract
243 population living in poverty, percent non-Hispanic Black, and population density, all
244 coded as three-level categorical variables based on their tertiles (Table 1). We selected
245 these variables, *a priori*, based on hypotheses that they might confound associations
246 between greenness and cardiovascular risk factors.

247 *Effect modification*

248 We assessed potential effect modification of associations by percentages of the census
249 tract population living below the poverty line and percent of non-Hispanic Black by
250 including an interaction term between the primary explanatory variable (the exposure
251 measure) and the potential effect modifier. We coded each modifier as a three-level

252 categorical variable, with categories based on their tertiles (Table 1). We report
253 stratified estimates for each one of the tertiles (low, medium, and high). We evaluated
254 improvement in model fit and statistical evidence of effect modification by comparing
255 AIC statistics from nested models, with and without the interaction terms.

256 We performed all analyses using R statistical software (RStudio Version 1.2.5033). We
257 used the package spdep (Bivand *et al.*, 2015) to run the spatial lag models.

258 3. Results

259 *Descriptive statistics*

260 There was substantial variability in population density and sociodemographic
261 composition across census tracts, with a mean of 7527.3 inhabitants/km² (range: 0.2 –
262 25754.0 inhabitants/km²), 42.0 (range: 0.0 - 99.5) for percent non-Hispanic black
263 population and 26.4 (range: 0.0 - 74.3) for percent of the population living in poverty.
264 There was also substantial heterogeneity in the distribution of greenness across the
265 census tracts; the mean values for NDVI, percent vegetation cover, and percent tree
266 canopy cover were 0.29 (range: 0.06 – 0.63), 34.9 (range: 4.6 - 92.7), and 15.4 (range:
267 1.8 - 80.4), respectively. The mean percent of residents reporting having access to a
268 park or outdoor space in their neighborhood was 75.2 (range: 45.3 - 94.9). On average,
269 fewer than half of residents across census tracts were obese (Mean: 31.5, range: 16.9 -
270 41.0) or reported having a diagnosis of high blood pressure (Mean: 33.4, range 20.4 -
271 42.0). The mean percent reporting a diabetes diagnosis was lower, with, on average, less
272 than one-fifth of the population in each census tract reporting this condition (Mean: 12.4
273 range 4.5 - 17.5) (TABLE 1).

TABLE 1: Descriptive statistics for the populated census tracts
from Philadelphia, PA, included in this analysis.

Variable	N = 377
Population density (population/km ²)	
Mean (SD)	7527.3 (4415.1)
Median [min,max]	6860.5 [0.2, 25754.0]
Percent non-Hispanic Black	
Mean (SD)	42.0 (34.9)
Median [min, max]	29.6 [0.0, 99.5]

Percent of population living in poverty	
Mean (SD)	26.4 (15.7)
Median [min,max]	24.8 [0.0 , 74.3]
NDVI	
Low	(0.06 - 0.23)
Tertiles	Medium (0.23 - 0.33)
	High (0.33 - 0.63)
	Mean (SD) 0.29 (0.11)
	Median [min,max] 0.27 [0.06, 0.63]
Percent vegetation cover	
Low	4.6 – 26.6
Tertiles	Medium 26.7 – 39.2
	High 39.3 – 92.7
	Mean (SD) 34.9 (16.5)
	Median [min,max] 31.5 [4.6, 92.7]
Percent tree canopy cover	
Low	1.8 – 9.5
Tertiles	Medium 9.5 – 15.9
	High 16.0 – 80.4
	Mean (SD) 15.4 (11.2)
	Median [min,max] 12.3 [1.8, 80.4]
Percept reporting perceived park or outdoor space access	
Low	45.3 – 71.9
Tertiles	Medium 72.0 – 79.0
	High 79.1- 94.9
	Mean (SD) 75.2 (9.2)
	Median [min,max] 75.4 [45.3, 94.9]
Percent obese	
	Mean (SD) 31.5 (5.8)
	Median [min,max] 32.4 [16.9, 41.0]
Percent reporting high blood pressure diagnosis	
	Mean (SD) 33.4 (5.3)
	Median [min,max] 34.0 [20.4, 42.0]
Percent reporting diabetes diagnosis	
	Mean (SD) 12.4 (3.0)
	Median [min,max] 13.2 [4.5, 17.5]

274 All objective greenness measures were highly correlated, with correlation coefficients
 275 greater than 0.8 (TABLE 2). Percentage of adult residents reporting perceived park or
 276 outdoor space access was only moderately correlated with the objective measures, and
 277 most highly correlated with percent tree canopy (correlation coefficient: 0.32), followed
 278 by percent vegetation cover (correlation coefficient: 0.21) and least with NDVI
 279 (correlation coefficient: 0.12). The CVD risk factors were highly correlated with one
 280 another; correlation coefficients were higher than 0.9. Percentage of the population that

281 was non-Hispanic Black population was moderately correlated with percent living in
282 poverty (correlation coefficient: 0.41). A complete correlation matrix showing
283 relationships between the greenness measures, health outcomes, and covariates is given
284 in TABLE S2.

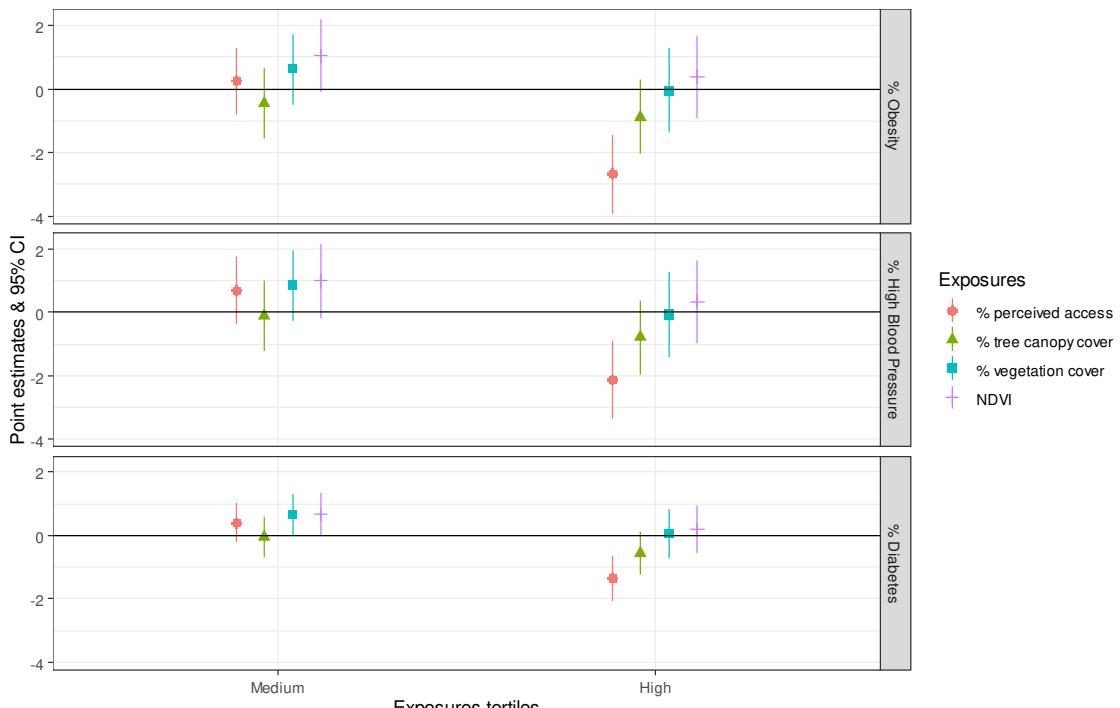
TABLE 2: Correlation matrix demonstrating relationships between the greenness measures.

	Percent tree canopy cover	Percent vegetatio n cover	Overall greennes s (NDVI)	Perceive d access to green space (% of adults reportin g)
Percent tree canopy cover	1.00	0.88	0.81	0.32
Percent vegetation cover		1.00	0.95	0.21
Overall greenness (NDVI)			1.00	0.12
Perceived access to green space (% of adults reporting)				1.00

285 *Main analysis*

286 Results from spatial lag models estimating associations between percentage of the
287 census tract's adult population reporting perceived park or outdoor space access, and
288 objective measures of percent tree cover, percent vegetation cover, and NDVI with
289 percentages of the adult population who were obese, who reported ever having a high
290 blood pressure diagnosis, and who reported ever having a diabetes diagnosis, adjusted
291 for census tract level population density, percent non-Hispanic Black, and percent of the
292 population living in poverty, are presented in FIGURE 1 (Quantitative estimates are
293 given in TABLE S3). Associations with all three outcomes followed similar patterns,
294 with the strongest protective associations with percent obese, followed by percent
295 reporting ever receiving a diagnosis of high blood pressure, and, finally, percent
296 reporting ever receiving a diagnosis of diabetes. Estimates comparing the second to the
297 first tertile were null or close to the null for all exposure and outcome combinations.
298 However, we observed evidence of protective associations based on comparing the third

299 vs. the first tertiles of exposure. Percent reporting perceived park or outdoor space
 300 access was protective against the cardiovascular risk factors (Beta: -2.68; 95% CI: -
 301 3.93, -1.43 for associations with percent obese, Beta: -2.13, 95% CI: -3.35, -0.9 for
 302 associations with percent with blood pressure diagnosis, Beta: -1.35 95% CI: -2.06, -
 303 0.64 for associations with percent with diabetes diagnosis). Percent tree canopy cover
 304 was also protective against the cardiovascular risk factors (Beta: -0.89; 95% CI: -2.05, -
 305 0.28 for associations with percent obese, Beta: -0.79 95% CI: -1.95, 0.37 for
 306 associations with percent with blood pressure diagnosis, Beta: -0.57 95% CI: -1.24, 0.1
 307 for associations with percent with diabetes diagnosis). However, estimates of
 308 association with percent vegetation cover and NDVI were close to null.



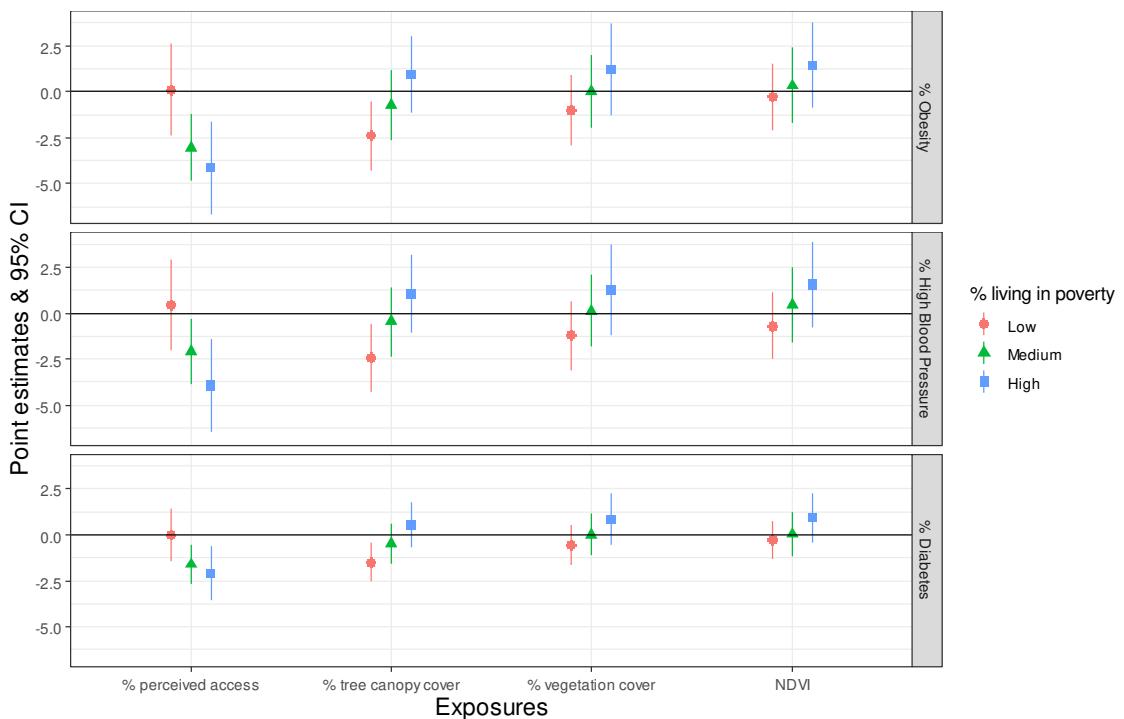
309

310 **FIGURE 1:** Estimates of association between the greenness measures and CVD risk factors, derived from
 311 spatial lag models adjusted for population density, percent living in poverty and percent non-Hispanic
 312 Black population.

313 *Effect modification by sociodemographics*

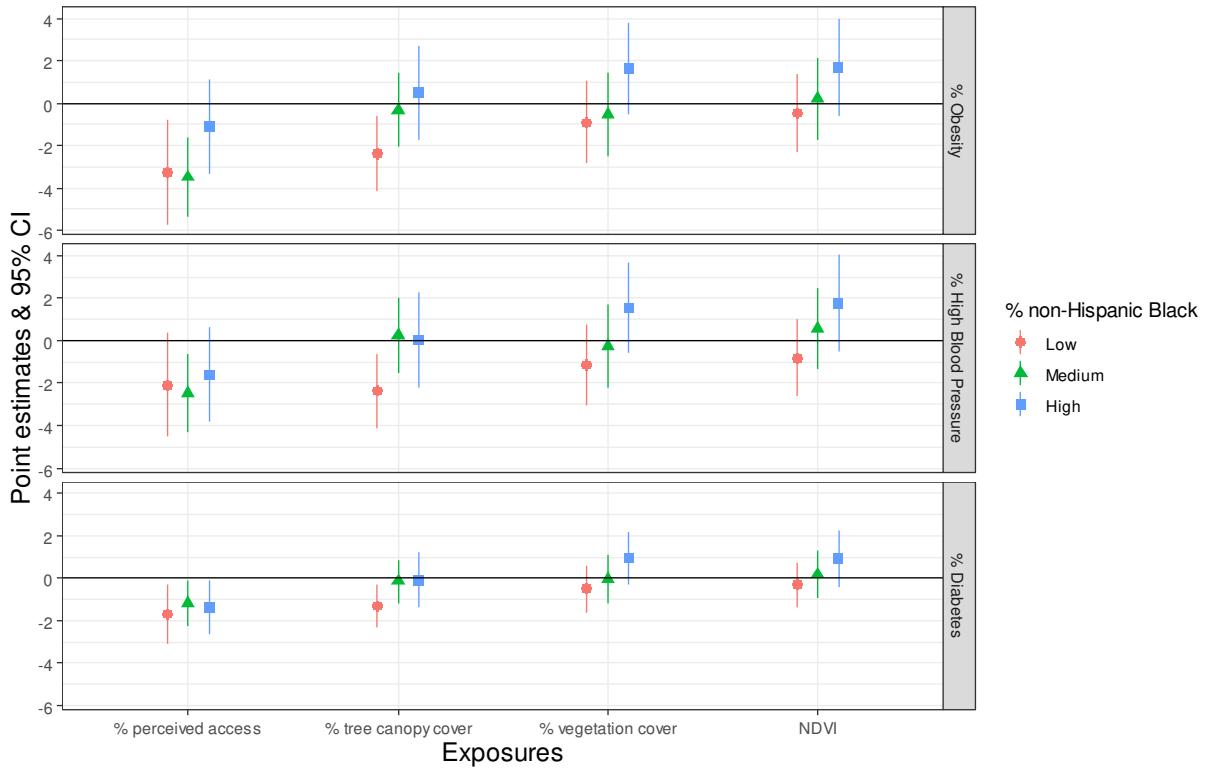
314 Stratified effect estimates were relatively imprecise with wide CIs, and we observed
 315 little statistical evidence effect modification of the greenness-CVD risk factor
 316 associations by neighborhood sociodemographic variables, based on examination of the

317 AIC statistics (Table S4). However, patterns in the magnitude and direction of the
318 stratified estimates were suggestive of heterogeneity in some of the greenness-CVD risk
319 factor associations across categories of percentage of the population living in poverty
320 (FIGURE 2, Table S5) and percent of the population that was non-Hispanic Black
321 (FIGURE 3, Table S6). Specifically, the protective association between percent
322 reporting perceived access to parks or outdoor spaces and the CVD risk factors was
323 restricted to medium and high percent poverty census tracts. For example, the protective
324 association between percent reporting perceived park or outdoor space access and
325 percent reporting a diagnosis of high blood pressure was restricted to high (Beta: -3.92,
326 95% CI: -6.42, -1.42) and medium (Beta: -2.08, 95% CI: -3.89, -0.28) percent poverty
327 census tracts, but close to null in low % poverty areas (Beta: 0.46, 95% CI: -2.00, 2.93,
328 Delta AIC after including interaction term: -0.919). By contrast, patterns suggested
329 protective associations of percent tree canopy cover the CVD risk factors were restricted
330 to the lowest poverty areas, although we did not observe statistical evidence of effect
331 modification, based on comparison of AIC statistics from nested models. For example,
332 high percent tree canopy cover appeared protective against obesity in low percent
333 poverty census tracts (Beta: -2.39, 95% CI: -4.26, -0.52), and close to null in medium
334 (Beta: -0.75, 95% CI: -2.66, 1.16) and high (Beta: 0.95, 95% CI: -1.15, 3.05) percent
335 poverty areas. Similarly, the protective association between percent tree canopy cover
336 and the CVD risk factors was restricted to census tracts with low % non-Hispanic Black
337 populations. For example, high percent tree canopy was protective against percent obese
338 in census tracts with low percentages of the population who were non-Hispanic Black
339 (Beta: -2.38; 95% CI: -4.14,-0.62), but estimates of association between percent tree
340 canopy and percent obese were close to null in census tracts with medium (Beta: -0.32,
341 95% CI: -2.08, 1.44) or high (Beta: -0.81, 95% CI: -2.70, 1.08) percent non-Hispanic
342 Black populations (delta AIC following the inclusion of interaction term: -1.933, Table
343 S4).



344

345 **FIGURE 2:** Stratified estimates of association between the greenness measures and CVD risk factors,
 346 derived from spatial lag models adjusted for population density, percent living in poverty and percent
 347 non-Hispanic Black population, and an interaction term between the greenness measures and percent of
 348 the population living in poverty. The estimates represent contrasts of the third vs. the first tertile of the
 349 greenness measure.



350

351 **FIGURE 3:** Stratified estimates of association between the greenness measures and CVD risk factors,
 352 derived from spatial lag models adjusted for population density, percent living in poverty and percent
 353 non-Hispanic Black population, and an interaction term between the greenness measures and percent non-
 354 Hispanic Black population.

355 **4. Discussion**

356 Results from this spatial analysis of associations of three objective measures of
 357 greenness, and one measure of perceived access to green spaces, with several CVD risk
 358 factors in Philadelphia, PA, suggest that greenness, and particularly perceived access to
 359 green space and higher percent tree canopy cover may protect against cardiovascular
 360 disease risk factors. These results contribute to mounting evidence of the salutogenic
 361 benefits of greenness. We also observed evidence that the protective association
 362 between perceived access to parks and outdoor spaces and CVD risk factors was
 363 restricted to census tracts with higher percentages of the population living in poverty.
 364 Meanwhile, the protective association between tree canopy cover and CVD risk factors
 365 was restricted to census tracts with low percent non-Hispanic Black populations.

366 We estimated the magnitude and direction of correlations of three different
367 objective greenness measures with an estimate of perceived access to green space (park
368 or outdoor spaces). There was low correlation between the perceived and objective
369 greenness measures. This is consistent with previous analyses that have estimated
370 correlations between objective and perceived greenness measures. For example, Orstad
371 *et al.* (2017) reviewed the agreement between objective and perceived greenness metrics
372 in physical activity studies, and 72.1% of the studies showed only slight-to-poor
373 agreement ($\kappa = .00 - .40$). There are several potential explanations for the low
374 correlation between objective and perceived measures. The disagreement could be due
375 to the green space question on the survey: questionnaires used to characterize green
376 space perception may ascertain different dimensions of exposure, such as perceptions of
377 access, utilization, and/or safety. For example, safety can be measured by perceived
378 measures and not by objective measures, at least in a reliable way (Schipperijn *et al.*,
379 2010). These perceived measures may play an important role in the association between
380 greenness and human health, especially regarding the beneficial effects that rely on
381 biological mechanisms. Reports of high levels of perceived access to safe green spaces
382 within one's neighborhood may better correspond to actual utilization of green space.
383 For example, a green space that is perceived as accessible and safe might better promote
384 physical activity than one perceived as being difficult to access or unsafe. Similarly, a
385 green space that is perceived as safe might harbor more social activities than one
386 perceived as unsafe (McCormack *et al.*, 2010).

387 Interestingly, of all the objective measures, percent tree canopy cover was most highly
388 correlated with percentages of the adult population reporting perceived park or outdoor
389 space access. This finding might indicate that tree canopy cover has important impacts
390 on community's perception of green space access. Further research is needed to explore
391 the reasons for the relatively low correlations between perceived and objective
392 greenness measures. In addition, our results have implications for future research
393 studies relying only on objective measures of greenness, as the interpretation of any
394 results should consider the potential that the exposure estimates are not necessarily
395 representative of actual perception of green space access or safety (or utilization of the
396 green space).

397 The different greenness measures that we used in this study were estimated using
398 different units (e.g., percent of residents reporting access to green space vs. % tree
399 canopy cover vs. greenness density measured using an index measure), making it
400 difficult, and potentially incorrect, to quantitatively compare the estimates of association
401 across the different measures. However, the stronger magnitude of the estimates of
402 association with the perceived vs. the objective measures suggested that perceived
403 access to green spaces may be more important for cardiovascular health promotion
404 compared to the objective greenness measures. This finding is consistent with the
405 conclusions from a review paper by Orstad *et al.* (2017), which found that a higher
406 percent of studies using perceived greenness measures found significant associations
407 with physical activity compared to studies that used objective greenness measures. Also
408 consistent with our results, Dadvand *et al.* (2016) found more robust associations with
409 perceived park or outdoor space access than with residential surrounding greenness
410 when analyzing associations with perceived general health, mental health, physical
411 activity, and social cohesion. We also found that, of the objective greenness measures,
412 percent tree canopy cover was most protective against CVD. This finding is consistent
413 with previous research on the health benefits of tree canopy cover. For example, Ulmer
414 *et al.* (2016) found that tree canopy cover was protective against self-reported overall
415 health and that this association was mediated by a reduction in percent obese, diabetes,
416 high blood pressure, and asthma. The finding is also consistent with research comparing
417 tree canopy cover with other objective measures. In New York City, New York, USA,
418 Reid *et al.* (2017) found a stronger beneficial association between percent tree canopy
419 cover and self-reported health compared to percent overall vegetation.

420 *Effect modification:*

421 To our knowledge, our study was one of the first to quantify heterogeneity of
422 associations between perceived and objective greenness measures and CVD across
423 neighborhood sociodemographic composition variables. In particular, our examination
424 of effect modification by percent non-Hispanic Black is an important contribution to
425 literature on greenness and health links. We found that percent reporting perceived park
426 or outdoor space access was protective against percent reporting ever having a high
427 blood pressure diagnosis, but only in medium or high poverty census tracts. This finding
428 is consistent with the equigenic hypothesis, that lower socioeconomic status groups

429 could benefit the most from more greenness access and exposure (Mitchell et al., 2015).
430 Consistent with our findings, a study from the United Kingdom observed lower
431 inequality in circulatory disease mortality in populations living in the greenest areas
432 (Mitchell & Popham, 2008). Similarly, another study from the United Kingdom found
433 that a protective association between green space access and cardiovascular disease
434 mortality was restricted to the most socioeconomically deprived subpopulations
435 (Lachowycz & Jones 2014). By contrast, in a study of associations of quality of
436 greenness with green space use, obesity, and physical activity in Barcelona (Spain),
437 Knobel et al. (2020) found that greenness was more protective against obesity among
438 participants with a high school education or higher. Other analyses have not observed
439 heterogeneity of associations between NDVI or tree canopy cover and obesity across
440 income levels (Browning *et al.*, 2018). Lower-income populations may be exposed to
441 several environmental or social stressors, such as air pollution (Hajat et al., 2015) or
442 extreme heat (Harlan et al., 2006). Greenness exposure and access may be particularly
443 important in impoverished areas by mitigating exposures to these stressors. Further
444 research is needed to quantify the heterogeneity of associations between greenness and
445 cardiovascular health across different neighborhood poverty levels and explore the
446 mechanisms that give rise to any additional health promotion in more deprived areas.

447 In addition to quantifying effect modification by percent living in poverty, we also
448 assessed heterogeneity across categories of neighborhood percent non-Hispanic Black
449 population. In our data, percent living in poverty was only moderately correlated with
450 percent non-Hispanic Black. Further, in general, these two indicators of
451 sociodemographic composition represent different constructs. In particular, ethnic and
452 racial minorities face different levels of racism (i.e., institutional, personally mediated)
453 (Jones, 2000), which may contribute to different relationships between greenness and
454 CVD. Here, we found that the protective association between percent tree canopy cover
455 and percent obese was restricted to census tracts with low percent non-Hispanic Black
456 populations. Literature regarding differences in greenness and human health
457 associations by race/ethnicity is scarce and inconsistent, and few studies have
458 considered heterogeneity across categories of neighborhood non-Hispanic Black
459 composition. When considering pregnant women, Dadvand *et al.* (2014) found a
460 positive association between greenness and birth outcomes, but only among white
461 females, not among Pakistani origin mothers. Contrarily, McEachan *et al.* (2016) found

462 no differences between ethnic groups in the association between greenness and
463 depression during pregnancy. The reasons that ethnic/racial minority neighborhood
464 residents may benefit less from greenness are complex and could be related to different
465 levels of racism (Jones, 2000). For example, residential racial segregation, a legacy of
466 structural racism in the United States, has led to the geographic concentration of social,
467 built environment, and environmental stressors in ethnic or racial minority areas (Gee &
468 Payne-Sturges). It may be that green space is not sufficient to overcome some of the
469 other barriers to cardiovascular health in these neighborhoods, where residents are faced
470 with such tremendous, and numerous, barriers to health and well-being. Besides, the
471 health impact of objective measures of exposure to greenness may be mediated by
472 personal perceptions, such as connectedness to greenness, which could, by itself, be
473 associated with sociodemographic variables such as age, gender, ethnicity, or
474 socioeconomic status (Shanahan *et al.*, 2016). Further, past research has indicated that
475 ethnic and racial minorities have a greater fear of crime in green spaces compared to
476 their white counterparts (Sreetheran & Van Den Bosch, 2014), suggesting differential
477 utilization or perception across racial categories. Therefore, the association between
478 greenness and human health might differ between census tracts with similar objective
479 greenness levels but different racial/ethnic composition.

480 *Strengths and limitations:*

481 The strengths of this study include the estimation of associations with several distinct
482 objective greenness measures and a survey-based measure of green space perception.
483 The inclusion of these various measures is a particularly important contribution to this
484 literature. We used spatial lag models to account for spatial autocorrelation and adjusted
485 for several sociodemographic compositional factors, which we hypothesized might
486 confound estimates. Finally, our stratification of analyses by two different
487 sociodemographic constructs - percent living in poverty and percent non-Hispanic
488 Black – is an important novelty and strength. Stratification by these two distinct
489 sociodemographic variables improves understanding of the salutogenic effects of
490 greenness by showcasing the importance of considering neighborhood context and
491 composition. Urban decision-makers can use this information to inform their
492 assessments and fine-tune their decisions to the specific context where they will take
493 place.

494 We acknowledge several limitations of this study. Because this study was ecological, it
495 is prone to the ecological fallacy. However, Philadelphia's census tracts are densely
496 populated, and ecologic level exposures might approximate individual ones. Moreover,
497 we cannot rule out reverse causation or bias due to self-selection, especially regarding
498 perceived park or outdoor space access in that healthy people might have fewer
499 requirements to define something as accessible or self-select themselves into living in
500 greener areas. We tried to reduce confounding by controlling for race, poverty, and
501 population density. However, like any other observational study, we cannot rule out the
502 potential for residual confounding.

503 To estimate overall greenness in each census tract, we calculated a mean annual NDVI
504 value, using all available images from the year 2013 of the MODIS Vegetation Indices
505 (MOD13Q1) Version 6 data. The MOD13Q1 NDVI data are produced on 16-day
506 intervals, and retrieved from daily, atmosphere-corrected, bi-directional surface
507 reflectance. The Version 6 data use a MODIS-specific compositing method to remove
508 low quality pixels (i.e., cloud contaminated and off-nadir sensor views). From the
509 remaining high-quality pixels, it selects a single value per pixel using Constrained View
510 Angle-Maximum Value Composite criteria (Didan et al., 2015). Despite these control
511 efforts, the quality of each composited image, or of the pixels within each image, may
512 still vary. In our processing of the images, we did not mask low-quality pixels, which
513 may have led to some level of exposure misclassification.

514 This analysis included only 377 census tracts; thus, we were relatively underpowered to
515 assess effect modification. As a result, the stratified effect estimates of association were
516 relatively imprecise, with wide confidence limits. Some of the results from our analyses
517 suggested interesting heterogeneity across sociodemographic categories, and further
518 research with larger data sets is needed to further explore these differences.

519 The survey question we used to estimate perceived access to green space ("Is there a
520 park or other outdoor space in your neighborhood that you are comfortable visiting
521 during the day?") made use of a broad definition of green space and accessibility.
522 Participants might be referring to non-green public open spaces instead of green spaces.
523 On the other hand, this question allows for the capture of accessibility to spaces that are
524 not defined explicitly, such as gardens or parks. Similarly, the definition of access is not

525 limited to physical access, as it includes the concept of perceived comfort. Comfort is a
526 construct that might include many factors, such as safety, maintenance, aesthetics, or
527 amenities.

528 The use of self-reported height and weight could have resulted in misclassification of
529 percent obese. However, previous studies have found a strong correlation between self-
530 reported and objective measures of BMI (McAdams, Van Dam, & Hu, 2007). Ever
531 having been diagnosed with high blood pressure and or with diabetes were also based
532 on self-reported survey data, which could have led to misclassification. However, we
533 hypothesize that the use of questions, including explicit mentions of a medical
534 diagnosis, reduces the risk of misclassification. Additionally, the outcomes have been
535 smoothed at the census tract level using Bayesian hierarchical models and should not be
536 interpreted as direct measures.

537 5. Conclusion

538 Our results suggest that tree canopy cover and perceived park or outdoor space access
539 may improve urban area residents' cardiovascular health. Urban greening strategies that
540 increase the amount of green in an area and particularly those that aim to make it more
541 accessible, safe, inclusive and usable, may provide additional health benefits. Our
542 results also suggest that any CVD protective effects of greenery may be heterogeneous
543 and vary based on neighborhood sociodemographic composition. Choosing the best
544 option between increasing the amount of green or facilitating access to the existing one
545 might depend on the sociodemographic context.

546 Further research with larger data sets is needed to explore, more deeply, the reasons for
547 heterogeneity across sociodemographic groups and to disentangle how
548 sociodemographic factors modify salutogenic pathways. Lastly, further research using
549 individual-level data are needed to confirm our results, especially those comparing
550 perceived access to green space with objective greenness measures.

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