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Research Paper

Relationships between vegetation in student environments and academic achievement across the continental U.S

Cody B. Hodson, Heather A. Sander*

Department of Geographical and Sustainability Sciences, University of Iowa, Iowa City, IA 52242, USA

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ABSTRACT

Recent studies suggest that vegetation in student environments can enhance academic achievement. Identified relationships vary, however, and our understanding of the links between urban nature and academic performance remains incomplete. This study broadens this understanding by investigating associations between vegetation and urban intensity in school attendance areas and high school reading and mathematics proficiency and graduation rates. We utilize a sample of schools from across the U.S. This study is the first to explore these relationships at this extent. We estimated relationships between these indicators of academic achievement and tree canopy cover, non-forest vegetation, agricultural vegetation, and urban intensity using negative-binomial, mixed-effects models. Models included indicators of socioeconomic status, race, ethnicity, poverty, and class size and state and ecoregion random effects to account for socioeconomic, political, and ecological factors that could influence achievement and vegetation abundance. We found no significant relationships between environmental variables and academic achievement indicators across the full sample. However, we did observe significant interactions between urban intensity and non-forest vegetation as well as between socioeconomic status and tree canopy cover. These interactions indicated a positive relationship between non-forest vegetation and graduation rate for schools in highly-urban settings, and a negative relationship between canopy cover and graduation rate for schools that serve primarily low socioeconomic status populations. These results indicate that the effects of some vegetation types on academic achievement vary with urban intensity and socioeconomic context. These findings also suggest that managing urban vegetation to support academic performance requires an understanding of population social and environmental context.

1. Introduction

Fifty-five percent of the global human population lives in urban areas. In the US and Europe, this proportion is higher, 82% and 74% respectively (United Nations, 2018). Urbanites often experience greatly reduced contact with nature and natural settings. Increasing evidence suggests that contact with nature benefits mental and physical health (Alcock, White, Wheeler, Fleming, & Depledge, 2014; Berman et al., 2012; Maas et al., 2009; Reid, Clougherty, Shmool, & Kubzansky, 2017; Reid, Kubzansky, Li, Shmool, & Clougherty, 2018; Twohig-Bennett & Jones, 2018; Van Herzele & De Vries, 2012; Wheeler et al., 2015; White, Alcock, Wheeler, & Depledge, 2013; Wu et al., 2018). Reduced exposure to nature in urban settings may thus reduce the quality-of-life of urbanites. Furthermore, the psychological and physiological benefits of nature may lead to additional benefits such as enhanced academic achievement (Browning & Rigolon, 2019) and cognitive (Dadvand et al., 2015) and behavioral development (Markevych et al., 2014) in children. Lack of interaction with nature may thus have particular implications for urban children and may influence their success in school and thus in later life. Understanding the implications of urban environments and of nature in those environments for human well-being, particularly that of children, is therefore key to environmental management and design to support the quality-of-life of present and future urban populations.

Research has documented academic, cognitive, and behavioral benefits of nature in student environments at the individual level. This work suggests that students perform better academically when their classrooms offer views of vegetated areas (Benfield, Rainbolt, Bell, & Donovan, 2015), when they are afforded the opportunity to experience natural environments at school (Pascoe & Wyatt-Smith, 2013; Skelly & Bradley, 2000), and when the environment near their homes includes high levels of canopy cover (Donovan, Michael, Gatziolis, & Hoyer, 2018). Research suggests that vegetation in student environments benefits working memory and attentional capacity (Dadvand et al.,

* Corresponding author.
E-mail addresses: cody-hodson@uiowa.edu (C.B. Hodson), heather-a-sander@uiowa.edu (H.A. Sander).

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2015; Schutte, Torquati, & Beattie, 2017), and that vegetation in play settings likely reduces symptom severity in children with attention deficit/hyperactivity disorder (Faber-Taylor & Kuo, 2011). Furthermore, living farther away from public green space has been linked to increased odds of behavioral problems in children (Markevych et al., 2014). These findings suggest that school environments and activities and residential landscapes could be designed to encourage contact with nature so as to support the learning of individuals.

Two key theories identify the mechanisms whereby academic benefits of vegetation may occur. The first, stress reduction theory (Ulrich et al., 1991), suggests that people recover from stress more effectively in non-threatening natural environments (Jiang, Li, Larsen, & Sullivan, 2016; Lee, Park, Tsunetsugu, Kagawa, & Miyazaki, 2009; Tsunetsugu et al., 2013; Tyrväinen et al., 2014). Under this theory, exposure to urban nature offers opportunities for enhanced stress recovery. Nature in student environments could thus reduce stress levels for individual students, enabling them to perform better academically given that stress can negatively impact achievement (Schraml, Perski, Grossi, & Makower, 2012). The second theory, attention restoration theory (Kaplan, 1995), suggests that exposure to nature facilitates recovery from mental fatigue (i.e., attention restoration), which may improve the ability of individual students to concentrate (Berman, Jonides, & Kaplan, 2008; Berto, Baroni, Zainaghi, & Bettella, 2010; Hauru, Lehvävirta, Korpela, & Kotze, 2012; Peschardt & Stigsdotter, 2013), thus supporting positive academic outcomes. Additionally, studies suggest that these positive academic and cognitive associations may be linked to the mitigating effects of vegetation on air pollution, which appears to negatively impact academic achievement (Mohai, Kweon, Lee, & Ard, 2011) and cognitive development (Sunyer et al., 2015).

Recent studies suggest that the benefits of nature on individual academic performance aggregate to the school level. Student populations have been found to perform better on standardized exams and finish high school at higher rates when their schools offer views of landscapes with more trees and shrubs from cafeteria and classroom windows (Matsuoka, 2010). Furthermore, school campuses with high tree canopy cover tend to have higher academic performance (Kweon, Ellis, Lee, & Jacobs, 2017; Sivarajah, Smith, & Thomas, 2018). Recent research also suggests that the vegetation in the area surrounding a school is related to school-level academic performance. Studies found positive relationships between reading and mathematics proficiency and vegetation around schools (Kuo, Browning, Sachdeva, Lee, & Westphal, 2018; Leung et al., 2019; Wu et al., 2014), and between canopy cover in school attendance areas (SAA) and third-grade reading proficiency (Hodson & Sander, 2017). Research has also documented positive associations between vegetation and standardized test scores (Li, Chiang, Sang, & Sullivan, 2019; Tallis, Bratman, Samhouri, & Fargione, 2018). These studies support the idea that vegetation in urban settings can enhance not only the academic performance of individuals, but also of entire school populations.

Studies have also identified negative relationships between school-level academic performance and vegetation in school settings (Beere & Kingham, 2017; Browning, Kuo, Sachdeva, Lee, & Westphal, 2018; Matsuoka, 2010; Wu et al., 2014), or did not find convincing evidence of any association (Markevych et al., 2019). The divergence of these studies' findings may reflect actual differences in the relationships between urban vegetation and academic performance among geographic and socioeconomic contexts or between different student populations (e.g., of different developmental stages). They may also result from differences in study design, for example, the manner in which urban nature and academic achievement were measured. Whatever the causes of these differences, these studies suggest that relationships between school-level academic performance and nature around schools are far from clear cut.

Gaps in our current understanding of relationships between vegetation and school-level academic success make it difficult to design urban vegetated environments to support student success. In addition to the aforementioned disagreement in study findings, most studies focus on one metropolitan area or region. Thus, while the existing literature sheds light on relationships between urban vegetation and academic performance in specific locations, it says little about the generalizability of these relationships to cities over broader extents and in a variety of cultural and biogeographic contexts (e.g., desert, forest, grassland). Existing studies also focus on identifying relationships across study areas, but do not consider the potential for these relationships to vary within them with urban intensity. For example, these studies have not explored relationships between urban vegetation and academic performance across urbanization gradients, or whether these relationships are stronger in particular urban settings. While studies provide support for a positive relationship between urban vegetation and school-level academic performance (Hodson & Sander, 2017; Kuo et al., 2018; Kweon et al., 2017; Leung et al., 2019; Li et al., 2019; Matsuoka, 2010; Sivarajah et al., 2018; Tallis et al., 2018; Wu et al., 2014), this relationship may vary with vegetation type. Such variation in relationships with vegetation type has been noted for health outcomes, for example, obesity (Sander, Ghosh, & Hodson, 2017), self-reported health (Reid et al., 2017), and sudden unexpected death (Wu et al., 2018). Such variation may therefore exist for academic performance given the possibility that the apparent health benefits of contact with nature may lead to healthier students that perform better in school as a result. Additionally, variation in these relationships may also occur with the arrangement of vegetation and with the social (Kuo et al., 2018; Sivarajah et al., 2018), cultural, and environmental context of a school. Understanding such variation is required to facilitate the management of vegetation on and off-campus to support student learning.

In this study, we sought to begin filling these gaps by identifying relationships between different types of urban vegetation, development intensity, and high school academic achievement in a large sample of US cities as well as how these relationships vary with development intensity and socioeconomic context. We examined associations between high school graduation rates and twelfth-grade reading and mathematics proficiency and different types of vegetation while considering the moderating effects of urban-intensity and socioeconomic deprivation (i.e., poverty, low educational attainment). We explored these relationships for over 1300 high schools in 39 states to identify relationships between urban vegetation and intensity and academic performance more broadly than is possible in single city or state studies. To our knowledge, this study represents the first to explore these relationships at the national scale, thereby broadening our understanding of associations between urban vegetation and academic performance and how those associations vary with urban setting and socioeconomic conditions. The knowledge gained could therefore support the design of built and vegetated spaces in cities to enhance student academic performance.

2. Data and methods

2.1. Study sample

We identified a sample of high schools in a series of metropolitan areas across the US using the School Attendance Boundary Information System (SABINS). SABINS is an online database that provides access to SAA geographic data for the 2009/10, 2010/11, and 2011/12 academic years (The College of William and Mary, 2011). Geographic coverage varies by year, and coverage is greatest for the 2009/10 period. Thus, to maximize the number of SAA included in our sample, we first identified public high schools for which 2009/10 SAA data existed and identified and selected urban high schools from this subset. We defined urban schools as those schools with SAA centroids within an urban extent delineated by the 2010 U.S. Decennial Census (U.S. Census Bureau, 2010). We used the SAA for each school as our areal unit of analysis given that SAA boundaries delineate the spaces where students are likely to spend a majority of their time both on and off-campus. This use

Fig. 1. Sample SAA.

of SAA rather than buffer areas around schools follows Hodson and Sander (2017), and is supported by the notion that relationships between vegetation and well-being are more detectable when geographic units of analysis more closely match the areal extents of perceived neighborhoods (Reid et al., 2018). We did not consider private, charter, or magnet schools that do not draw students from predefined areas, and are therefore not associated with an SAA. We also removed some schools with missing data from the sample. Our final sample consisted of 1374 schools in 39 states across the contiguous U.S. (Fig. 1).

2.2. Measurement of academic achievement

We used three indicators of academic achievement retrieved from the U.S. Department of Education's ED*facts* online database (https://www2.ed.gov/about/inits/ed/edfacts/data-files/index.html#acgr): high school graduation rate, proportion of high school students that met reading standards, and proportion of high school students that met mathematics standards. The importance of a high school diploma in determining life outcomes such as occupation and income level provides the rationale for investigating graduation rates. Additionally, high school seniors are likely to have spent many years attending schools in the area of the high school. Thus, achieving a high school diploma (or not) may, in part, reflect extended exposure to the vegetation in those settings. The importance of reading and basic math skills in finding and maintaining employment provides the rationale for investigating reading and mathematics proficiency rates. Standards and their attainment were determined and measured on a state-by-state basis through standardized exams. We removed some observations with missing data for these dependent variables from our initial sample. Removing these observations resulted in samples of 1333, 1350, and 1322 schools for graduation rate, reading proficiency, and mathematics proficiency analyses respectively.

2.3. Socioeconomic and school-related variables

Attributes of schools and socio-economic characteristics of local populations exert well-recognized influences on academic performance. To control for these attributes, we calculated twelfth-grade percentages of African-American and Latino students for each school and school-wide percentages of students eligible for free or reduced price lunch to represent race, ethnicity, and poverty status respectively. We calculated student-teacher ratios at schools to indicate class size and access to personalized instruction. We retrieved data for these variables from the 2009/10 Common Core of Data, a nationwide dataset of select school attributes available from the U.S. Department of Education's National Center for Education Statistics (National Center for Education Statistics, n.d.).

We included additional indicators in our analysis to account for the role of SES in educational attainment (Lucas, 2001). We used the 2010 Five Year American Community Survey available from the US Census Bureau to generate covariates related to household income, education, and household size (from American FactFinder). These covariates included the proportion of SAA households with low (i.e., under $35,000 US), medium (i.e., $35,000–$99,999 US), and high (i.e., over $100,000 US) household income, and of small (i.e., under three members), medium (i.e., four or five members), and large (i.e., over five members) family households given that household income as an indicator of economic status depends on household size. For example, a single-person household with an income of $35,000 US per year would be considered a medium-income household depending on metropolitan area, while a three-person household with the same income in the same metropolitan area would be considered low income (Pew Research Center, 2016). We also identified the proportion of the population in each SAA that was 25 years of age or older with low (i.e., no high school diploma), medium (i.e., high school diploma, some college, four-year degree), and high (i.e., advanced degree) educational attainment. We used the 2010 Decennial Census available from the U.S. Census

Bureau's American Fact Finder to identify the proportion of renters in each SAA (from American FactFinder).

Because SES data were aggregated to unified school districts (UNSD) and not available for all of the schools in our sample or at the SAA level, we employed dasymetric mapping (Mennis, 2003), a form of areal interpolation, to estimate values at the SAA level (Appendix C). Given counts of people or households in geographic space, dasymetric mapping utilizes ancillary datasets to interpolate data aggregated to a particular set of geographic enumeration units (e.g., US Census block groups or tracts) to another set of units at a finer resolution (e.g., Census blocks, SAA). The incorporation of ancillary data to indicate underlying spatial variation in population density (e.g., presence of water, cadastral parcels) ensures higher prediction accuracy than more traditional forms of areal interpolation that assume even spatial distributions of populations across geographic units. We used the arcpy library with python 2.7 and ArcMap v10.5 (ESRI, 2016) to run our dasymetric mapping process. Using this method, we first identified unpopulated locations based on US Census block total population counts from the 2010 Decennial Census (from American FactFinder) and masked these locations from the remainder of the analysis. Given that land-use classifications at finer resolutions were not readily available for the entire U.S., these Census data were the best option for identifying unpopulated locations. We next used the 30-m 2011 Percent Developed Imperviousness product available from the Multi-Resolution Land Characteristics Consortium's (MRLC) 2011 National Land Cover Database (NLCD, Xian et al., 2011) to identify additional unpopulated locations (i.e., areas with no impervious surface) to also mask from the analysis.

The next step in applying dasymetric mapping involved the distribution of population counts from coarser to finer resolutions based on raster data derived from estimates of imperviousness. Imperviousness has been shown to predict population density (Lu, Weng, & Li, 2006), and is an indicator of urban development intensity. We also used the 2011 NLCD Percent Developed Imperviousness product in this step, identifying low, medium, and high urban development intensity cells for each UNSD using the lower and upper quartiles of imperviousness. We then distributed UNSD population and household counts (e.g., population with no high school diploma or living in rented housing, number of households with fewer than four members) across grid cells by dividing these counts by the number of inhabited cells in each UNSD.

The next step in the dasymetric mapping process involved adjusting the per-cell population density values calculated in the previous step using a weighting function based on relative differences in density between urbanization classes. These relative differences are determined through a sampling procedure that identifies population densities most representative of each class. This process involved selecting UNSD representative of the urban intensity class in question and averaging their per-cell population densities (i.e., the values calculated before applying the weighting function) to obtain estimates of class-specific population density. Because the proportion of low urban intensity cells in UNSD was never above 0.5 and the proportion of high intensity cells never exceeded the proportion of low or medium intensity cells in any UNSD, we used three criteria to identify representative UNSD. First, we identified UNSD as representative of low urban intensity if their proportion of low imperviousness grid cells exceeded their proportional composition of medium or high imperviousness grid cells. Second, medium urban intensity UNSD included UNSD dominated by medium impervious grid cells. Lastly, high urban intensity UNSD exhibited imperviousness grid cell proportions in the upper decile for the remaining UNSD.

We derived a population density weighting function from the urbanization class-specific population density estimates as follows:

$$D_u = P_u/(P_l + P_m + P_h) \tag{1}$$

where D_u is the weight for a particular urban intensity class u, P_u is the average sampled population density for urban intensity class u, and P_l, P_m, and P_h are the average sampled population densities for low, medium, and high urban intensity classes respectively. We used these weights to adjust ratios of the areas of each urbanization class to the total inhabited area in each UNSD and used the results from those calculations to calculate three final vectors of weights for each urbanization class for each UNSD known as total fractions. Thus the final weights account for not only relative differences in population density between classes, but also relative differences in the balance of urbanization class areas for each UNSD. We applied the total fractions to the grid cell population density values for each UNSD. This produced a population distribution raster dataset for each UNSD for each SES variable. We then summed the cells of the population raster datasets within SAA, and used the resulting SAA-level counts to calculate proportions of people or households in SAA with low, medium, and high academic achievement; household income; household size; and the proportion of the population in SAA that were renters.

We addressed multicollinearity between the indicators of SES, race, ethnicity, and poverty status using principal components analysis (PCA) in SPSS 24 (IBM Corp., 2016). All variables were mean-centered and scaled prior to the analysis by subtracting their means from their individual values and dividing those differences by the standard deviation of each respective variable. We extracted four uncorrelated principal components (PCs) with eigenvalues greater than one from the input space, to which we had applied a varimax rotation. We chose varimax because when compared with no rotation or the other rotations available, it minimized the number of variables with high loadings (0.5 or above) on multiple PCs, while maximizing the number of high loadings overall. We used the four vectors of factor scores derived from the PCs as covariates in our final models.

2.4. Environmental variables

We calculated a series of variables related to vegetation and development intensity in SAA. We used the 30-m 2011 NLCD cartographic tree canopy dataset developed by the U.S. Forest Service (Coulston et al., 2012; Coulston, Jacobs, King, & Elmore, 2013; Tipton, Moisen, Patterson, Jackson, & Coulston, 2012) to identify the mean percent canopy coverage in each SAA. We used the 30-m 2011 NLCD land cover dataset (Homer et al., 2015) to quantify the extent of vegetated, non-forested and agricultural land in each SAA. We calculated non-forested vegetated land coverage by summing the percent areal coverage of shrub/scrub, grassland/herbaceous, and emergent herbaceous wetlands in each SAA. We calculated agricultural land cover by summing the percent areal coverage of pasture/hay and cultivated crops. We did not include forested land cover due to multicollinearity with canopy coverage. We calculated the mean percent imperviousness in SAA using the 30-m NLCD Percent Developed Imperviousness dataset to indicate development intensity (Xian et al., 2011).

We standardized the environmental variables in our dataset to account for variation among urban areas in their dominant vegetation and development patterns. Standardized canopy coverage values indicate differences between SAA mean canopy coverage and the mean coverage of their respective urban areas and were calculated as simple Z-scores such that:

$$Z_c = (C_{SAA} - C_{UA})/(SD_{C_{ua}}/\sqrt{g_{SAA}}) \tag{2}$$

C_{SAA} indicates SAA mean tree canopy, C_{UA} indicates mean tree canopy in the urban area containing a given SAA, $SD_{C_{ua}}$ indicates the standard deviation of urban area tree canopy, and g_{SAA} indicates the number of grid cells in the SAA. We standardized imperviousness in the same manner. The standardized non-forest and agricultural vegetated cover variables indicate differences between proportions of a given land-cover class in an SAA and the proportion of its respective urban area. These differences were normalized in a manner similar to that

Table 1
Variable summary statistics for each school and school attendance area.

Variable	Description	Min	Max	Mean	SD
Graduation	High school graduation rate	0.050	0.995	0.794	0.137
Reading proficiency	Reading proficiency rate	0.050	0.995	0.708	0.228
Math proficiency	Mathematics proficiency rate	0.025	0.995	0.654	0.235
Lunch	Percentage of students eligible for free/reduced price lunch	0.000	99.830	41.411	27.196
Black	12th grade percent Black	0.000	100.000	29.255	30.854
Latinx	12th grade percent Latino/a	0.000	95.620	12.719	16.568
Low income	Percentage of households with HHI < $35 K/yr	4.640	69.894	31.953	11.917
Medium income	Percentage of households with $35 K/yr ≤ HHI < $100 K/yr	10.663	61.773	44.660	5.659
High income	Percentage of households with HHI ≥ $100 K/yr	1.493	77.890	23.448	12.524
Low education	Percentage of individuals 25 or older with no HS degree	0.284	37.265	12.545	5.703
Medium education	Percentage of individual 25 or older with HS or undergraduate degree	51.592	90.597	75.035	5.925
High education	Percentage of individuals 25 or older with advanced degree	1.782	45.593	12.419	6.737
Small households	Percentage of households with less than 4 people	50.012	88.544	76.538	5.716
Medium households	Percentage of households with 4 or 5 people	9.761	38.912	19.333	4.531
Large households	Percentage of households with more than 5 people	0.923	21.158	4.148	1.934
Renters	Percentage of population living in rental housing	4.399	79.319	34.578	13.080
Student-teacher ratio	Number of students per instructor	6.182	36.625	17.120	3.564
Canopy	Mean tree canopy cover (%)	0.000	86.166	25.983	17.330
Z_canopy	Mean intensity of tree canopy in SAA normalized	−286.534	861.958	12.700	99.998
Non-forest	Non-forest vegetation cover (%)	0.000	0.742	0.049	0.080
Z_non-forest	Normalized non-forest vegetation cover	−135.465	650.413	−6.467	52.112
Ag	Agricultural cover (%)	0.000	0.772	0.064	0.106
Z_ag	Normalized agricultural	−224.660	743.522	−14.720	83.325
Imperviousness	Mean impervious cover (%)	0.747	84.098	27.474	16.475
Z_imperviousness	Normalized mean impervious cover	−591.986	436.167	−0.731	128.510

used for canopy coverage and imperviousness:

$$Z = \frac{PLC_{SAA} - PLC_{UA}}{\sqrt{(PLC_{UA} * (1 - PLC_{UA}))/g_{SAA}}} \quad (3)$$

PLC_{SAA} indicates the SAA proportion of the land cover in question, and PLC_{UA} indicates the urban area proportion of the land cover in question. In this way, our environmental covariates identify the coverage of a variable in an SAA relative to its urban area. For example, a positive value for non-forest vegetated land cover indicates an SAA with higher coverage of that type than its urban area as a whole, while a negative value indicates one with less.

2.5. Analysis of relationships with academic achievement

We estimated three negative binomial mixed-effects models using version 1.1–17 of the R package lme4 in R 3.5.1 to analyze relationships between the explanatory variables described above and each of our outcome variables (Bates, Maechler, Bolker, & Walker, 2015; R Core Team, 2017). The following equation summarizes those three models:

$$\log[E(y)] = \log(offset) + X\beta + Z_{state} + Z_{eco} \quad (4)$$

Here, $\log[E(y)]$ is the natural logarithm of predicted count values for the response variable y, $\log(offset)$ is the natural logarithm of student cohort size, $X\beta$ is a matrix of predictors and fixed-effect estimates, and Z_{state} and Z_{eco} are each a list of estimates of changes in model intercepts for state and ecoregion random effects, respectively. We also tested for interactions with imperviousness and low-SES African-American PCs for each vegetation variable. All explanatory variables were mean-centered and scaled by their standard deviations as described above prior to analysis. Mixed-effects models, also known as multilevel or hierarchical models, incorporate one or more additional terms (i.e., random effects) into the standard linear regression equation to account for collinearity between observations of the dependent variable (Scott, Simonoff, & Marx, 2013). Random effect estimates indicate how the model intercept varies based on some grouping factor of the dependent variable. Models of this type can also account for differences in regression line slope that result from interactions between grouping factors and one or more covariates. We chose a generalized regression approach to our analyses given that our response variables were not normally distributed. More specifically, we employed negative binomial regression, which models counts or rates, similar to Poisson regression (Hilbe, 2011). The former relaxes the assumption that the variance of the dependent variable is equal to its mean. None of our response variables met this assumption, thus negative binomial models were appropriate. We calculated variance inflation factors (VIFs) and examined bivariate correlations between explanatory variables to assess multicollinearity.

The herbaceous vegetation and canopy coverage in an SAA depends at least in part on ecoregional context. For example, cities in a forested ecoregion are likely to have more tree canopy than cities in desert ecoregions. We included ecoregion membership as a grouping factor in our analyses in order to represent this dependency based on North America level two ecoregions as defined by the U.S. Environmental Protection Agency (Omernik & Griffith, 2014). These ecoregions are part of a four-tiered hierarchy in which level one consists of large areas of broadly similar ecosystems (e.g., Great Plains, Southeastern Forested Plains, Northwestern Forested Mountains). Ecoregions for successive levels are nested within the prior level, and represent increasing detail in the attributes used to delineate regions. We chose level two because it was the most detailed level for which we could ensure accurate model estimation (i.e., model convergence) given our sample sizes. We also included the US state in which each SAA is located as a grouping factor to address variation in graduation requirements and reading and mathematics proficiency standards among states, including at what grade level reading and mathematics evaluations were administered. Using these variables, we fit our models under the assumption of varying intercepts only, as accurately estimating more complex models that allow for varying slopes and intercepts was impractical given our sample sizes. We used likelihood ratio tests to verify the significance of each random effect.

3. Results

3.1. Sample composition

Our sampling methodology resulted in a final sample of 1374 schools in 229 metropolitan areas across the continental US. Academic achievement and the composition of SAA varied greatly among schools

Table 2
PCA factor loadings with an absolute value of 0.5 or higher.

Variables	Loadings
PC1 (Low-SES African-American)	
% no high school diploma	0.892
% HHI < $35 K/yr	0.864
% free/reduced lunch	0.863
% renters	0.842
% African-American	0.717
% graduate degree	−0.505
% HHI ≥ 100 K/yr	−0.775
PC2 (Medium-SES)	
% high school diploma – 4 year degree	0.901
% 35 K/yr ≤ HHI < 100 K/yr	0.861
% HHI ≥ 100 K/yr	−0.515
% graduate degree	−0.815
PC3 (Large households)	
% > 5 person household	0.846
% 4–5 person household	0.835
% < 4 person household	−0.954
PC4 (Latino/a)	
% Latino/a	0.909
% African-American	−0.528

(Table 1). Graduation rates ranged from 5–99.5% (mean = 79.4%, SD = 14). Reading proficiency rates also ranged from 5–99.5% (mean = 70.8%, SD = 22.8). Mathematics proficiency rates exhibited more variation, 2.5–99.5% (mean = 99.5%, SD = 23.5%). Schools also varied greatly in attributes related to their population structure and SES, and in their student-teacher ratios (6.2:1–36.6:1, mean = 17.2, SD = 3.6). Considerable variation also existed in the vegetation and land cover in SAA with schools that exhibited much higher, average, and much lower coverage of many land covers compared to their surrounding urban area. Canopy coverage and urban intensity as represented by percent imperviousness exhibited much more variation than percent of non-forest vegetation or agriculture, although the distributions of the latter two exhibited high right skew. Our sample thus included a set of schools that were diverse not only in their academic achievement, but also in their social and physical environments.

3.2. PCA

Our PCA identified four social components that we included in our models (Table 2, Fig. 2). Schools with large proportions of African-American twelfth-grade students, and of students qualified for free or reduced priced lunch scored highly on the first PC. The SAA for these schools also had higher proportions of renters, of adults without high school diplomas, and of households with annual incomes under $35,000, and lower proportions of households with annual incomes over $100,000. Schools in SAA with high proportions of adults with high school diplomas or undergraduate degrees, and low proportions of adults with advanced degrees scored highly on the second component. Those SAA were also characterized by high proportions of households with annual incomes of $35,000–$99,999, and low proportions of households with annual incomes of $100,000 or greater. Schools with high proportions of households with four or more people, and lower proportions of households with less than four people had high factor scores for the third PC. Schools that scored high with respect to the fourth factor had large Latino/a twelfth-grade student bodies. The four variables we derived from PCs one through four are hereafter referred to as low-SES African-American, medium-SES, large households, and Latino/a, respectively.

3.3. Relationships with academic achievement

Our models indicated significant, negative relationships between academic success measures and the low-SES African-American PC ($\beta_{grad} = -0.114$, $p \leq 0.001$; $\beta_{read} = -0.190$, $p \leq 0.001$; $\beta_{math} = -0.224$, $p \leq 0.001$). These estimates demonstrate that graduation and proficiency rates in our sample decreased with increasing socio-economic deprivation in SAA and increasing numbers of African-American twelfth-grade students at schools. The medium-SES PC had a significant, positive relationship with all three dependent variables ($\beta_{grad} = 0.011$, $p \leq 0.01$; $\beta_{read} = 0.035$, $p \leq 0.001$; $\beta_{math} = 0.040$, $p \leq 0.001$), while the large households PC was negatively and significantly related to reading and mathematics proficiency ($\beta_{read} = -0.033$, $p \leq 0.001$; $\beta_{math} = -0.023$, $p \leq 0.01$). Our models therefore suggest that schools serving neighborhoods with more medium-SES residents tended to report higher graduation and proficiency rates, while those serving neighborhoods with more large-family households tended to report lower proficiency rates. Student-teacher ratio exhibited a significant, positive relationship with academic achievement in all three models ($\beta_{grad} = 0.038$, $p \leq 0.001$; $\beta_{read} = 0.062$, $p \leq 0.001$; $\beta_{math} = 0.062$, $p \leq 0.001$). Thus, our models indicate a tendency for graduation and proficiency rates in our sample to be higher at schools with more students per each instructor.

The relationships we observed between environmental covariates and academic success were not as expected (Tables 3–5). With the exception of agricultural cover and imperviousness and graduation rate, these relationships were not significant. Imperviousness exhibited a significant negative association with graduation rate ($\beta = -0.017$, $p \leq 0.05$). Thus, as SAA imperviousness increases graduation rates decline. The relationship between agricultural land cover and graduation rate was negative and nearly significant ($\beta = -0.008$, $p = 0.083$), thus graduation rates in SAA with more agricultural vegetation tend to be lower. VIFs indicated that multicollinearity was not a serious issue in our models. Likelihood ratio tests indicated that both random effects terms (states tested first, ecoregions second) significantly improved model fit (Appendix A, Table 1).

We observed significant interactions between non-forest vegetation and imperviousness ($\beta = 0.004$, $p \leq 0.05$), and between tree canopy coverage and the low-SES African-American PC ($\beta = -0.008$, $p \leq 0.05$) (Figs. 3 and 4). The former indicates a positive relationship between non-forest vegetation and graduation rate for schools with SAA that have high impervious cover (i.e., highly urban SAA), and a slightly negative relationship for those with low levels of impervious cover in their SAA. Thus, non-forest vegetation may only be linked to higher graduation rates in more intensively-developed urban settings. The latter indicates a negative relationship between tree canopy coverage and graduation rate for schools that scored high on the low-SES African-American PC one (low-income, African-American), and a slightly positive relationship for those with low scores on that PC. This finding suggests that canopy coverage may be linked to higher graduation rates for schools with wealthier, low African American student populations, and that canopy cover may actually be linked to lower rates for low-SES and African-American student populations.

4. Discussion and conclusion

Recent studies suggest that vegetation in student environments enhances academic achievement (Benfield et al., 2015; Donovan et al., 2018; Hodson & Sander, 2017; Kuo et al., 2018; Kweon et al., 2017; Leung et al., 2019; Li et al., 2019; Matsuoka, 2010; Pascoe & Wyatt-Smith, 2013; Sivarajah et al., 2018; Tallis et al., 2018; Wu et al., 2014). These studies have documented positive associations between canopy cover and vegetation in general and various measures of academic achievement. Such associations may result from enhanced recovery from stress and mental fatigue that occurs through exposure to nature (Berman et al., 2008; Berto et al., 2010; Hauru et al., 2012; Jiang et al., 2016; Kaplan, 1995; Lee et al., 2009; Peschardt & Stigsdotter, 2013; Tsunetsugu et al., 2013; Tyrväinen et al., 2014; Ulrich et al., 1991), as stress and mental fatigue may negatively impact academic achievement

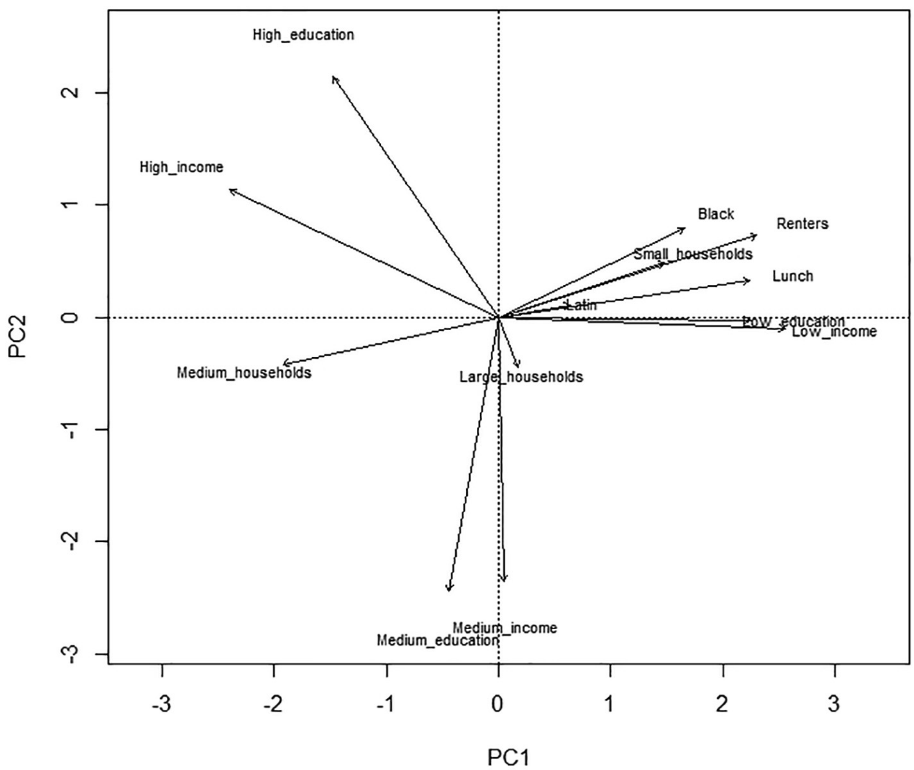

Fig. 2. PCA biplot indicating variable mean scores on PC1 (i.e., low-income, African American) and PC2 (i.e., middle-income, high school degree, some college, or four-year degree).

Table 3
Coefficient estimates for high school graduation rates. Estimates indicate change in rate for one unit increase in explanatory variable value, with the exception of the intercept estimate, which indicates the sample mean graduation rate estimate. Explanatory variables were mean centered and scaled prior to model fitting.

Parameter	β	SE	Z	95% CI	
Intercept	0.774	0.020	−13.269	0.735, 0.813	***
Low-SES African-American	−0.114	0.004	−28.293	−0.122, −0.106	***
Medium-SES	0.011	0.004	2.817	0.003, 0.019	**
Large households	0.001	0.004	0.354	−0.007, 0.009	
Latino/a	−0.001	0.004	−0.190	−0.009, 0.007	
Student-teacher ratio	0.038	0.005	6.976	0.028, 0.048	***
Canopy	−0.003	0.005	−0.618	−0.013, 0.007	
Non-forest vegetation	−0.002	0.004	−0.502	−0.010, 0.006	
Ag	−0.008	0.004	−1.731	−0.016, 0.000	•
Imperviousness	−0.017	0.008	−2.217	−0.033, −0.001	*

• ($p \le 0.1$), * ($p \le 0.05$), ** ($p \le 0.01$), *** ($p \le 0.001$).

Table 4
Coefficient estimates for mathematics proficiency rates. Estimates indicate change in rate for one unit increase in explanatory variable value, with the exception of the intercept estimate, which indicates the sample mean mathematics proficiency rate estimate. Explanatory variables were mean centered and scaled prior to model fitting.

Parameter	β	SE	Z	95% CI	
Intercept	0.558	0.057	−10.513	0.446, 0.670	***
Low-SES African-American	−0.224	0.009	−28.586	−0.242, −0.206	***
Medium-SES	0.040	0.008	4.844	0.024, 0.056	***
Large households	−0.023	0.008	−2.916	−0.039, −0.007	**
Latino/a	0.008	0.008	0.932	−0.008, 0.024	
Student-teacher ratio	0.062	0.011	5.509	0.040, 0.084	***
Canopy	−0.010	0.011	−0.976	−0.032, 0.012	
Non-forest vegetation	0.002	0.008	0.251	−0.014, 0.018	
Ag	−0.003	0.009	−0.284	−0.021, 0.015	
Imperviousness	−0.008	0.016	−0.513	−0.039, 0.023	

• ($p \le 0.1$), * ($p \le 0.05$), ** ($p \le 0.01$), *** ($p \le 0.001$).

(Schraml et al., 2012; Tuominen-Soini & Salmela-Aro, 2014), or from reduced exposure to pollution in student environments (Mohai et al., 2011). Recent studies have cast some doubt on the universality of these findings, however, and at least suggest that vegetation does not benefit student academic performance in all geographic and socioeconomic contexts (Beere & Kingham, 2017; Browning et al., 2018; Wu et al., 2014), and that certain types of vegetation may indicate lower academic achievement (Matsuoka, 2010). Thus, questions remain regarding the academic benefits of different types of vegetation, and how benefits vary with urban and social context. This study began to answer these questions by analyzing these relationships using a nationwide sample of schools, thereby identifying patterns across a range of biogeographic and socioeconomic contexts.

Contrary to past studies that identified positive relationships between school-level academic performance and tree cover (Hodson & Sander, 2017; Kuo et al., 2018; Kweon et al., 2017; Li et al., 2019; Sivarajah et al., 2018; Tallis et al., 2018) and vegetation in general (Leung et al., 2019; Matsuoka, 2010; Wu et al., 2014), we found no significant relationships between urban vegetation and academic performance in cities across the US. However, our findings suggest that relationships between non-forest vegetation and academic performance vary with urban intensity. For example, non-forest vegetation exhibited a positive relationship with graduation rate for schools in environments characterized by high impervious cover and a negative relationship for schools in environments with low levels of imperviousness.

Several possible reasons for these relationships exist. Firstly, these

Table 5
Coefficient estimates for reading proficiency rates. Estimates indicate change in rate for one unit increase in explanatory variable value, with the exception of the intercept estimate, which indicates the sample mean reading proficiency rate estimate. Explanatory variables were mean centered and scaled prior to model fitting.

Parameter	β	SE	Z	95% CI	
Intercept	0.665	0.034	−10.725	0.598, 0.732	***
Low-SES African-American	−0.190	0.007	−30.664	−0.204, −0.176	***
Medium-SES	0.035	0.006	5.537	0.023, 0.047	***
Large households	−0.033	0.006	−5.391	−0.045, −0.021	***
Latino/a	0.004	0.007	0.556	−0.010, 0.018	
Student-teacher ratio	0.062	0.008	7.117	0.046, 0.078	***
Canopy	−0.011	0.008	−1.382	−0.027, 0.005	
Non-forest vegetation	−0.009	0.006	−1.437	−0.021, 0.003	
Ag	0.002	0.007	0.307	−0.012, 0.016	
Imperviousness	−0.008	0.013	−0.630	−0.033, 0.017	

($p \leq 0.1$), * ($p \leq 0.05$), ** ($p \leq 0.01$), *** ($p \leq 0.001$).

relationships may stem from responses to the scarcity of non-forest vegetation in specific settings. In this case, the tendency for highly impervious urban environments to contain less overall non-forest vegetation than less impervious suburban settings (Iverson & Cook, 2000; Pauleit, Ennos, & Golding, 2005; Zhao et al., 2012) may intensify the effect of the little vegetation that does exist. Secondly, non-forest vegetation in older, more intensively developed areas may represent highly-desirable, publicly-accessible managed green spaces such as large parks, while the same land-cover classification could represent undeveloped land in newer suburban areas with low levels of imperviousness. In the case of the latter, these vegetated spaces may be inaccessible and perhaps undesirable, leading to the slightly negative influence of non-forest vegetation observed for those environments. In the case of the former, a positive relationship would be expected given that the land-cover class would represent functional green space from the perspective of human use. Future research should examine these environments in greater detail, considering the timing of development and the actual land use associated with the non-forest vegetated land-cover classification, as well as the accessibility and the scarcity of non-forest vegetation. Such research should also explore threshold levels where relationships with academic performance change.

Our results also suggest that the influence of tree canopy coverage on academic achievement varies according to social context. Tree canopy coverage exhibits a negative relationship with graduation rate in communities characterized by high levels of socioeconomic deprivation (i.e., poverty and low educational attainment) and a higher prevalence of African-American students. This relationship becomes slightly positive in communities with low levels of socioeconomic deprivation. This difference may occur for a number of reasons. For example, trees in low-SES neighborhoods may be unmaintained trees on vacant or abandoned land, land that often has higher levels of vegetation (Deng & Ma, 2015; Endsley, Brown, & Bruch, 2018; Pearsall & Christman, 2012). Thus, tree cover in such neighborhoods could reflect spaces that are not accessible or that may be sites of illicit activities. In higher-SES communities, such tree cover could be in more desirable (Rigolon, Browning, & Jennings, 2018) or accessible settings (Dai, 2011). For instance, it could consist of well-maintained street or yard trees (Lin, Meyers, & Barnett, 2015), or trees in forested parks. Future studies should seek to quantify the attributes of such vegetation in greater detail to better understand these relationships. Differences in cultural values related to vegetation might also contribute to this variation, however, further research is needed to elucidate these differences, particularly qualitative research with a focus on variation in cultural perceptions of different types of vegetation.

The following considerations are important when interpreting these results. First, this study examined a sample of schools that covers a large extent characterized by an incredible diversity of landscapes and social conditions. As such, relationships averaged across such a large and diverse sample do not necessarily represent accurate estimates of relationships among particular subsets of the sample. Second, standards for graduation and reading and mathematics proficiency vary from state to state, and proficiency exams, although administered at the high

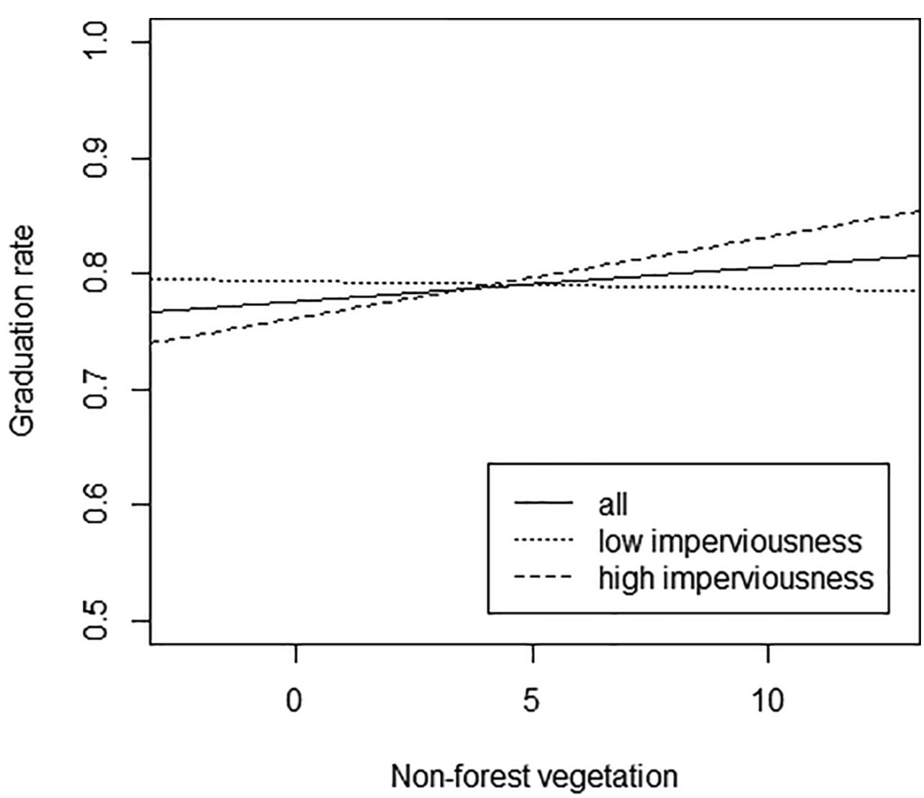

Fig. 3. Associations between non-forest vegetation and graduation rate for the entire sample and for schools with low and high SAA imperviousness. Low refers to SAA with imperviousness below the first decile of the sample distribution of SAA imperviousness (13.0%), while high refers to those above the ninth decile (67.6%) in that distribution.

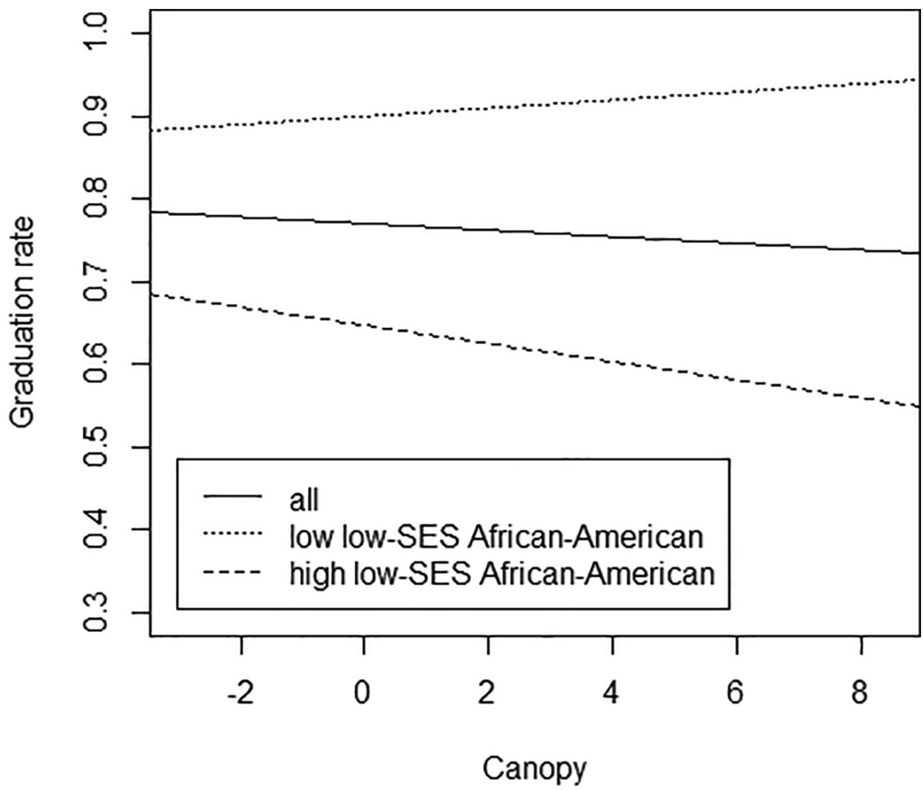

Fig. 4. Associations between canopy coverage and graduation rate for the entire sample and for schools with high and low values on the low-SES African-American variable. Low refers to schools below the first decile (−1.3) of the distribution of the low-SES African-American variable, while high refers to those above the ninth decile (1.4).

school level, may have been given at different grade levels in different states. Despite the inclusion of a state-level random effect, these differences likely influenced our results, although it is difficult to say exactly how. Furthermore, certain SAA may have had a high proportion of students attending private or charter schools not considered in this analysis, as opposed to the public school associated with the SAA, which lessens the generalizability of these results. Also, the ecological nature of this study precluded the generalization of our findings to individuals, and its cross-sectional nature means that the possibility exists that the associations we observed were unique to the populations considered and the 2010/11 academic year. Furthermore, the cross-sectional nature of our dependent variables, which only indicated twelfth-grade academic achievement, precluded investigation of whether or not relationships for high school populations are a result of the culmination of influences of vegetation across students' childhoods and adolescences, although we suggest that they may be. This issue warrants consideration in future studies that attempt to identify the influence of student environments on academic achievement over the course of primary and secondary education, perhaps conducted at the individual-level.

Additional considerations regarding the NLCD 2011 datasets are worth noting. Non-forest and agricultural vegetated land covers exist primarily on the urban fringe of cities in the NLCD 2011 land cover dataset, as more densely developed areas are represented by a four-level development intensity scheme. The effects of those land covers may therefore be an artifact of social conditions particular to rural areas or urban fringe settlements. Also, the 30-m resolution of the NLCD 2011 datasets masks heterogeneity in land cover detectable only at finer resolutions. The potential influences of arrangements of vegetation apparent only at finer geographic scales therefore cannot be investigated with those datasets.

This research represents the first study to explore relationships between academic performance and urban nature across the continental United States. Previous studies focused more narrowly on a single metropolitan areas or state. In exploring these relationships at this level, we provide a more extensive examination of the influences of vegetation in student environments on academic achievement than previously found in the literature. Notably, we considered a large number of cities across a range of biogeographic contexts, as opposed to one case study area. Thus our results provide a degree of generalizability not found in prior studies. The findings of this study in conjunction with the findings of other studies that more clearly identified academic benefits of nature in student environments (e.g., Hodson & Sander, 2017; Kweon et al., 2017; Wu et al., 2014) suggest that these benefits may be highly dependent on local context, as those studies were focused on relatively small areas. The average effects of nature on student achievement at a national scale may be small, non-existent, or even negative; however, that does not mean that certain populations do not experience considerable benefits. Thus future research should focus on identifying those populations and the cities and neighborhoods in which they reside in order to better target landscape management to locations where it can most support academic performance.

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Appendix A. State random effect estimates (change in intercept) for graduation, mathematics, and reading models. Values of −999 indicate no data for the dependent variable for a given state.

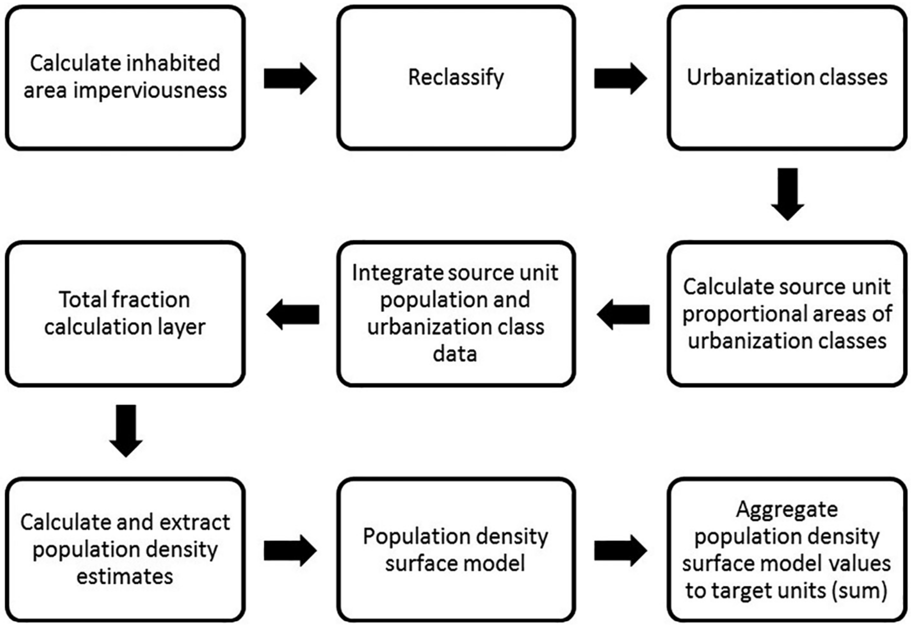
State	Graduation	Reading	Math
Alaska	−0.006	0.035	−0.037
Arizona	0.093	0.037	0.002

Arkansas	0.046	0.026	0.235
Colorado	−0.045	0.145	0.013
Connecticut	0.007	0.160	0.223
Delaware	−0.062	−0.107	−0.124
District of Columbia	−0.115	−0.388	−0.274
Florida	−0.028	−0.432	0.186
Georgia	−0.065	0.384	0.334
Idaho	−999	0.053	0.116
Illinois	0.053	−0.505	−0.407
Indiana	0.074	−0.071	0.108
Iowa	0.063	−0.016	0.163
Kentucky	−999	−0.147	−0.453
Louisiana	−0.011	0.079	0.345
Maine	0.025	−0.130	−0.045
Maryland	0.046	0.188	0.373
Michigan	−0.002	−0.299	−0.544
Minnesota	−0.074	−0.085	−0.388
Mississippi	0.047	−0.006	0.207
Missouri	−0.024	0.015	−0.276
Nebraska	−0.011	−0.155	0.433
Nevada	−0.216	0.240	0.163
New Jersey	0.110	0.286	0.234
New Mexico	−0.030	−0.092	−0.123
New York	0.064	0.304	0.435
North Carolina	0.065	0.007	0.323
Ohio	0.042	0.235	0.371
Oklahoma	−999	0.163	0.302
Oregon	−0.072	−0.102	−0.171
Pennsylvania	0.050	−0.114	−0.063
Rhode Island	0.008	0.106	−0.124
South Carolina	−0.026	0.053	0.143
Tennessee	0.090	−0.275	−0.546
Utah	−0.052	0.145	−0.558
Vermont	−0.006	0.013	−0.621
Virginia	−0.023	0.267	0.374
Washington	−0.019	0.039	−0.349
Wisconsin	0.005	−0.045	0.041

Appendix B. Ecoregion random effect estimates (change in intercept) for graduation, mathematics, and reading models. Values of −999 indicates no data on the dependent variable for schools in a given ecoregion.

Ecoregion	Graduation	Reading	Math
Atlantic Highlands	−0.027	−0.047	−0.038
Central USA Plains	0.042	−0.007	−0.023
Cold Deserts	−0.032	0.006	−0.014
Everglades	0.051	0.010	0.041
Marine West Coast Forest	−0.065	−0.016	−0.020
Mississippi Alluvial & SE Coastal Plains	−0.018	−0.059	−0.030
Mixed Wood Plains	0.034	−0.034	−0.027
Mixed Wood Shield	−999	0.002	−0.011
Ozark/Ouachita-Appalachian Forests	0.047	0.078	0.071
South Central Semiarid Prairies	−0.018	0.019	0.002
Southeastern USA Plains	−0.001	0.000	0.031
Temperate Prairies	0.011	0.014	0.005
Texas-Louisiana Coastal Plain	−0.001	0.005	0.005
Warm Deserts	−0.049	0.016	0.004
Western Cordillera	0.026	0.014	0.006

Appendix C. Flow chart of the dasymetric mapping process used in this study. Parallelograms indicate a data input/output, while rectangles indicate analysis steps. The source units in our analysis were UNSD, while the target units were SAA.



Appendix D. Correlation matrix (Pearson coefficients) of PCA input variables

	Low education	Medium education	High education	Low income
Low education	1.000	−0.308	−0.560	0.754
Medium education	−0.308	1.000	−0.613	−0.084
High education	−0.560	−0.613	1.000	−0.552
Low income	0.754	−0.084	−0.552	1.000
Medium income	−0.035	0.697	−0.573	−0.071
High income	−0.682	−0.232	0.770	−0.895
Small households	0.111	−0.043	−0.053	0.524
Medium households	−0.293	0.101	0.155	−0.655
Large households	0.368	−0.111	−0.211	0.004
Renters	0.710	−0.415	−0.232	0.738
Lunch	0.695	−0.261	−0.353	0.685
Black	0.475	−0.310	−0.130	0.482
Latino/a	0.372	−0.241	−0.096	0.130

	Medium income	High income	Small households	Medium households
Low education	−0.035	−0.682	0.111	−0.293
Medium education	0.697	−0.232	−0.043	0.101
High education	−0.573	0.770	−0.053	0.155
Low income	−0.071	−0.895	0.524	−0.655
Medium income	1.000	−0.373	−0.049	0.017
High income	−0.373	1.000	−0.462	0.601
Small households	−0.049	−0.462	1.000	−0.953
Medium households	0.017	0.601	−0.953	1.000
Large households	0.112	−0.056	−0.701	0.455
Renters	−0.168	−0.613	0.394	−0.566
Lunch	−0.071	−0.604	0.268	−0.429
Black	−0.209	−0.360	0.212	−0.323
Latino/a	0.017	−0.121	−0.113	0.015

	Large households	Renters	Lunch	Black
Low education	0.368	0.710	0.695	0.475
Medium education	−0.111	−0.415	−0.261	−0.310
High education	−0.211	−0.232	−0.353	−0.130
Low income	0.004	0.738	0.685	0.482
Medium income	0.112	−0.168	−0.071	−0.209
High income	−0.056	−0.613	−0.604	−0.360

Small households	−0.701	0.394	0.268	0.212
Medium households	0.455	−0.566	−0.429	−0.323
Large households	1.000	0.173	0.227	0.139
Renters	0.173	1.000	0.679	0.541
Lunch	0.227	0.679	1.000	0.651
Black	0.139	0.541	0.651	1.000
Latino/a	0.308	0.314	0.324	−0.186

	Latino/a
Low education	0.372
Medium education	−0.241
High education	−0.096
Low income	0.130
Medium income	0.017
High income	−0.121
Small households	−0.113
Medium households	0.015
Large households	0.308
Renters	0.314
Lunch	0.324
Black	−0.186
Latino/a	1.000

Appendix E. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2019.04.027.

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