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The greenspace-academic performance link varies by remote sensing measure and urbanicity around Maryland public schools

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ABSTRACT

Greenspace is increasingly examined as a low-cost way to increase standardized test scores in public schools. However, the evidence for this intervention is mixed. One potential explanation is the variety of ways that greenspace is measured using remotely sensed data. For instance, aggregate measures can be captured from tree, grass, and shrub cover classifications in high-resolution (1 m^2) land cover datasets or they can be measured with normalized difference vegetative index (NDVI) values from sensors at different resolutions (e.g., 30 m^2 or 250 m^2). In the current cross-sectional observational study, we tested the relationship between five greenspace measures and third-grade math and reading standardized tests scores in Maryland public schools (n = 668) around schools and in children's neighborhoods. Low- and high-resolution greenspace measures were highly correlated with each other, but moderate-resolution measures were not. Multivariate regression models revealed positive associations between academic performance and low-resolution NDVI measures around schools and in neighborhoods as well as between performance and tree cover in neighborhoods. These effects were attenuated when an understudied confounder in this body of literature was included: population density as a measure of urbanicity. Grass cover showed associations with performance in models adjusted for urbanicity, but the direction of these associations was negative. These findings suggest that the possible association between greenspace and academic performance is complex and tenuous when examined with observational, cross-sectional study designs in limited geographic regions.

1. Introduction

A growing number of scholars are interested in the relationship between greenspace and academic performance. The notion is intriguing. Investments in tree canopy and other vegetated spaces are low-cost interventions that might boost student's standardized test scores, graduation rates, exam scores, and other forms of academic achievement.

There are several theories to support this notion. Attention restoration theory states that natural landscapes can effortlessly capture attention and allow cognitive resources to restore (Kaplan, 1995). Stress Reduction Theory and Scanning for Threats theory indicate that natural landscapes can be familiar, non-threatening, and stress-buffering because of people's evolutionary history (Ulrich, 1983) and personal experience (Browning & Alvarez, 2019). When students are exposed to chronic stressors at home or schools, their academic performance suffers (Berman et al., 2018; Dixson, Keltner, Worrell, & Mello, 2018; Durán-Narucki, 2008; Grineski, Clark-Reyna, & Collins, 2016; Welsh, 2001; White et al., 2016). Greenspace may also support self-discipline, engagement, physical activity, autonomy, and "loose parts" for creative play while providing calm, quiet, safe, and cooperative social environments (Kuo, Barnes, & Jordan, 2019).

The empirical evidence on this notion is mixed. On the one hand, several experimental studies support a causal link between nature exposure and academic performance. Direct exposure shows beneficial effects on working memory, cognitive flexibility and attentional control (Stevenson, Schilhab, & Bentsen, 2018) as well as emotional regulation and time-on-task in classrooms (Kuo, Penner, & Browning, 2018). High school students perform better on cognitive tasks when randomly assigned to green window views (Li & Sullivan, 2016). In Denmark, teaching curriculum outdoors for at least two hours per week elevates reading test scores (Otte et al., 2019) and increases motivation to learn (Bølling, Otte, Elsborg, Nielsen, & Bentsen, 2018) when compared to teaching entirely indoors. College students randomly assigned to

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window views of greenspace earn higher end-of-semester grades than students assigned to windows with views of concrete walls (Benfield, Rainbolt, Bell, & Donovan, 2015).

On the other hand, a review of the studies on standardized forms of academic performance and school greenspace found inconclusive evidence for this notion (Browning & Rigolon, 2019a). At least two studies showed negative associations between greenspace and performance (Beere & Kingham, 2017; Browning, Kuo, Sachdeva, Lee, & Westphal, 2018) and a third showed non-significant associations (Markevych et al., 2019). Two other studies showed positive associations (Kweon, Ellis, Lee, & Jacobs, 2017; Leung et al., 2019), and six showed a combination of positive and non-significant findings (Hodson & Sander, 2017; Kuo, Browning, Sachdeva, Lee, & Westphal, 2018; Matsuoka, 2010; Sivarajah, Smith, & Thomas, 2018; Tallis, Bratman, Samhouri, & Fargione, 2018; Wu et al., 2014).

Studies not captured in Browning and Rigolon's review (2019a) also provide mixed support for the notion that greenspace is associated with academic performance. High schools across the United States did not show statistically significant associations between performance and tree, total vegetation, or agricultural cover (Hodson & Sander, 2019). However, students in schools with more tree cover in Portland, OR, performed better on reading test scores in models not adjusted for urbanicity (Donovan, Michael, Gatziolis, & Hoyer, 2018), and students who spent more time in forested landscapes during childhood earned higher grades in college (Spero, Balster, & Bajcz, 2018). Another review of the impacts of outdoor education on academic performance also found inconclusive evidence that greenspace exposure improves performance (Becker, Lauterbach, Spengler, Dettweiler, & Mess, 2017).

The inconsistent evidence for greenspace supporting academic performance are likely the result of a multitude of factors. For instance, different results could stem from different study designs, residual confounding, overly simplistic statistical analyses, and varying geographic regions (Browning & Rigolon, 2019a). One factor that is particularly worthy of further investigation regards the type of greenspace measurement. Different remote sensing measures of greenspace have been shown to swing the pendulum in the same population of schools from negative associations (Browning et al., 2018) to positive associations (Kuo, Browning et al., 2018). To our knowledge, no studies have directly compared the sensitivity of results with different measures in the same sample of schools. The means and variance of greenspace measures can vary by remote sensor data (Smith, Zhou, Cadenasso, Grove, & Band, 2010), and greenspace values derived from different datasets show varying associations with human health (Su, Dadvand, Nieuwenhuijsen, Bartoll, & Jerrett, 2019; Tsai, Davis, & Jackson, 2019). Furthermore, small patches of greenspace can only be captured with higher resolution measures (Markevych et al., 2017), and small greenspace patches may be important components of children's exposure to nature (Browning & Rigolon, 2019b). Studies comparing greenspace datasets, including higher-resolution datasets, might provide the most robust estimates of the possible association between greenspace and academic performance.

The degree of urbanicity is another potentially important factor explaining variation amongst greenspace and academic performance studies. Some benefits of greenspace may be stronger in urban areas, and others may be stronger in rural areas (Markevych et al., 2017; Verheij, Maas, & Groenewegen, 2008). Several measures of urbanicity are readily available, easily calculated from national datasets, and substitutable (Browning & Rigolon, 2018). Not accounting for the confounding effects of urbanicity may produce spurious relationships between greenspace and the outcome of interest. For instance, greenspace measures from coarse-resolution remote sensing datasets may represent urban density as much as they represent greenspace density (Grove, Locke, & O'Neil-Dunne, 2014).

The most robust academic performance models should, therefore, have high-resolution measures of greenspace with urbanicity covariates (e.g., population or residential density). Few studies have specifically tested for confounding urbanicity. One study that indirectly examined urbanicity with high-resolution measures found no benefits of greenspace (Markevych et al., 2019). Another study that found greenspace benefits academic performance used an ordinal variable with only three categories of urbanicity (Li, Chiang, Sang, & Sullivan, 2018); as such, this study may have failed to capture the complexity of a continuous population gradient. A third study used the percentage of impervious land cover as a proxy for urbanicity (Hodson & Sander, 2017), and this proxy may correlate more highly with greenspace cover than with population density per se.

In the current study, we seek to better understand the proposed link between greenspace and academic performance by considering the impact of greenspace sensor data and the confounding effects of urbanicity. Our first objective is to compare remote sensing measures of greenspace in and around schools to see to what extent these measures describe different levels of exposure. Our second objective is to examine associations between different greenspace measures and academic performance levels—both with and without adjustments for urbanicity.

2. Methods

2.1. Study area

We selected an area of the United States with high-resolution land cover data and with sufficient numbers of schools across the rural-urban continuum to test for associations between greenspace and academic performance. This study area was the State of Maryland. Maryland is approximately 10,460 miles^2 and includes Census tracts comprised of only three people per km^2 as well as tracts comprised of as many as 10,000 people per km^2. The state experiences a wide range of climatic zones that influence the availability and type of greenspace around schools. The average freeze-free season ranges from 130 days on the Alleghany Plateau in Garrett County to 230 days in the southern and central regions of the state (National Climatic Data Center, n.d.). Similar to the majority of other observational studies on this topic, Maryland is located at a latitude that represents a temperature climate with moderate levels of rainfall and primarily deciduous forest cover (Smith et al., 2010). Studying this ecoregion makes our findings directly comparable to much of the current body of literature on greenspace and academic performance, which examined a similar climatic and ecological region (Browning & Rigolon, 2019a).

2.2. Data

2.2.1. Greenspace

We considered five greenspace measures. Three came from a high-resolution (1 m^2) land cover data set (Chesapeake Conservancy, 2019) and two were derived from red and infrared wavelengths that were transformed into normalized difference vegetative index (NDVI) values.

The developers of the land cover dataset used an object-oriented approach built from Light Detection and Ranging (LiDAR), aerial imagery, orthoimagery, planimetrics, highway, and National Wetlands Inventory datasets (Chesapeake Conservancy, 2019). We used three measures from this high-resolution dataset: (1) tree cover, (2) herbaceous/low vegetation and shrub cover (hereafter, "grass cover"), and (3) total vegetation cover. The third measure was the sum of the other two. The accuracy of land cover classifications across the dataset is 91%, but the accuracy for these three measures are generally higher: up to 98% for tree cover (Pallai & Wesson, 2017). Fig. 1 compares the level of detail (resolution and vegetation type) between the greenspace measures we used.

The moderate and coarse greenspace measures were calculated as NDVI values. These range from −1.0 to 1.0, where −1.0 is water; 0.0 is ice, snow, barren area, or rock; and 1.0 is abundant leafy green vegetation. The NDVI measures were retrieved from sensors at different resolutions: 30 m^2 Landsat 7 satellite (https://landsat.gsfc.nasa.gov),

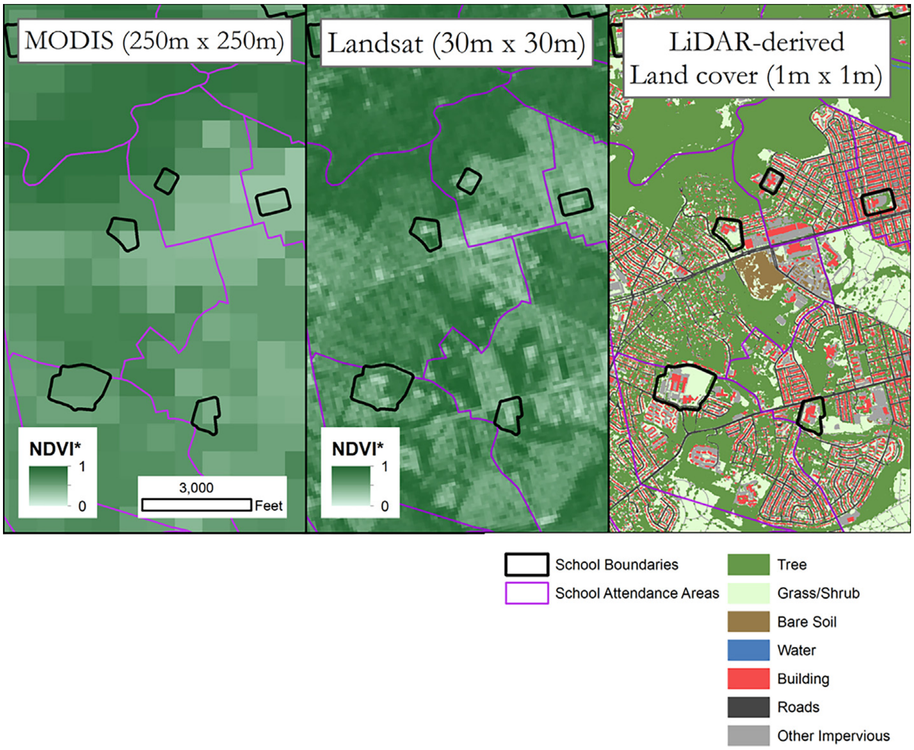

Fig. 1. We calculated greenspace in two zones: 25 m buffered school boundaries ("school zones," see black polygons) and school attendance boundaries with the buffered school boundaries erased ("neighborhood zones," see purple polygons). In each of these two zones, we calculated five measures of greenness: NDVI from satellites with two different resolutions (250 m^2 and 30 m^2) and three high-resolution land cover classes (trees, grass/shrub, trees, and grass/shrub combined). *NDVI = normalized difference vegetative index, a common measure of greenness. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

and NASA's 250 m^2 Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Indices (https://modis-land.gsfc.nasa.gov.vi.html). All imagery used to calculate NDVI values were cloud-free and taken in June or July 2016, when vegetation was fully leafed-out. We were unable to find cloud-free Landsat images in the mountainous Garrett, Allegany and Washington Counties, so schools in those counties were excluded.

High-resolution data (Chesapeake Conservancy, 2019) demonstrated some regions had open water ("bluespace"). Approximately 15% (n = 88) of the included schools had bluespace in the "school zone" (see description of geographic zones below). In total, bluespace covered less than 0.5% of the aggregated school zones examined in this study. To prevent suppressing the abundance of greenspace, we reclassified negative NDVI values as missing data.

Greenspace measures were calculated in two zones: around the school and in the school attendance boundaries. Delineation of zones followed the guidance provided by Kuo, Browning et al. (2018). Each school was associated with one school attendance boundary ("neighborhood zone") and one "school zone." The latter describes the area corresponding to the student's experience of greenspace at school and encompasses the school parcel and a 25 m buffer. The former ("neighborhood zone") describes the greenspace inside the school attendance boundary but outside the school parcel and its 25 m buffer. Attendance boundaries describe the residential areas where students live and determine which school students attended. In each zone, the percentage of each of the three high-resolution measures and the average values of each of the two NDVI sources were calculated using Zonal Statistics in ArcGIS version 10.2.2 (ESRI, Redlands, CA). We multiplied NDVI values by 100.0 to make their ranges comparable to high-resolution ranges (i.e., 0.0 to 100.0).

Non-greenspace spatial data came from three sources. Point data for schools were retrieved from the Maryland GIS Data Catalog (http://data.imap.maryland.gov/datasets/maryland-education-facilities-k-thru-12-education-public-schools). Attendance areas were retrieved from the National Center for Education Statistics (https://nces.ed.gov). School parcel polygons were accessed via Maryland Property View (https://planning.maryland.gov/Pages/OurProducts/DownloadFiles.aspx) for all counties except Cecil. Cecil county does not make its parcel data publicly available. Point locations of schools were matched with parcel polygons to obtain school polygons. Schools were filtered to include only standard public schools (i.e., not special education, Montessori, or magnet) and only those that served third-grade students.

We investigated third-grader test scores for several reasons. First, third-grade (year four in the United Kingdom) consists of students usually between eight and nine years of age. This age range is particularly appropriate for studying academic performance at the school-level since children's academic success beyond third-grade is strongly predicted by individual-level characteristics (Kieffer, 2011). As such, school-level analyses from third-grade may be less prone to ecology fallacy than school-level analyses from later grades. Also, the cognitive performance of children in earlier grades is not tested with standardized measures (Kieffer, 2011). Further rationale for selecting third-grade comes from the fact that these test scores predict future outcomes, including high school graduation and college enrollment (Lesnick, Goerge, Smithgall, & Gwynne, 2010) as well as future earning potential (Chetty et al., 2011). The selection of third grade test scores is consistent with prior research on greenspace and academic performance, so results are comparable to several previous studies (i.e., Browning et al., 2018; Hodson & Sander, 2017; Kuo, Browning et al., 2018; Wu et al., 2014).

2.2.2. Academic performance data

Math and reading test scores from 2016 were retrieved from the Maryland School Report Cards (http://reportcard.msde.maryland.gov). These scores represent the percentage of third-grade students who met or exceeded PARCC standards in each school (Partnership for Assessment of Readiness for College and Careers, 2014). These exact measures or analogous measures (i.e., percentage proficient or advanced beyond proficiency) have been used in several other papers on greenspace and academic performance (e.g., Browning et al., 2018; Kuo, Browning et al., 2018; Kweon et al., 2017).

2.2.3. Covariates

Covariates were selected from past research on greenspace and

Table 1
Characteristics of schools in sample (n = 668).

Variable	Mean	SD	Range	Skewness
Reading (% meet or exceed)	35.24	21.14	0–87.67	0.31
Math (% meet or exceed)	41.98	22.34	0–90.91	0.1
Disadvantage (index of % non-White and % low-income)	2.95	0.6	0.46–4.01	−0.92
Low-income (% students eligible for free-or-reduced lunch)	49.81	26.8	0 – 100	−0.18
White (% students)	36	31	0 – 96	0.34
Black (% students)	37	31	0 – 99	0.7
Asian (% students)	5.82	8.07	0–49.22	2.64
Hispanic (% students)	16.83	18.46	0.29–91.81	1.89
Attendance (% days attended)	98.65	2.62	89.1–100	−1.58
Mobility (% students moved)	19.49	11.11	0–63.9	0.81
Enrollment (total number of students)[a]	511.82	174.42	80–1108	0.32
Ratio (student-to-teacher ratio)	16.83	18.46	0.29 – 91.81	1.9
Female (% students)	48.55	2.6	38.69–59.54	0.03
Density (population per km^2 in census tract)	1690	1691	2.89 – 10,270.11	1.88

[a] All students in the school, not just third graders

academic performance (Browning & Rigolon, 2019a) and obtained from state and national data sources. Attendance rates, the total number of students in each school (i.e., enrollment), percentage of students who moved in and out of a school (i.e., mobility), and percentage of students eligible for free or reduced lunch (i.e., low-income) were obtained from the same source as the academic performance data. Racial, ethnic, and gender composition of students, as well as student-to-teacher ratios, were obtained from the National Center for Education Statistics (https://nces.ed.gov). Each of these measures was from the 2015–2016 academic year.

Urbanicity was calculated for each U.S. Census tract as the density of total population per km^2 using 2012–2016 American Community Survey data (United States Census Bureau, 2018). As a sensitivity analysis, we calculated the number of residential units with the same data and substituted it for total population (see Analyses below).

2.3. Analyses

First, Pearson correlations were calculated to compare relationships between all the variables. To compare just the greenspace measures, one-way ANOVAs were run between the three summative measures (i.e., 250 m^2 NDVI, 30 m^2 NDVI, and total vegetation from the high-resolution dataset).

Next, linear mixed models were run with either of the two academic outcomes (math or reading test scores) and at least one measure of greenspace. For models with summative measures of greenspace, a single measure was used. For models with non-summative measures (tree cover and grass cover), multiple measures were used. All models adjusted for the random effects attributable to the broader social, geographic, and environmental context of the United States county in which each school was located.

The initial series of linear mixed models contained all covariates except for urbanicity. These covariates included percent Asian, percent Hispanic, attendance rates, mobility rate, enrollment, student-to-teacher ratio, and percent female. To control for levels of disadvantage at a school and to avoid multicollinearity, two variables related to socio-economic status were mean-centered and the averages were calculated: percentage of students who did not identify as White, and percentage of students who were eligible for free or reduced lunch (Kuo, Browning et al., 2018). The resulting disadvantage index ranged from −1.0 to 1.0. Greater numbers represented higher percentages of non-White and low-income students.

The next set of multivariate models were identical to the initial set but included urbanicity as a covariate. Urbanicity was first measured as population density (people per km^2) and then as residential density (households per km^2). After these models were run, a final set of models with an interaction term was run. This term represented the potential for effect modification of greenspace by urbanicity (i.e., population density * 250 m^2 NDVI).

Model fit statistics showed assumptions of regression were not violated. Multicollinearity was not present (VIF values < 2.01). Global Moran's I values were used to test for spatial autocorrelation in the model residuals, and none were found to be statistically significant. Among the 16 models fit for the main effects of greenspace on academic performance, Moran's I ranged from −0.012 to −0.008, with associated p-values ranging from 0.071 to 0.91.

Models were run in R Version 3.5.2 (Vienna, Austria). The code for merging datasets and running analyses accompanies this manuscript, as do the spreadsheet and spatial datasets.

3. Results

3.1. School characteristics

Complete sets of data were available for 668 schools, and these schools showed moderate levels of disadvantage. Approximately one-third of the student populations were White, one-third were Black, and one-half were eligible for free or reduced lunch (Table 1). The average student-to-teacher ratio was one teacher per every 17 students. Less than half of the students met or exceeded math or reading test score standards. There were 509 schools (72.2% of the sample) classified as urban (versus rural) as defined by the U.S. Census Bureau cutoff of 1000 people per mile^2 (van Dijk & van der Valk, 2007). The aerial coverage of the school zones ranged from a minimum of 8916 m^2 to a maximum of 1,259,319 m^2 (mean = 99,806 m^2). The attendance zones ranged from a minimum of 208,524 m^2 to a maximum of 595,991,237 m^2 (mean = 28,747,005 m^2). Bivariate correlations between variables are available in the Supplemental Materials (Fig. S1).

3.2. Greenspace measure comparisons

Fig. 2 and Table 2 show the distribution of greenspace measures. Comparisons across school and neighborhood zones showed few differences, but there were two notable findings. First, tree cover was greater in neighborhood zones than in school zones. Second, grass cover was greater in school zones than in neighborhood zones. Other greenspace means were approximately equal between zones. Also, greenspace measures were positively correlated with each other with two exceptions; grass cover and tree cover were negatively associated with one another in both zones (see Supplemental Materials Fig. S1).

Comparisons of the three summative measures of greenspace also showed differences (Fig. 3). Total vegetation and 250 m^2 NDVI showed approximately equal means. In contrast, 30 m^2 NDVI showed means nearly half those of the other two summative measures (Table 2). The median values for each of the three measures were statistically significantly different from each other (see Supplemental Materials, Table S1), but the distribution of the 30 m^2 NDVI measure showed lower averages and a compressed range of values (see ranges in Table 2).

All greenspace measures were negatively correlated with urbanicity (data not shown). The 250 m^2 NDVI measures in school zones and neighborhood zones showed the strongest associations with urbanicity ($r = -0.69$ and -0.58, respectively).

3.3. Academic performance models

Bivariate correlations suggested all measures of greenspace were positively and significantly related to math and reading test scores, $p < .05$ (data not shown). However, in multivariate models, only four out of twenty measures (20%) predicted test scores (see A and C in

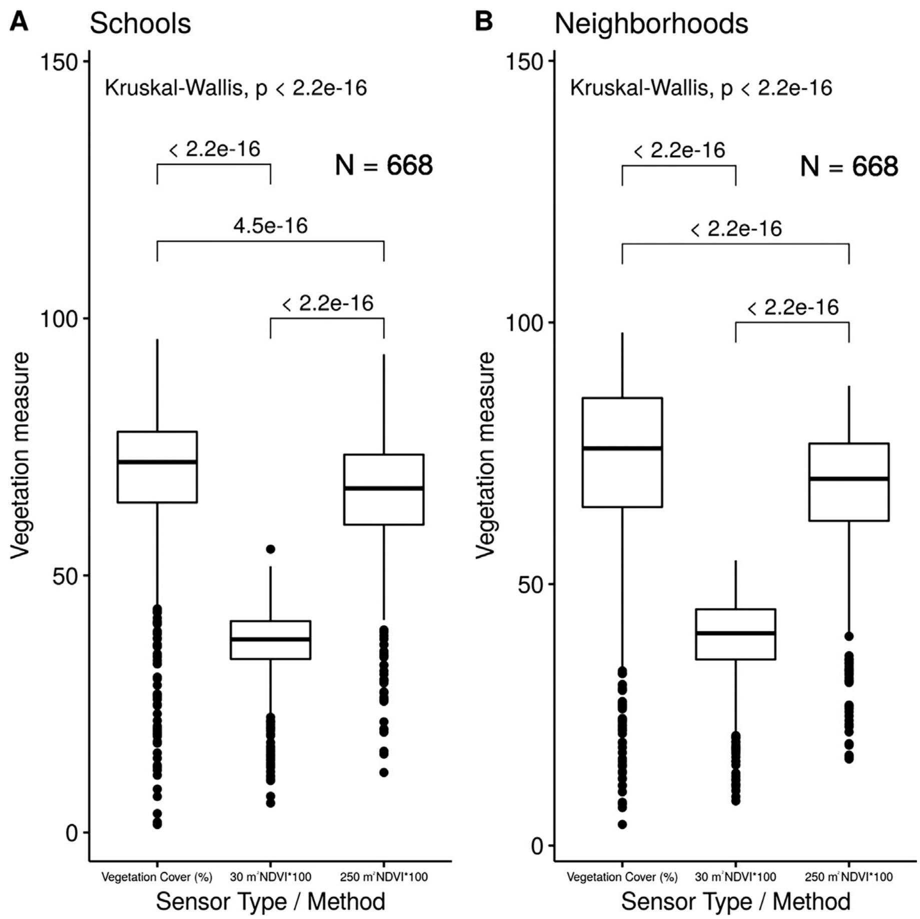

Fig. 2. Distribution of summative measures of greenspace in school zones (A) and neighborhood zones (B). Values above brackets show the results of paired Wilcoxon tests of differences between measures.

Table 2
Description of greenspace measures around schools and in the neighborhood.

Zone and Variable	Mean	SD	Range	Skewness
School				
Tree	31.75	16.91	0.55–85.71	0.44
Grass	36.47	14.56	0.34–79.07	0.1
Total Vegetation	68.21	16.01	1.57–95.99	−1.68
30 m^2 NDVI[a]	36.57	7.06	5.74–55.14	−1.27
250 m^2 NDVI[a]	65.13	12.64	11.67–93.02	−1.23
Neighborhood				
Tree	45.07	16.59	1.37–82.4	−0.45
Grass	26.75	12.52	2.65–71.45	1.09
Total Vegetation	71.81	19.62	4.03–98.09	−1.25
30 m^2 NDVI[a]	39.45	7.89	8.53–54.54	−1.15
250 m^2 NDVI[a]	67.55	12.69	16.55–87.9	−1.47

[a] NDVI measures were multiplied by 100 to standardize ranges and compare to other greenspace measures.

Fig. 4 as well as Supplemental Materials Tables S2–S5). The coarsest summative measure of greenspace (250 m^2 NDVI) was significantly and positively associated with reading and math scores in school zones and neighborhood zones. Tree cover in school zones and grass cover in neighborhood zones were positively associated with reading scores. No other greenspace measures were related to test scores.

Models adjusting for urbanicity (i.e., population density) showed attenuated effects of greenspace on academic performance (see B and D in Fig. 4 as well as Supplemental Materials, Tables S6–S9). In these models, 250 m^2 NDVI was no longer associated with math or reading test scores. Similarly, tree cover was no longer associated with reading scores. Grass cover, on the other hand, showed negative associations with performance. Statistically significant negative associations were found for math scores in neighborhood zones (Std. Beta = −0.09, Std. 95% C.I. = −0.14, −0.03, $p = .002$) and school zones (Std. Beta = −0.07, Std. 95% C.I. = −0.14, −0.01, $p = .025$) as well as reading scores in neighborhood zones (Std. Beta = −0.042, Std. 95% C.I. = −0.12, −0.001, $p = .043$). Models with residential density showed similar results as models with population density. No other statistically significant associations between greenspace measures and academic performance were observed.

Including interaction terms showed little effect modification by urbanicity. No interaction terms were statistically significant in models with school zone greenspace measures, $p > .05$. Only two interaction terms were statistically significant in models with neighborhood zone greenspace measures: 30 m^2 NDVI in math models (Std. Beta = 0.25, Std. 95% C.I. = 0.01 – 0.49, $p = .043$) and 30 m^2 NDVI in reading models (Std. Beta = 0.25, Std. 95% C.I. = 0.02 – 0.48, $p = .035$). To test for the direction of this potential effect modification, we ran models without interaction terms in subsamples split by the median value of population density (urban ≥ 1255 people per km^2, n = 344; not-urban < 1255 people per km^2, n = 344). These models suggested schools in more densely populated areas benefitted from 30 m^2 NDVI in neighborhood zones more than schools in less densely populated areas. However, the associations between greenspace measures and test scores failed to reach statistical significance in these subsample analyses, $p > .10$.

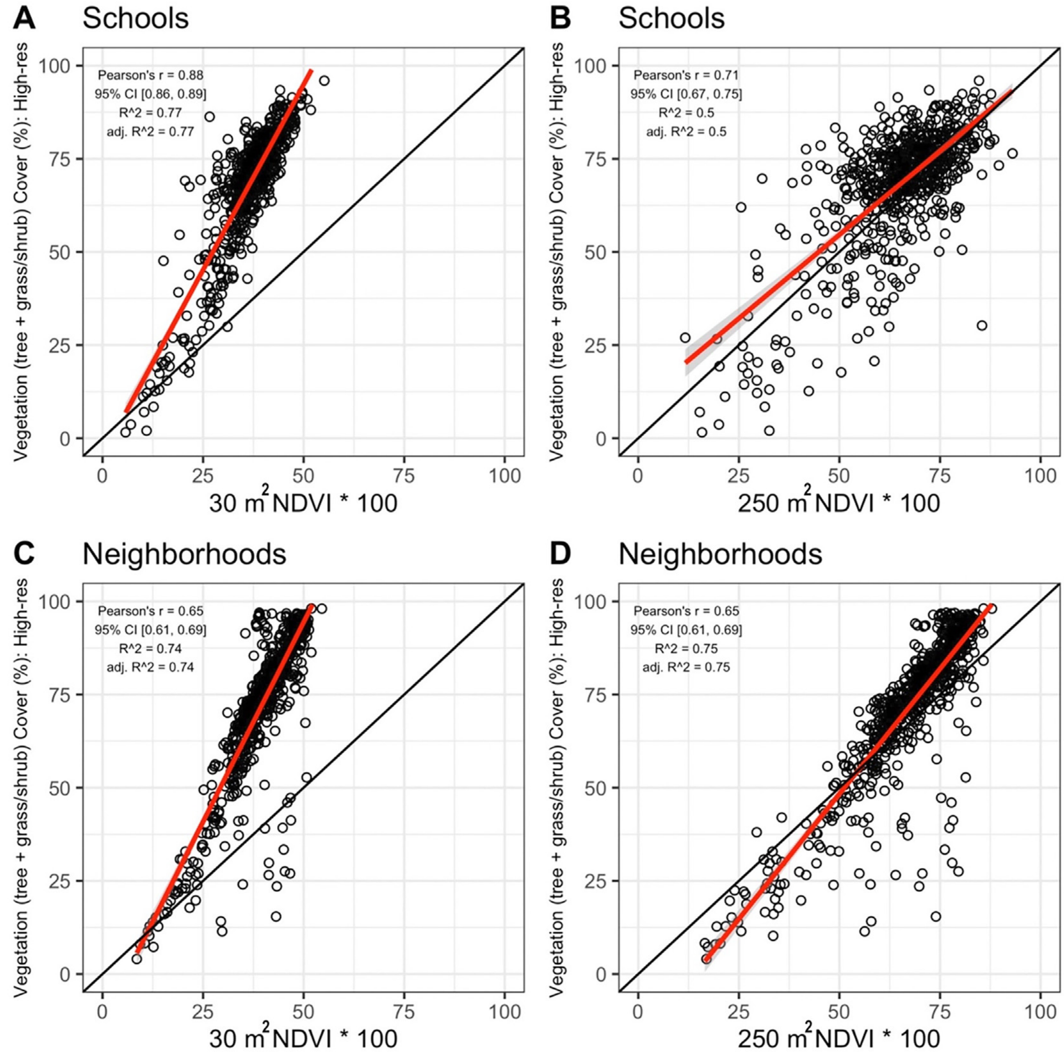

Fig. 3. High-resolution (1 m^2) vegetation cover compared to NDVI from Landsat (30 m^2) and MODIS (250 m^2) imagery in school zones (A, B) and neighborhood zones (C, D).

4. Discussion

To examine whether past discrepancies in the literature on greenspace and academic performance were attributable to different remote sensing datasets and residual confounding, we compared five greenspace measures and their associations with standardized test scores. We found different sensors and greenspace measures resulted in different values assigned to school and neighborhood greenspace (Objective 1). While coarse-resolution measures (250 m^2 NDVI) were similar to high-resolution measures of total vegetation, moderate-resolution measures (30 m^2 NDVI) were not. We also found beneficial associations of greenspace were partially attributable to urbanicity (Objective 2). Coarse-resolution greenness measures predicted academic performance in initial models, but these associations disappeared when urbanicity was controlled for. Moreover, high-resolution measures of grass cover showed scattered *negative* relationships with performance in models that controlled for urbanicity.

This is the sixth observational, school-level study that does not provide strong support for a beneficial relationship between standardized test scores and school greenspace (Beere & Kingham, 2017; Browning et al., 2018; Hodson & Sander, 2019; Markevych et al., 2019; Tallis et al., 2018). While some empirical evidence supports greenspace exposure providing attention restoration (Li & Sullivan, 2016) and increasing college grades (Benfield et al., 2015), the evidence for greenspace exposure boosting other measures of academic performance is mixed (Browning & Rigolon, 2019a).

This study is part of another body of literature regarding the influence of different remote sensing data and their impact of associations between greenspace and human health and cognitive functioning. Reviews of the association between greenspace and academic performance (Browning & Rigolon, 2019a) and physical health (Browning & Lee, 2017) show outcomes vary widely by the way greenspace is measured. Additional evidence comes from individual studies of the relationships between greenspace and mental and physical health (Browning & Rigolon, 2018), health care expenditures (Becker, Browning, Kuo, & Van Den Eeden, 2019), self-reported health (Reid, Kubzansky, Li, Shmool, & Clougherty, 2018), and life expectancy (Tsai, Leung, McHale, Floyd, & Reich, 2018). Tree and forest cover generally show stronger protective effects than total vegetation cover or herbaceous/grass cover. These findings have been observed in studies of academic performance (i.e., Kuo, Browning et al., 2018) as well as studies of self-reported well-being (Zhang & Tan, 2019) and birth outcomes (Donovan, Gatziolis, Jakstis, & Comess, 2019).

Differences between vegetation types are likely a result of differing levels of ecosystem service provision and landscape preferences. Trees provide air filtration and climate amelioration (Vieira et al., 2018) and heat island mitigation (Eisenman et al., 2019) better than grassy lawns do. Students find trees more restorative than grassy lawns, so students

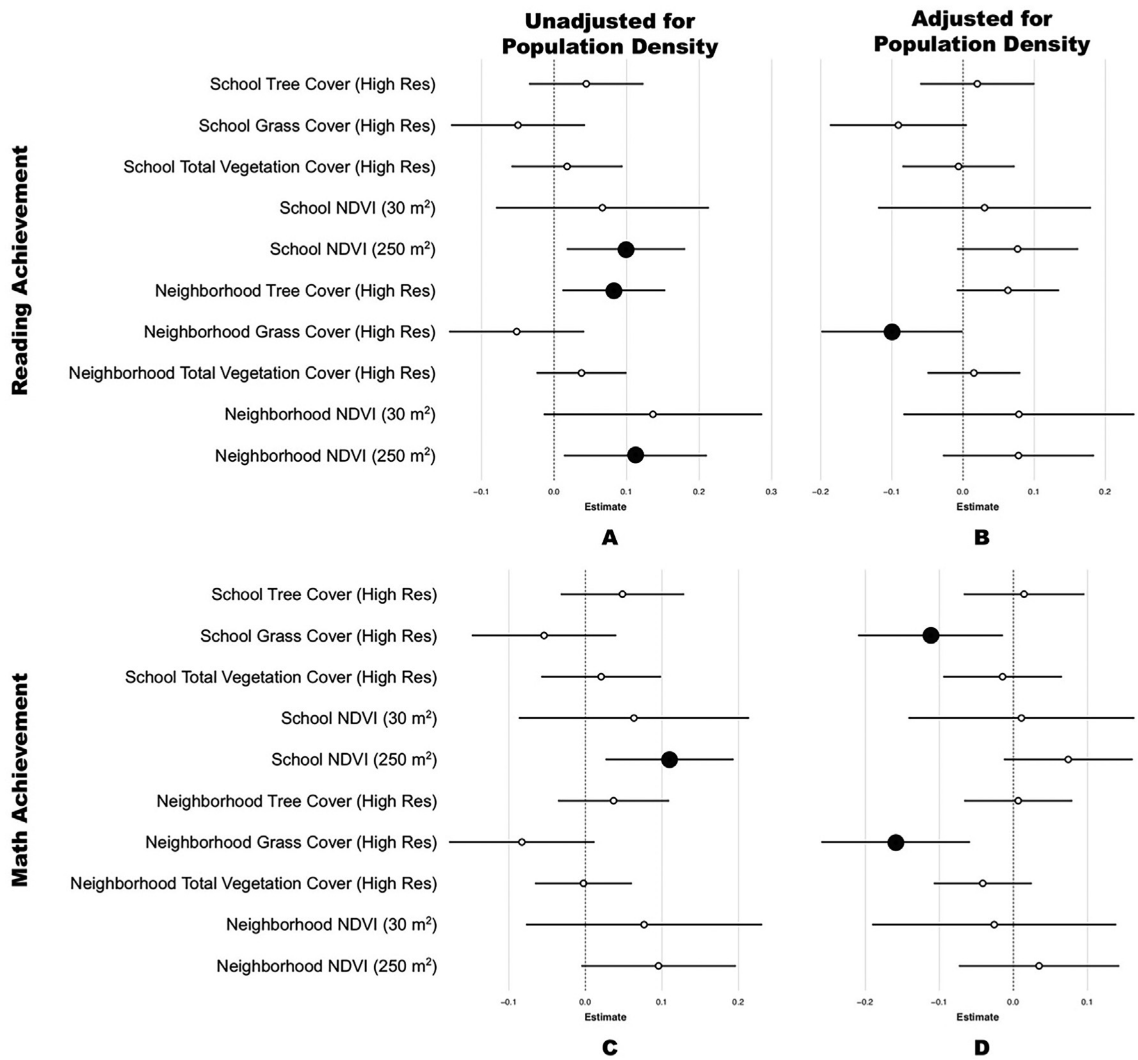

Fig. 4. Coefficient estimates and 95% confidence intervals for greenspace measures regressed on third-grade test scores in Maryland public schools (n = 668) in models unadjusted for population density (reading scores = A, math scores = C) and in models adjusted for population density (reading scores = B, math scores = D) in school zones and neighborhood zones. Results are from linear mixed models controlling for levels of disadvantage (an index composed of percent White and free or reduced lunch eligible students), percent Asian, percent Hispanic, attendance rates, mobility rates, enrollment numbers, student-to-teacher ratios, percent female, and county random effects. Models with summative measures of greenspace include a single greenspace measure. Models with non-summative measures (i.e., tree cover and grass cover) include multiple measures. The labels with numeric values (i.e., 250 m^2, 30 m^2) indicate resolutions at which NDVI is measured. Filled-in circles indicate confidence intervals that do not cross zero; these show statistically significant associations between greenspace and academic performance, $p < .05$. Significant, positive associations are not present in models adjusted for urbanicity.

may receive more mental and physical health restoration from forested school yards (Akpinar, 2016; Paddle & Gilliland, 2016). Grass and herbaceous cover—but not forest cover—are likely to represent unmaintained vacant lots that attract crime activities and increase stress levels rather than provide health and well-being benefits (Browning et al., 2018; Garvin, Cannuscio, & Branas, 2013). Also, different types of vegetation vary across socio-economic gradients differently. Certain greenspace types may be more vulnerable to the confounding effects of socioeconomic status and self-selection bias than others (Mockrin, Locke, Stewart, Hammer, & Radeloff, 2019).

We found support for the resolution of greenspace measures influencing spatial associations as well. In contrast to research from Europe and New York City, we found greenspace measures from high-resolution (1 m^2) land cover data were very similar to those from coarse-resolution (250 m^2) NDVI data (Reid et al., 2018; Su et al., 2019). Moreover, we found that coarse-resolution data predicted academic performance in at least some models while other data rarely predicted performance. This deviation from past work may be explained by coarse-resolution data accurately estimating greenspace exposure in population-based studies with large units of analysis. Also, NDVI data consists of pixels that ranged from 0 (not at all green) to 1 (completely green). Moderate-resolution data might produce skewed results if the regions in which greenspace exposure is being calculated contain vegetation that is concentrated in a few pixels. If these pixels contain high levels of chlorophyll, than regional greenspace levels may be higher than expected. Coarse-resolution data might be less vulnerable to a few, highly-vegetated pixels influencing regional greenspace exposure levels. High-resolution data might also be less vulnerable to this bias, since they calculate regional greenspace exposure from pixels with binary—not continuous—values. Ultimately, which greenspace measures correlate with one another is less important than the implications of our findings paired with past work (Reid et al., 2018; Su et al., 2019). The selection of remote sensing data may influence the associations between greenspace exposure and human health or cognitive performance outcomes.

We recommend future research include sensitivity analyses with a multitude of greenspace measures to ensure robust results. All remote sensing measures are limited by the extent to which they accurately capture lived experience—that is, vegetation experienced from eye-level rather than seen from overhead. Even the "gold standard" of remote sensing datasets (high-resolution land cover classifications; Su et al., 2019) fails to capture the vertical character of vegetation (Lu, Yang, Sun, & Gou, 2019; Seiferling, Naik, Ratti, & Proulx, 2017). Therefore, street-view imagery should be used in conjunction with remote sensing imagery when possible. Many methods of extracting greenspace from street-view imagery are being tested, including computer vision algorithms (Seiferling et al., 2017), modified green view index (Li et al., 2015), imaging processing of pedestrian video (Hong, Tsin, van den Bosch, Brauer, & Henderson, 2019), Sky View Factor (Lu et al., 2019), Green Index Extractor (Suppakittpaisarn, Jiang, Slavenas, & Sullivan, 2018), Treepedia project (http://senseable.mit.edu/treepedia), and more (for review, see Larkin & Hystad, 2018). Studies that report associations with coarse-resolution remote sensing greenspace measures should be read with caution unless the confounding effects of urban fabric characteristics—such as density or sprawl—are accounted for (Browning & Rigolon, 2018; Frumkin, 2002), or comparisons to street-view imagery are made (Lu et al., 2019; Seiferling et al., 2017).

While we found no clear effect modification by urbanicity, this is only a single study, and we cannot claim this variable is merely a covariate rather than a moderator in the relationship between greenspace and academic performance. Students in urban areas are more likely to be exposed to an array of individual and neighborhood-level factors that influence academic performance, such as violent crime, illicit drug use, traffic noise, and air pollution (Berman et al., 2018, Troy, Morgan Grove, & O'Neil-Dunne, 2012; Radcliff, Crouch, & Strompolis, 2018). These factors may be inadequately controlled for with a singular covariate (i.e., population density). We did not find a statistically significant interaction term between greenspace and urbanicity, but a more comprehensive measure may indeed have shown the association between greenspace and academic performance varies across the urban-rural spectrum. Further research is needed to clarify the appropriate selection of greenspace measures and their interaction with urban form variables in environmental exposure research.

4.1. Limitations

Our study was primarily limited by its focus on a specific geographic area. Eastern Maryland is relatively densely populated and experiences a moderate, temperate climate. The findings reported here may not generalize to other areas with different climates or urban-rural compositions, including the few studies in other climates where protective effects of greenspace have been observed (i.e., Donovan et al., 2018; Hodson & Sander, 2019; Tallis et al., 2018). Other protective benefits of some types of greenspace appear to vary by climate (Tsai et al., 2019) and proximity to specific greenspaces where people recreate (Wu et al., 2018).

Our study is also limited by its cross-sectional design. Students experience changes in greenspace around their schools and neighborhoods over the course of an academic year. These cumulative effects may have a greater effect on mental health and cognitive performance outcomes than effects of environments captured at a single point in time (Engemann et al., 2019). Vegetation is also greenest precisely when school is out of session. For much of the school year in northern latitudes, there may be few green leaves on the trees (Wu et al., 2014). Cross-sectional measures of "full leaf-on" greenness during summer months may not necessarily correspond to the children's lived experience, at least as it pertains to near-school exposure.

We included several covariates that were found to be significant in fully adjusted models, but additional variables may further confound effects. Variables influencing student outcomes also consist of school safety and neighborhood crime levels (Berman et al., 2018). Exposure to greenspace is linked to reduced criminal activity (Garvin et al., 2013; Jansson, Fors, Lindgren, & Wiström, 2013) and aggressive behavior (Kuo & Sullivan, 2001; Poon, Teng, Wong, & Chen, 2016; Ulrich, Bogren, Gardiner, & Lundin, 2018). More generally, exposure to greenspace improves emotional regulation and mental health for children (Chawla, 2015; Gascon et al., 2015; Gill, 2014; McCormick, 2017; Vanaken & Danckaerts, 2018). The link between greenspace and performance may be partially explained by changes in aggression both inside and outside the school, but such confounding effects were not controlled for here. Bluespace also has beneficial psychological and physiological effects (Almanza, Jerrett, Dunton, Seto, & Pentz, 2012; Bloemsma et al., 2018). Testing for these effects on academic performance was not possible due to the limited number of schools with nearby water. We are unaware of other studies that have explicitly tested for a relationship between test scores, greenspace, water, and aggression. Consideration of such factors may further clarify the potential association between greenspace and student outcomes.

5. Conclusion

This paper reinforces the tenuous nature of the link between greenspace and academic performance. Positive correlations between greenspace measures attenuated when urbanicity was controlled for, and greenspace values differed by remote sensing measure used. These results were limited by the study's ecological design, however. This was a cross-sectional study in a single state with schools as the unit of the analysis. Investigation of residual confounding from urbanicity and other factors (i.e., aggression and water) with a stronger study design would better determine whether greening interventions could boost student performance.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2019.103706.

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