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RESEARCH ARTICLE

Neighborhood Greenspace and Changes in Pediatric Obesity During COVID-19

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Introduction: Pediatric obesity rates increased during the COVID-19 pandemic. This study examined the associations of neighborhood greenspace with changes in pediatric obesity during the pandemic.

Methods: Electronic health record data from a large pediatric primary care network were extracted to create a retrospective cohort of patients aged 2−17 years with a visit in each of 2 periods: June 2019−December 2019 (before pandemic) and June 2020−December 2020 (pandemic). Multivariable longitudinal generalized estimating equations Poisson regression estimated the associations of census tract–level Normalized Difference Vegetation Index with (1) changes in obesity risk during the pandemic and (2) risk of new-onset obesity among children who were not obese prepandemic. Analyses were conducted between November 2021 and May 2022.

Results: Among 81,418 children (mean age: 8.4 years, 18% Black), the percentage of children who were obese increased by 3.2% during the pandemic. Children in Normalized Difference Vegetation Index Quartiles 2−4 had smaller increases in obesity risk during the pandemic than those in Quartile 1 (risk ratio=0.96, 95% CI=0.93, 0.99; Quartile 3 risk ratio=0.95; 95% CI=0.91, 0.98; Quartile 4 risk ratio=0.95, 95% CI=0.92, 0.99). Among the subset who were not obese before the pandemic, children in Normalized Difference Vegetation Index quartiles 3−4 had a lower risk of new-onset obesity during the pandemic (Quartile 3 risk ratio=0.82, 95% CI=0.71, 0.95; Quartile 4 risk ratio=0.73, 95% CI=0.62, 0.85). Higher Normalized Difference Vegetation Index was associated with smaller increases in obesity risk and lower risk of new-onset obesity among children in urban and suburban areas, but results were in the opposite direction for children in rural areas.

Conclusions: Children living in greener neighborhoods experienced smaller increases in obesity during the pandemic than children in less green neighborhoods, although findings differed by urbanicity.
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INTRODUCTION

During the coronavirus disease 2019 (COVID-19) pandemic, stay-at-home orders and cancellation of recreational activities limited opportunities for physical activity and increased sedentary activity among youth.[1−3] Moreover, stress and mental health concerns increased among youth.[4,5] Stress may contribute to obesity through biological (e.g., inflammation[6]) and behavioral (e.g., stress related overeating[7]) mechanisms. However, there is emerging evidence that neighborhood greenspace (parks, trees, grass, other

greenery) may mitigate these trends.[8−10] Among children, neighborhood greenspace is associated with higher physical activity and better mental health,[11] although evidence for an association with obesity is mixed.[11]

Several recent studies support the potential importance of greenspace for child health during the pandemic. Among Canadian adolescents in high-density neighborhoods, greater access to parks was associated with higher odds of participating in outdoor activities during the pandemic.[8] Among a nationally representative sample of U.S. children and their parents, park access was associated with greater coparticipation in outdoor activities (e.g., walking, playing outside) during the pandemic.[10] However, because park closures were common early in the pandemic,[12] it is important to examine the role of overall residential greenspace, which might support physical activity (e.g., walking, playing on streets/sidewalks near home[2]) and reduce stress even if public park access was limited.

In a large pediatric primary care network in the northeastern U.S., obesity prevalence was fairly stable prepandemic and increased markedly early in the pandemic.[13] This increase was largest among youth from racially/ethnically minoritized populations and low-income neighborhoods, widening existing disparities.[13] Neighborhoods experiencing persistent impacts of structural racism, manifested through racial residential segregation and disinvestment, have lower levels of greenspace than wealthier and predominantly White neighborhoods.[14,15] These differences might have placed children living in disinvested neighborhoods at greater risk for reduced physical activity and weight gain during the pandemic.

This study's objective was to examine the associations of neighborhood greenspace with changes in obesity risk among children and adolescents during the pandemic. The increase in obesity risk during the pandemic was hypothesized to be smaller among children living in greener neighborhoods than among children in neighborhoods with less greenspace. Furthermore, among the subset who were not obese at baseline, neighborhood greenspace was hypothesized to be associated with a lower incidence of new-onset obesity during the pandemic.

METHODS

Study Population

This study took place within the Children's Hospital of Philadelphia Care Network, a pediatric primary care network, including 31 clinics in urban, suburban, and semirural areas in Pennsylvania and New Jersey that provide care for nearly 300,000 patients.[16] Data were extracted from electronic health records (EHRs) of children aged 2−17 years who attended primary care visits with a measured height and weight in June 2019−December 2019 (prepandemic) or June 2020−December 2020 (pandemic) (Appendix Figure 1, available online; n=190,778). Visits in March 2020−May 2020 were excluded because visit volume declined dramatically but had returned to normal by June 2020.[13] Patients who lived outside of the study region (Pennsylvania, New Jersey, and Delaware) and with missing data for BMI, neighborhood exposures, or covariates were excluded (n=889). Analyses were restricted to patients with a visit in each of the 2 time periods (n=108,471 excluded), yielding a final sample of 81,418 children. Secondarily, another cohort was defined, which comprised patients who were not obese at baseline (n=71,454; 87.8% of the full cohort), to examine incident obesity. The Children's Hospital of Philadelphia IRB determined this study to be exempt from review.

Measures

Height and weight were measured at each visit. BMI was calculated by dividing weight in kilograms by height in meters squared. Centers for Disease Control and Prevention−modified age- and sex-adjusted growth curves were used to convert BMI values to percentiles.[17] The primary outcome was obesity (BMI percentile ≥95%).

The primary exposure was neighborhood Normalized Difference Vegetation Index (NDVI),[18] a satellite imagery-based measure of overall greenness that is widely used as an indicator of greenspace exposure.[19] NDVI is calculated from near-infrared and visible light radiation reflected by vegetation and ranges from −1 to 1, with higher values indicating greater vegetation. The 16-day composite satellite images at a 250-m resolution were downloaded from the Moderate Resolution Imaging Spectroradiometer of the National Aeronautics and Space Administration's Terra satellite from the National Aeronautics and Space Administration EarthData website.[20] NDVI values were truncated at 0 (values <0 indicate water). The mean NDVI was calculated from all imagery between June 2019 and December 2019 for each census tract in the study region. Patient addresses were extracted from the EHR and geocoded to the census tract level.

Covariates included variables identified a priori as potential confounders of the relationship between neighborhood greenspace and obesity. Individual-level covariates extracted from the EHR included age, sex, race/ethnicity (included as a social construct and marker for exposure to racism), insurance status, visit month, and length of time in months between visits. Census tract−level covariates included economic deprivation and social fragmentation indices[21] calculated from U.S. Census variables[22]; neighborhood supermarket access (classified as low if ≥500 people or 33% of the tract population lived >1 mile from the nearest supermarket or large grocery store in urban areas or >10 miles in rural areas[23]); and urbanicity, categorized as urban (within Philadelphia), suburban (outside Philadelphia but classified as urbanized area or urban cluster by the U.S. Census Bureau[24]), and rural (classified as rural by the Census Bureau).

Statistical Analysis

Covariate distributions were assessed overall and by NDVI Quartile using descriptive statistics. Demographics of the cohort were compared with all children aged 2−17 years with a primary care visit in the years 2019−2020 to determine how representative the cohort was of the underlying population of children in the network. Spearman correlation coefficients were calculated to assess the potential risk of collinearity between neighborhood measures.

To descriptively examine the relationship between NDVI and obesity change during the pandemic, the change in the percentage of children who were obese from the prepandemic visit to the pandemic visit was calculated across NDVI quartiles. Then, generalized estimating equations (GEE)−modified Poisson regression[25] was used to estimate the associations of NDVI with changes in obesity risk during the pandemic. GEE is an appropriate method for estimating the average associations of neighborhood characteristics in a population while accounting for nonindependence of observations within the same neighborhood, assuming the number of neighborhoods is relatively large.[26] Modified Poisson regression was used to estimate risk ratios of obesity risk with increasing levels of NDVI.[25] All models included main effects for neighborhood NDVI Quartile and time period (before pandemic versus pandemic) and an NDVI X time period interaction term. Models were estimated using Stata's xtgee package with robust variance estimation and an exchangeable working correlation structure and were progressively adjusted for the covariates described earlier. Marginal standardization was then used to estimate the differences by NDVI Quartile in the change in obesity during the pandemic on a probability scale, using GEE logistic regression and Stata's margins package. Marginal standardization calculates weighted averages for each exposure category that reflect the covariate distribution of the full population[27]—that is, estimating the percentage of children in each NDVI Quartile who would be obese if that quartile had the same distribution of covariates as the full population.

Next, associations of neighborhood NDVI with new-onset obesity were estimated among the subset of the cohort that was not obese at baseline. First, the cumulative incidence of obesity was calculated for each NDVI Quartile by dividing the number of children who were newly classified as obese during the pandemic by the total number of children who were not obese at baseline. Then, adjusted risk ratios for the association of NDVI Quartile with obesity incidence were estimated using multivariable GEE-modified Poisson models. Finally, logistic regression followed by marginal standardization was used to estimate adjusted differences in obesity incidence on a probability scale across NDVI quartiles.

Some studies have shown greenspace to have stronger associations with health outcomes in urban areas.[28] In addition, the relationships between greenspace and obesity might differ by age because of differences in whether and how children interact with greenspace. Thus, additional analyses were conducted separately stratifying by age and urbanicity. Finally, to determine robustness to differing definitions of neighborhood greenspace exposure, the models mentioned earlier were repeated with neighborhood greenspace defined as (1) continuous NDVI *z*-score; (2) average NDVI within 0.5 km, 1 km, and 2 km buffers around the census tract centroid; and (3) using percent tree canopy cover instead of NDVI.[29,30]

Analyses were conducted using R, Version 4.1.0, and Stata, Version 16.1. Data analyses were conducted between November 2021 and May 2022. The study followed the STROBE guidelines.

RESULTS

Among 81,418 children and adolescents, the mean age was 8.4 years (Table 1). A total of 48.8% were female, and 25.5% were publicly insured. Race/ethnicity percentages were as follows: 18.1% for non-Hispanic Black,

56.9% for non-Hispanic White, 7.8% for Hispanic, and 17.2% for non-Hispanic Other race. The analytic cohort included a smaller percentage of publicly insured and non-Hispanic Black children than the overall population of patients in the network in 2019−2020 (Appendix Table 1, available online). Black children and publicly insured children were overrepresented in the lowest NDVI Quartile, whereas White and commercially insured children were overrepresented in the highest NDVI Quartile (Table 1). Figure 1 displays a map of census tract−level NDVI throughout the study region. Higher neighborhood NDVI showed a weak to moderate correlation with lower economic deprivation, lower social fragmentation, lower urbanicity, and higher supermarket access (Appendix Table 2, available online).

In the prepandemic period, 9,964 children were obese (12.2%), which increased to 12,528 (15.4%) during the pandemic. The percentage of children who were obese increased across all quartiles of NDVI (Figure 2, Appendix Table 3, available online), with a declining magnitude as neighborhood NDVI increased. The change in the percentage obese was 5.1% for NDVI Quartile 1 (least green), 3.0% for Quartile 2, 2.4% for Quartile 3, and 2.0% for Quartile 4. After adjustment for individual and neighborhood covariates, children in NDVI Quartiles 3 and 4 had 14%−27% lower obesity risk at baseline than the children in Quartile 1, and children in Quartiles 2−4 had 4%−5% lower change in obesity risk during the pandemic (Table 2). After accounting for covariates through marginal standardization, the predicted percentage point increase in obesity during the pandemic was 1−2 percentage points smaller for Quartiles 2−4 vs for Quartile 1 (Appendix Table 4, available online).

Of the 81,814 children in the full cohort, 71,454 were not obese at baseline (87.8%). Among this subset, 3,838 (5.4%) were obese during the pandemic period. By NDVI Quartile, the cumulative incidence of new-onset obesity during the pandemic was 8.1% for Quartile 1, 5.5% for Quartile 2, 4.4% for Quartile 3, and 3.7% for Quartile 4. After covariate adjustment, children in Quartiles 3 and 4 had an 18% and 27%, respectively, lower risk of incident obesity during the pandemic than children in Quartile 1 (relative risk for Quartile 3 vs Quartile 1: 0.82 [95% CI=0.71, 0.95]; relative risk for Quartile 4 vs Quartile 1: 0.73 [95% CI=0.62, 0.85]). On a probability scale, the percentage of children who became obese during the pandemic was 1.1 percentage points lower for Quartile 3 than for Quartile 1 (95% CI= −1.9, −0.3) and 1.7 percentage points lower for Quartile 4 than for Quartile 1 (95% CI= −2.5, −0.9).

Patterns were generally similar across age groups (Appendix Tables 5 and 6, available online). In models stratified by urbanicity, the patterns among children in

Table 1. Characteristics of the Study Population, Overall and by NDVI Quartile (N=81,418)

Characteristics	Overall,*n* (%)	NDVI Q1,*n* (%)	NDVI Q2,*n* (%)	NDVI Q3,*n* (%)	NDVI Q4,*n* (%)
n	81,418	20,415	20,301	20,383	20,319
Age, mean (SD)	8.4 (4.4)	7.8 (4.4)	8.2 (4.4)	8.6 (4.4)	9.0 (4.4)
Sex					
Male	41,707 (51.2)	10,411 (51.0)	10,360 (51.0)	10,491 (51.5)	10,445 (51.4)
Female	39,711 (48.8)	10,004 (49.0)	9,941 (49.0)	9,892 (48.5)	9,874 (48.6)
Race/ethnicity					
Non-Hispanic Black	14,693 (18.1)	10,156 (49.8)	2,875 (14.2)	1,115 (5.5)	547 (2.7)
Non-Hispanic White	46,350 (56.9)	5,509 (27.0)	11,961 (58.9)	13,965 (68.5)	14,915 (73.4)
Hispanic/Latino	6,356 (7.8)	1,984 (9.7)	1,789 (8.8)	1,476 (7.2)	1,107 (5.4)
Non-Hispanic Other race	14,019 (17.2)	2,766 (13.5)	3,676 (18.1)	3,827 (18.8)	3,750 (18.5)
Insurance payer					
Commercial/other	60,640 (74.5)	9,562 (46.8)	15,653 (77.1)	17,261 (84.7)	18,164 (89.4)
Public	20,778 (25.5)	10,853 (53.2)	4,648 (22.9)	3,122 (15.3)	2,155 (10.6)
Time in months between measurements, mean (SD)	12.4 (2.1)	12.7 (2.1)	12.4 (2.1)	12.4 (2.0)	12.3 (2.1)
Neighborhood measures					
Economic deprivation,[a] mean (SD)	0.0 (1.0)	1.0 (1.4)	−0.4 (0.5)	−0.4 (0.5)	−0.2 (0.5)
Social fragmentation,[b] mean (SD)	0.0 (1.0)	1.0 (1.0)	0.0 (0.9)	−0.4 (0.7)	−0.6 (0.6)
Supermarket access[c]					
Low access	39,303 (48.3)	2,052 (10.1)	7,943 (39.1)	13,236 (64.9)	16,072 (79.1)
High access	42,115 (51.7)	18,363 (89.9)	12,358 (60.9)	7,147 (35.1)	4,247 (20.9)
Urbanicity[d]					
Urban	14,514 (17.8)	13,001 (63.7)	1,134 (5.6)	217 (1.1)	162 (0.8)
Suburban	60,859 (74.8)	7,193 (35.2)	18,938 (93.3)	18,079 (88.7)	16,649 (81.9)
Rural	6,045 (7.4)	221 (1.1)	229 (1.1)	2,087 (10.2)	3,508 (17.3)

Note: NDVI values ranged from 0 to 0.77 (higher positive score indicating greater vegetation). Quartile definition: Q1, 0.0—0.50; Q2, 0.50—0.62; Q3, 0.62—0.67; and Q4, 0.67—0.77.
[a]Economic deprivation index calculated by summing *z*-scores of the following U.S. Census variables from the 2015—2019 American Community Survey 5-year estimates: percent receiving public assistance, median household income (reverse coded), and percent in poverty. The summary score was then restandardized to a *z*-score with mean 0 and SD 1.
[b]Social fragmentation index calculated by summing *z*-scores of the following U.S. Census variables from the 2015—2019 American Community Survey 5-year estimates: percent renter occupied housing units, percent vacant housing units, and percent residents living in the current home for <1 year. The summary score was then restandardized to a *z*-score with mean 0 and SD 1.
[c]From the USDA Food Access Research Atlas. *Low access* is defined as at least 500 people or 33% of the tract population living further than 1 mile in urban areas or 10 miles in rural areas from the nearest supermarket or large grocery store.
[d]Urban indicates a tract located in Philadelphia, suburban indicates a tract outside of Philadelphia and designated by the U.S. Census Bureau as urbanized, and rural indicates a tract designated by the Census Bureau as rural.
NDVI, Normalized Difference Vegetation Index; Q1, Quartile 1; Q2, Quartile 2; Q3, Quartile 3; Q4, Quartile 4; USDA, U.S. Department of Agriculture.

urban and suburban areas were similar to the main results (Appendix Tables 5 and 6, available online). Point estimates in urban areas suggested a larger protective association of greenspace, although some CIs were wide and crossed the null, likely because of the small sample size of urban children in NDVI Quartile 4. For children in rural areas, associations were in the opposite direction, with greater obesity risk during the pandemic among children in higher quartiles of NDVI than in Quartile 1.

When NDVI was expressed as a *z*-score, each SD higher in neighborhood NDVI was associated with an 8% lower risk of obesity at baseline, a 2% smaller change in obesity risk during the pandemic, and a 9% lower risk of incident obesity during the pandemic (Appendix Table 6,

available online). *Associations for neighborhood* NDVI, defined using buffers around the tract centroid and for percent tree canopy cover, were largely similar to the primary results (Appendix Table 7, available online).

DISCUSSION

In this longitudinal cohort of children and adolescents aged 2—17 years from a large pediatric primary care network, higher relative to lower neighborhood greenspace was associated with smaller increases in obesity risk during the COVID-19 pandemic. Higher neighborhood greenspace was also associated with lower obesity incidence among children who were not obese at baseline. The percentage of children who were newly obese was
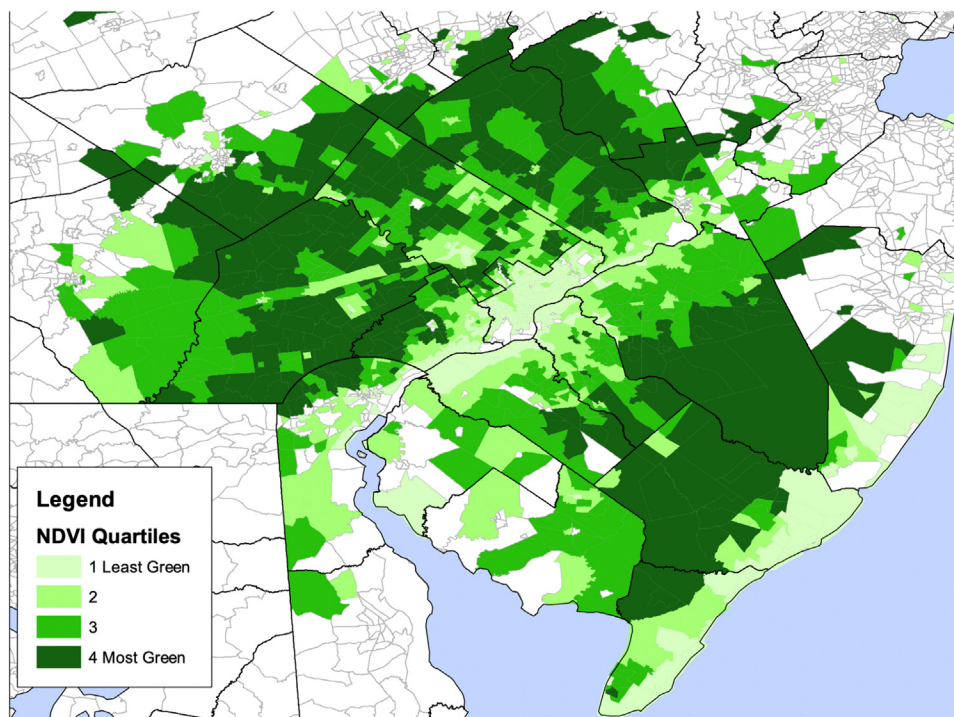
Figure 1. Neighborhood NDVI levels in the study region.
Note: NDVI is a satellite imagery-based measure of overall greenness. Average NDVI values from June 2019 to December 2019 were calculated for each census tract and categorized into quartiles. Census tract–level NDVI ranged from 0 to 0.77 (on a possible scale of 0 to 1; mean=0.56, SD=0.16). Quartile definition: Q1, 0.0−0.50; Q2, 0.50−0.62; Q3, 0.62−0.67; and Q4, 0.67−0.77.
NDVI, Normalized Difference Vegetation Index; Q1, Quartile 1; Q2, Quartile 2; Q3, Quartile 3; Q4, Quartile 4.
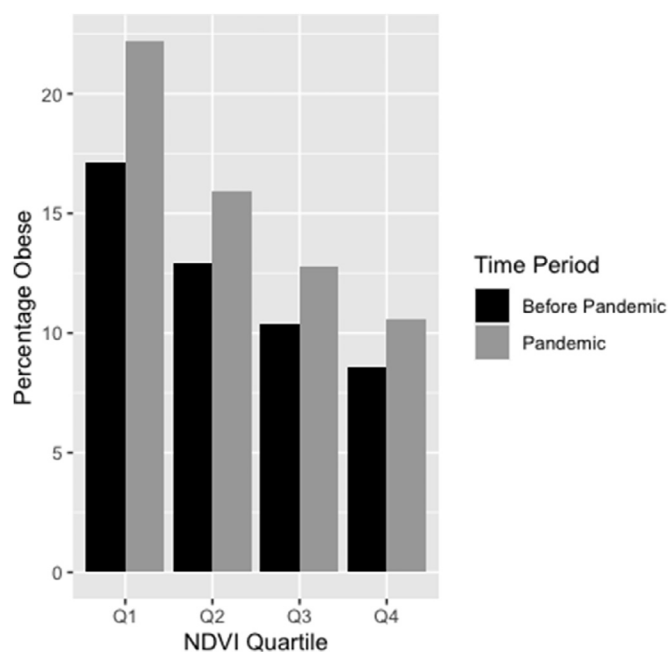
Figure 2. Percentage of children who were obese before and during the COVID-19 pandemic by NDVI Quartile.
Note: Obesity was defined as BMI >95th percentile. NDVI Quartile definition: Q1, 0.0−0.50; Q2, 0.50−0.62; Q3, 0.62−0.67; and Q4, 0.67−0.77. Before pandemic period: June−December 2019. Pandemic period: June 2020−December 2020.
NDVI, Normalized Difference Vegetation Index; Q1, Quartile 1; Q2, Quartile 2; Q3, Quartile 3; Q4, Quartile 4.

Table 2. Associations of Neighborhood Normalized Difference Vegetation Index With (A) Obesity Risk Before and During the COVID-19 Pandemic in the Full Study Population (N=81,418) and (B) Incident Obesity During the Pandemic Among Children Who Were Not Obese at Baseline (*n*=71,454)

NDVI Quartile	Model 1		Model 2		Model 3	
	Baseline NDVI[a]	Baseline NDVI X time interaction[b,c]	Baseline NDVI[a]	Baseline NDVI X time interaction[b,c]	Baseline NDVI[a]	Baseline NDVI X time interaction[b,c]
(A) Obesity risk ratio (95% CI)[d]						
Quartile 1 (least green)	ref	ref	ref	ref	ref	ref
Quartile 2	0.83 (0.78, 0.89)	0.94 (0.91, 0.97)	1.03 (0.96, 1.09)	0.96 (0.93, 0.99)	1.00 (0.93, 1.08)	0.96 (0.93, 0.99)
Quartile 3	0.67 (0.62, 0.73)	0.93 (0.90, 0.97)	0.90 (0.83, 0.97)	0.95 (0.91, 0.98)	0.86 (0.78, 0.94)	0.95 (0.91, 0.98)
Quartile 4 (most green)	0.57 (0.53, 0.63)	0.93 (0.90, 0.97)	0.79 (0.73, 0.86)	0.95 (0.93, 0.99)	0.73 (0.66, 0.81)	0.95 (0.92, 0.99)
(B) Incident obesity risk ratio (95% CI)[e]						
Quartile 1 (least green)	ref		ref		ref	
Quartile 2	0.70 (0.64, 0.77)		0.94 (0.86, 1.02)		0.92 (0.83, 1.03)	
Quartile 3	0.56 (0.51, 0.63)		0.84 (0.75, 0.93)		0.82 (0.71, 0.95)	
Quartile 4 (most green)	0.47 (0.42, 0.53)		0.75 (0.66, 0.84)		0.73 (0.62, 0.85)	

[a]Risk ratio for the NDVI main effect reflects the relative risk of obesity in the prepandemic period compared with that in NDVI Quartile 1. Example interpretation from Model 1: At baseline, the risk of obesity was 43% lower among children in NDVI Quartile 4 than among those in Quartile 1.
[b]Risk ratio for NDVI X time interaction reflects the relative change in obesity risk from the prepandemic to the pandemic period compared with that in NDVI Quartile 1. Example interpretation from Model 1: the change in obesity risk from the prepandemic to the pandemic period was 7% lower among children in Quartile 4 than among those in Quartile 1.
[c]*p*-value for global test of interaction for NDVI quartileχtime: Model 1, *p*<0.001; Model 2, *p*=0.004; and Model 3, *p*=0.005.
[d]Risk ratios estimated from generalized estimating equations–modified Poisson regression model with exchangeable correlation structure, accounting for clustering of children within census tracts. Model 1: unadjusted; Model 2: adjusted for age, sex, race/ethnicity, payer, visit month, and the time between measurements; and Model 3: Model 2 + neighborhood economic deprivation score, social fragmentation score, supermarket access, and urbanicity.
[e]Risk ratios estimated among the subset of children who were not obese at baseline using generalized estimating equations–modified Poisson regression model with exchangeable correlation structure, accounting for clustering of children within census tracts. Covariate adjustment is the same as for the models described earlier. Example interpretation from Model 3: among children not obese at baseline, children living in the greenest neighborhoods had 0.73 times the risk of becoming obese during the pandemic as children in the least green neighborhoods (27% lower risk), adjusting for individual and neighborhood covariates.
NDVI, Normalized Difference Vegetation Index.

1−2 percentage points lower when comparing higher quartiles of NDVI with the lowest quartile, a meaningful difference when considered in the context of a large population of children. These patterns were observed for children in urban and suburban areas. In rural areas, higher NDVI was associated with greater increases in obesity risk and higher obesity incidence.

An abundance of previous research supports the importance of neighborhood context for health.[31] Previous analyses of EHR data from children in Philadelphia reported that higher neighborhood greenspace was associated with lower BMI *z*-scores.[32,33] Overall, however, findings regarding the relationship between greenspace and obesity among children have been mixed.[11] This study adds to the existing literature by reporting the associations of higher neighborhood greenspace with

smaller obesity changes during the first year of the COVID-19 pandemic, a period in which schools were largely closed, and formal opportunities for physical activity were not available. These patterns were present among children in urban and suburban areas, whereas greenspace was associated with increased obesity risk in rural areas. The evidence is mixed on whether urbanicity modifies the associations between greenspace and obesity, although stronger associations were reported for more urbanized areas in some studies.[28] It is hypothesized that greenspace may be particularly important in urban areas because of the greater prevalence of environmental and social stressors.[28] In addition, the type of vegetation present may differ by urbanicity, with higher NDVI in more urbanized areas reflecting street trees and parks, whereas vegetation in rural areas might reflect

farmland or other land uses not suitable for recreational physical activity.

Results align with recommendations to keep greenspaces, including parks and trails, accessible to the public should there be future periods of physical distancing.[12] Several studies have reported reduced park visits early in the pandemic,[34−37] especially among minoritized or lower SES communities who had lower access to high-quality parks before the pandemic.[35,38,39] This may be owing to policies that temporarily closed parks in an effort to reduce disease transmission[37] or because of individuals' concerns about contagion in public spaces. Surveys of parents from 35 states indicated that the location of children's physical activity shifted during the pandemic, with activity increasingly taking place at home or on streets/sidewalks in the neighborhood.[2] Neighborhood greenspace, which includes trees and other forms of vegetation as well as parks, might support physical activity around the home even when public parks are closed or avoided. However, families with less neighborhood greenspace may be more reliant on public parks and thus more impacted by park closures. In addition, parents in low-income families were more likely to be essential workers in jobs that remained in person,[40] which may have limited time and resources available to supervise children's physical activity.

These findings also support calls to make access to greenspaces more equitable across neighborhoods.[12,41] Historical redlining policies, which resulted in racial residential segregation and economic disinvestment in neighborhoods with majority Black or immigrant residents, are associated with lower levels of present-day greenspace.[14,15] Likely reflecting these patterns, relatively few non-Hispanic Black children in this study lived in neighborhoods with high levels of greenspace. Interventions that increase neighborhood greenspace, for example, greening of vacant lots, have been found to reduce crime,[42] increase perceived safety and social cohesion,[42] and improve mental health,[43] all of which might promote greater physical activity and thus impact obesity. Importantly, such interventions should be implemented in partnership with communities to avoid green gentrification,[44] in which greening initiatives spark neighborhood socioeconomic and social changes that exclude existing residents of marginalized neighborhoods.

Limitations
The strengths of this study include the large and diverse population of children, the use of clinically measured BMI, and the longitudinal design. However, several limitations should be noted. First, observational data have limitations related to causal inference, including the inability to rule out unmeasured confounding. The EHR contains limited data on individual-level sociodemographic and family/household characteristics. Information on diet, physical activity, and sedentary behaviors was not available nor were data on school closure status. Residential self-selection may have biased findings if families of children with lower underlying risk of obesity preferentially lived in greener neighborhoods. Finally, neighborhood greenspace might reflect underlying structural advantages between neighborhoods not captured by the included covariates (e.g., greater access to recreational physical activity resources in higher income areas). Second, although NDVI is a widely used measure, it does not reflect the quality or actual use of greenspace. Information on access to parks was not available for the full study area. Third, neighborhoods were defined using census tracts, as commonly done in neighborhood studies. It is possible that census tracts do not reflect the most relevant spatial context and do not match how individuals perceive their neighborhoods; however, results were robust to buffer-based neighborhood definitions. Fourth, patients who did not attend visits during both study time periods were excluded. The cohort slightly underrepresented publicly insured and non-Hispanic Black children relative to the underlying patient population of the network, reducing generalizability. Loss of insurance coverage because of parent job loss, and reductions in healthcare utilization because of fears of contagion, may also have impacted primary care visit patterns. Participants were not matched, which might lead to differences in access to or use of health care. Finally, although the study population included urban, suburban, and semirural areas, this study was conducted in a single primary care network in 1 region of the country and may not generalize to other areas.

CONCLUSIONS

In this longitudinal cohort of children from a large pediatric primary care network, higher neighborhood greenspace was associated with a smaller increase in obesity risk during the COVID-19 pandemic than low neighborhood greenspace, among children in urban and suburban but not rural areas. Findings suggest that increasing greenspace within neighborhoods and preserving existing greenspaces may be beneficial for mitigating the impacts of future public health emergencies on obesity in children but that results may differ by urbanicity.

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CREDIT AUTHOR STATEMENT

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SUPPLEMENTAL MATERIAL

Supplemental materials associated with this article can be found in the online version at https://doi.org/10.1016/j.amepre.2022.07.014.

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