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Varying age-gender associations between body mass index and urban greenspace

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Abstract

Urban greenspace benefits urbanites in numerous ways ranging from regulating flooding, air quality, and local climate to providing opportunities for exercise and relaxation. These benefits may influence human health. Greenspace, for example, may facilitate exercise, thereby helping to reduce body mass index (BMI) and combat obesity, a current epidemic of great public health concern. Little evidence exists to support this assertion, however, and we lack a full understanding of the mechanisms whereby this relationship operates, the populations for whom greenspace is linked to weight status, and the aspects of urban greenspace that are linked to weight status. This study seeks to identify relationships among the composition and arrangement of greenspace and BMI for different populations using regression models for eight age and gender groups in Cleveland, Ohio, US. We find that several greenspace variables are related to BMI for women under 65 years and males under 51 years, but not for older groups, and that the aspects and types of greenspace that are significantly related to BMI vary among groups. Relationships between greenspace attributes and BMI are generally stronger for female groups and for younger groups. Providing access to greenspace with particular attributes such as greenspaces with water, canopy cover, or connected greenspaces could support a healthy weight status for some populations, but these attributes are not consistent across age and gender groups. These results could help to inform policy aimed at designing urban greenspace to benefit the health of different population subgroups.

Keywords

Urban greenspace; body mass index; obesity

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Introduction

Over half of the human population lives in cities, a number expected to rise to nearly three-quarters by mid-century (UNPD, 2012). Health concerns for this increasingly urban population include sedentary lifestyles that contribute to obesity and associated illnesses (e.g., diabetes, hypertension, cardiovascular disease) (Tamosiunas et al., 2014, Tseng et al., 2014, Groth et al., 2015, Koohsari et al., 2015). Urban greenspaces may influence weight status and are increasingly identified as valuable resources for supporting active lifestyles and enhancing health. Evidence supporting this association exists, but is inconsistent (Hartig et al., 2011, de Vries et al., 2011, Groenewegen et al., 2012, Hartig et al., 2014), restricting management of urban greenspaces as public health resources and venues for behavioral intervention.

Obesity rates rose dramatically in the last fifty years and obesity is considered a global epidemic linked to numerous health conditions, including cardiovascular illness (Richardson et al., 2013, Tamosiunas et al., 2014, Bixby et al., 2015, Nayyar and Hwang, 2015), diabetes (Astell-Burt et al., 2014), and hypertension (Bassett et al., 2002). Obesity results from a complex, multi-causal process. Urban living, which limits physical activity due to sedentary lifestyles and reduced locations for outdoor activities, is among the myriad contributing factors to obesity (Caballero, 2007). Urban greenspace may influence obesity directly via enhanced opportunities for physical exercise (Hartig et al., 2011, de Vries et al., 2011, Groenewegen et al., 2012, Hartig et al., 2014, Villanueva et al., 2015), or indirectly by providing areas for building social connections (Hartig et al., 2014), reducing stress (Groenewegen et al., 2012, Hartig et al., 2014), and attention restoration (Berman et al., 2008, Berman et al., 2012, Hartig et al., 2014, Kaplan, 1995). These benefits may further influence willingness to exercise or overall quality of life and thus obesity. Obesity itself may impact ability and willingness to participate in physical activity, and, at least in children, increased adiposity may reduce physical activity (Richmond et al., 2014).

Studies indicate positive associations between greenspace availability and physical activity (Kaczynski and Henderson, 2007, Jiang et al., 2016) and qualitative studies suggest that greenspace attributes (e.g., safety, aesthetics, amenities, maintenance) influence physical activity (McCormack et al., 2011, Koohsari et al., 2015). Recent studies found inverse relationships between urban parks and natural amenities and weight status such that locations with greater access experienced lower body mass indices (BMI) (Pitts et al., 2013, Rundle et al., 2013, Stark et al., 2014, Boncinelli et al., 2015, Xu et al., 2015). Several studies, however, found no or a positive relationship between greenspace exposure and weight status (Rundle et al., 2013, Lachowycz and Jones, 2011). As contact with urban nature may encourage physical activity and healthy lifestyles that could reduce obesity (Hartig et al., 2014), better understanding the relationships among obesity and greenspace could improve management of urban environments to reduce obesity rates.

A number of factors may contribute to inconsistencies observed in the relationships between greenspace and obesity, including inadequate adjustment for socioeconomic factors and reliance on self-reported measures of obesity and physical activity and crude greenspace metrics (Lachowycz and Jones, 2011, Koohsari, et al. 2015, van den Berg et al., 2015).

Relationships between greenspace and weight status may also vary demographically (e.g., with age, gender, race/ethnicity) (van den Berg et al., 2015). These relationships have received little study, but evidence suggests that greenspaces reduce the odds of overweight/obesity for women generally (Veitch et al., 2016) and for women of color, over 40-years old, and without college degrees (Ransdell and Wells, 1998, Bassett et al., 2002), but not for men (Veitch et al., 2016, Astell-Burt et al., 2014). Some studies found relationships between greenspace attributes and weight status, with publicly-owned (Ghimire et al., 2017), cleaner (Stark et al., 2014), larger (Rundle et al., 2013), and forested (Ghimire et al., 2017) greenspaces and greenspaces that provide resources for outdoor recreation such as biking and hiking trails (Ghimire et al., 2017) exhibiting a significant relationship to weight status not observed for other greenspaces. As such, the current literature suggests that relationships between greenspace and weight status vary among population subgroups and with greenspace attributes, but does not definitively identify these differences or the factors that contribute to them.

Previous studies leave critical questions regarding relationships between urban greenspace and weight status unanswered. These questions relate particularly to identifying ‘where’ and for ‘whom’ weight status is associated with greenspace, ‘what’ greenspace characteristics are correlated with weight status, and mechanisms whereby associations occur (Lachowycz and Jones, 2011, Lachowycz and Jones, 2013). We seek to identify relationships among weight status and greenspace type, composition, and spatial arrangement (‘what’/‘where’), and variation in these relationships with age and gender (‘for whom’) while adjusting for population attributes (e.g., wealth, education, race/ethnicity) previously found to impact health (Kaczynski and Henderson, 2007, Lachowycz and Jones, 2011, Koohsari et al., 2015).

Methods

We focus on 546 US Census block groups in Cleveland, Ohio, USA (Fig. 1) ranging in area from 0.65 km²–2152.42 km² (mean=3.92 km², SD=4.98). In 2009, 35% of Cleveland adults were obese (Bruckman, 2012), with higher rates for women (41%) than men (32%). Rates were lowest in the 18–29 year-old age group (29%) and highest amongst individuals aged 30–49 (41%).

Body Mass Index

We measured weight status using BMI, a summary measure of height and weight that is commonly-used for monitoring prevalence of overweight/obesity at individual and population levels. We estimated BMI using the US Centers for Disease Control’s algorithm by dividing an individual’s weight (kg) by the square of their height (m) (http://www.cdc.gov/healthyweight/assessing/bmi/adult_bmi/index.html#Interpreted) and data from the Ohio Bureau of Motor Vehicles (BMV) state driver’s license and identification card applications. This dataset included age, gender, self-reported height and weight, and residential location for Cleveland residents aged 18–84 years with driver’s licenses or state identification cards between January, 2010 and December, 2012 (305,295 individuals, 149,797 males, 155,498 females). Ohio BMV data may be seen as generally representative of Ohio’s overall population as 87.2% of Ohio’s driving-age population possess driver’s

licenses and overall proportions of male and female licensed drivers correspond closely to the gender composition of the state's driving-age population (US Department of Transportation Federal Highway Administration, 2010). Some groups (e.g., the elderly, very poor, disabled, undocumented) are less likely to possess driver's licenses. Including data from state identification cards enhances representativeness of these groups as individuals without driving licenses require an identification card to access services. As a result of the large size of this dataset and its coverage of a very large proportion of the population, we consider this dataset to provide a general representation of the overall Cleveland population, but acknowledge that some groups may be less well-represented.

We used GIS functions to calculate average block group male and female BMI for the following age groups: 18–29 (young adult), 30–50 (middle adult), 51–65 (older adult), and 65–84 (retiree). We aggregated to this level because, while the agreement with the BMV allows individual-level analysis, reporting must occur at aggregated scales. Smaller aggregation units (e.g., Census blocks) would threaten confidentiality. We included only block groups with over ten individuals per group. Additionally, to facilitate comparison with US Census-derived variables, we excluded individuals under 18 and over 84 years from analysis.

Greenspace Variables

Cleveland supports 143.20 km² of protected greenspace: conservation lands (47.84 km²), recreational parks (71.69 km²), and cemeteries (23.67 km²). All conservation lands and recreational parks included in this analysis were publicly-accessible. Cemeteries were semi-accessible (i.e., publicly-accessible during the day on most days, but typically gated and closed at other times). We identified greenspace locations and types using parcel data from the Cuyahoga County Geographical Information Systems Department (CCGISD) and used ten variables in four groups to quantify greenspace attributes. The first group included three variables that identify greenspace exposure as the percentage of block group area occupied by each greenspace type. The second group quantified greenspace connectivity which might facilitate activities requiring larger extents (e.g., walking, jogging, cycling). We included two connectivity variables, collective recreational park and conservation land contiguity and contiguity of cemetery. These variables were calculated using the contiguity index, a common landscape metric that identifies spatial connectedness, using Fragstats version 4.2 (McGarigal et al., 2012). This index ranges from 0–1. Zero values indicate either low connectedness or the absence of a greenspace type, values near 1 indicate high connectedness of that type.

Greenspace land-cover composition and arrangement may influence usage. To measure greenspace composition, we calculated two groups of variables. First, we estimated the percentage of greenspace in each block group covered by water, forest, impervious surfaces, and grass using 2011, high-resolution (1-m) land-cover data from the CCGISD. Second, we calculated mean block group greenspace percent canopy coverage using the 2011 National Landcover Dataset (NLCD) Tree Canopy product (Homer et al., 2015). Canopy coverage is distinct from forest as it includes canopy over pavement and grass rather than contiguous forest.

Socio-economic variables

Using 2010 US Census data, we identified block group percent composition of Black, Asian, and Hispanic individuals. We obtained economic and educational attainment data from the US Census 2010 American Community Survey (ACS) five-year estimates at the Census tract-level. We used dasymetric mapping, an areal interpolation technique for refining spatially-aggregated data from coarser to finer resolutions (Mennis, 2003), to interpolate educational attainment data to finer-resolution block groups. We first combined 30-m 2011 NLCD Percent Developed Imperviousness data (Xian et al., 2011) with CCGISD parcel-based land-use data to identify and remove uninhabited areas. We classified remaining urban locations with imperviousness below the median as low-intensity development and those at or above the median as high-intensity. We calculated relative differences in population density between classes by sampling densities for block groups composed predominantly of each class, facilitating redistribution of tract-level population counts to individual pixels. We weighted the resulting population surface with tract-level educational-attainment data to derive per-pixel count estimates for educational attainment (i.e., no high school diploma, high school diploma to associate's degree, bachelor's degree plus). Using the resulting three weighted surfaces, we calculated variables representing estimated proportions of block group populations with each educational-attainment level. We disaggregated tract-level economic status data to block groups using ordinary kriging because these data were not based on counts or densities, making dasymetric mapping inappropriate. We estimated a continuous surface for median household income from the 2010 ACS tract-level data, then calculated median household income for each block group using this surface.

Analysis

We identified regions with age and gender-specific high and low BMI via a cluster analysis using the hot-spot analysis tool in ESRI's ArcGIS 10.3. Given a weighted variable and assuming random spatial distribution of data values, this function identifies "hotspots", clusters of higher than expected mean BMI, and "cold-spots", clusters of lower than expected BMI. We assessed the statistical significance of identified clusters using *z*-scores and *p*-values.

We estimated ordinary least squares (OLS) regression models for each age and gender group to identify relationships among independent variables and BMI. To test model assumptions of evenness and independence of errors, we used Breusch-Pagan tests and Moran's *I* statistics to assess heteroscedasticity and spatial autocorrelation (i.e., spatial patterning) of model residuals. When Breusch-Pagan tests were significant, we estimated heteroscedasticity-consistent standard errors (White, 1980). Where Moran's *I* was significant, we calculated Lagrangian multiplier diagnostics to identify whether lag (i.e., in the dependent variable) or error (i.e., resulting from the omission of a spatially-structured predictor variable) processes dominated and calculated appropriate spatially-simultaneous autoregressive (SAR) models (Cressie, 1993, Haining, 2003). These models require a spatial-weight matrix, *W*, generally specified such that near neighbors exert larger influences than distant neighbors, to indicate the influence neighbors exert on observations (Anselin and Bera, 1998, Fortin and Dale, 2005). We used a queen-contiguity method (Anselin and Bera, 1998, Fortin and Dale, 2005) given the contiguous nature of block groups. SAR

models may address error spatial autocorrelation, augmenting the OLS regression with a term to represent the spatial structure of the error term, $\lambda W\mu$, such that:

$$Y = X\beta + \varepsilon_i + \lambda W\mu \quad (1)$$

where Y is the dependent variable (BMI), X is a matrix of the independent variables, β is a vector of the slopes of the independent variables in the original matrix, and μ represents spatially-dependent error. Where lag spatial autocorrelation dominates, SAR lag models that include ρ , the autoregression coefficient are estimated as:

$$Y_i = X\beta + \varepsilon_i + \rho WY \quad (2)$$

SAR mixed models include an autoregression coefficient, γ , addressing both lag and error autocorrelation as:

$$Y_i = X\beta + \varepsilon_i + \rho WY + W X\gamma \quad (3)$$

Results

Greenspace availability varies spatially across Cleveland (Fig. 1) and is generally lower in central Cleveland. Conservation land availability is higher in western Cleveland. Greenspace canopy cover is patchily-distributed and is higher in older residential areas and along waterways and lower in central Cleveland. Mean canopy coverage is highest on conservation lands (51%), followed by cemeteries (24%), and recreational parks (15%). Thus, residents of different block groups experience different levels of canopy and greenspace in their home environments.

Mean block group BMI ranged from 21.14–34.73 (mean=27.87) and varied among groups (Table 1). Mean BMI was highest (28.65) for older-adult females and lowest (26.28) for young-adult males. All groups averaged within the overweight range. Young-adult males and females had the lowest mean BMI and BMI was comparable among middle-and older-adult age groups. Retiree male and female groups had lower mean BMIs than middle- and older-adult groups for their gender, but higher BMIs than young-adult groups. Female and male BMIs within age groups were similar. While variation occurred in descriptive statistics for predictor variables among groups, none deviated greatly from the statistics for all block groups.

Hotspot analysis revealed distinct, age-and-gender-specific spatial patterns in BMI (Fig. 2). Hotspots of statistically-significant high BMI occurred east of the Cuyahoga River and cold-spots with statistically-significant low BMI occurred in western Cleveland for all groups except young-adult and retiree males. Eastern Cleveland, however, had more females with high BMI than males across all age categories. Among females, hotspot size and number were greatest for middle adults followed by young-adult, older-adult, and retiree groups. Hotspots across all age groups occurred east of the downtown area with higher proportions

of black and low-income individuals. Hotspots for male BMI occurred for middle and older adults, concentrated east of downtown. The University neighborhood, which includes Case Western University with high young, male, and Asian populations, was a low-BMI cold-spot surrounded by block groups with high BMI for all groups. Consistent cold-spots across groups were identified in western and southwestern Cleveland.

We estimated regression models for each age and gender group (Tables 2–3; Fig. 3–4). Tests for residual spatial autocorrelation indicated lag autocorrelation in the middle–adult female model; thus we estimated a SAR lag model for this group. No significant residual autocorrelation occurred in other models, hence we used these OLS models. Breusch-Pagan tests indicated heteroscedasticity in young and middle-adult female and middle and older-adult male models. We calculated heteroscedasticity-consistent standard errors following White’s method (White, 1980) for these models.

Predictor variables accounted for greater variation in some groups’ BMI than others. Fit for middle-adult females was highest (*pseudo* $R^2=0.739$), then young-adult females (*adjusted* $R^2=0.658$), middle-adult males (*adjusted* $R^2=0.4817$), and older-adult (*adjusted* $R^2=0.448$) and retiree-females (*adjusted* $R^2=0.4038$). Goodness-of-fit was lower for young-adult (*adjusted* $R^2=0.229$), older-adult (*adjusted* $R^2=0.137$), and retiree males (*adjusted* $R^2=0.093$).

Associations with socio-economic variables were as expected. Average age exhibited statistically-significant, positive relationships to BMI for young-adult and middle-adult males and females ($p<0.05$). Retiree females exhibited decreasing BMI with increasing age ($\beta=-0.1583$, $p<0.001$) which can be explained by weight loss due to comorbidities of aging and increasing frailty (Fried et al., 2004). The block group proportion Asian was significantly ($p<0.001$), negatively related to BMI for all groups and was strongest for young-adult females ($\beta=-0.05556$) and weakest for older-adult females ($\beta=-0.03553$). Block group proportion Black was significantly and positively related to BMI for all female groups and middle-adult males ($p<0.001$), was highest for middle-adult females ($\beta=0.024832$), and lowest for older-adult females ($\beta=0.01202$). Block group percentage Hispanic or Latino was significantly and positively related to BMI for middle-adult males ($\beta=0.01142$, $p<0.01$) and females ($\beta=0.03121$, $p<0.001$) and older-adult females ($\beta=0.01522$, $p<0.01$). Relationships between BMI and economic and education variables varied among groups. Block group household income exhibited significant, negative relationships to BMI for all female groups ($\beta=-0.000037$ to -0.000011 , $p<0.05$), but was not significant for male groups. The block group proportion without a high school diploma exhibited a significant positive relationship for retiree females ($\beta=0.0236$, $p<0.05$) and negative relationship for older-adult males ($\beta=-0.01689$, $p<0.05$). Relationships between block group BMI and percentage with at least a bachelor’s degree were significant and negative ($p<0.001$) for all groups except older-adult females with similar coefficients (range: -0.037856 to -0.02127).

All greenspace variables except percent conservation showed significant relationships to BMI for some groups. Recreational park percentage was significantly negatively related to mean BMI for only middle-adult females ($\beta=-0.014588$, $p<0.05$). The relationship between

block group percent cemetery and BMI was significant and negative for young-adult females ($\beta=0.009338$, $p<0.01$), but positive and significant for middle-adult females ($\beta=0.017044$, $p<0.05$). Greenspace contiguity was significantly related to BMI for three groups. Recreational parks and conservation land contiguity was positively related to young-adult female BMI ($\beta=0.56173$, $p<0.05$) and negatively related to older-adult female BMI ($\beta=-0.50810$, $p<0.05$). Cemetery contiguity showed a positive relationship for middle-adult females ($\beta=0.497170$, $p<0.05$).

Greenspace composition varied in its relationship to BMI by group. Young-adult males exhibited the only significant relationships with greenspace canopy ($\beta=0.16703$, $p<0.01$), forest ($\beta=-0.01074$, $p<0.01$), and grass ($\beta=0.005776$, $p<0.05$). Greenspace impervious surface was significantly and negatively related to BMI for middle-adult females ($\beta=-0.008203$, $p<0.05$) and males ($\beta=-0.005231$, $p<0.05$). Water in greenspaces exhibited significant, negative relationships to BMI for older-adult females ($\beta=-0.045170$, $p<0.05$) and middle-adult males ($\beta=-0.039734$, $p<0.01$).

Discussion

We sought to identify associations among greenspace characteristics and age and gender specific BMI, aiming to answer questions related to for ‘whom’ and for ‘what’ greenspaces these relationships occur, thereby contributing to our ability to (re)design urban greenspace to benefit public health. We found greenspaces to be associated with weight status for some age and gender groups, but associations are inconsistent amongst groups. We also found variation in greenspace attributes associated with BMI amongst groups. These varied relationships suggest that these groups perceive and use greenspace differently, thus greenspace management to support public health broadly may be complex.

Our hotspot analysis identified a distinct east-west divide in the prevalence of overweight and obesity in Cleveland. Block groups east of the Cuyahoga River and downtown had significantly higher average BMI than block groups west of the river. This trend occurred for all gender and age groups, but females were generally more obese than males in eastern Cleveland (Fig. 2). Findings for non-greenspace variables largely agreed with previous research (Caballero, 2007) and supported the spatial pattern of BMI. BMI hotspots had low household income, high percentages of Black and low percentages of Asian populations, variables with statistically-significant associations with BMI in regression models.

Female BMI showed greater linkages to greenspace attributes than male BMI and younger groups showed greater linkages than older groups. This agrees with past work that showed greenspace proximity reduced the risk of overweight and obesity for women, but not men (Astell-Burt et al., 2014). Such links between BMI and weight status may be tied to enhanced opportunities for physical activity in greenspaces. Past studies found a higher likelihood of residents of greener areas, particularly females, participating in physical activity and that this relationship was greatest for younger adults (Veitch et al., 2016, McMorris et al., 2015, Kaczynski et al., 2009). Our finding that lower mean block group BMI was associated with greater recreational park availability for middle-adult females could reflect similar increased physical activity in local parks for this group. We found a

similar relationship between recreational greenspace and the mean BMI of middle-adult males, suggesting that this effect may also occur for males in this life stage. Social or physiological effects of greenspace may contribute to this relationship, encouraging generally healthier lifestyles in areas with more greenspace. Self-selection processes whereby more active, lower BMI individuals opt to live in greener locations may also explain the observed relationships.

Our results identify aspects of greenspace associated with BMI. Cemeteries were not significantly related to BMI for most groups and exhibited positive, significant relationships to BMI for middle-adult females, suggesting that cemeteries do not facilitate physical exercise or healthier lifestyles, possibly because socio-cultural norms preclude their use or because cemeteries are semi-accessible, with access only during daylight hours and on specific days of the week thereby restricting their use by local populations. Cemetery contiguity was positively-related to BMI for middle-adult females, suggesting that large amounts of connected cemetery reduce opportunities for exercise and other activities that could reduce BMI for this group, possibly by displacing other greenspaces. Young-adult female BMI, however, exhibited a significant, negative relationship with cemetery area, suggesting that cemeteries potentially encourage exercise in this group or provide stress reduction or attention restoration benefits that could support weight status via other pathways. We could not find studies that explored such relationships. Thus, this finding warrants further investigation.

Connected greenspaces form networks that may support walking, cycling, and jogging (Smith, 1993). We found relationships between collective recreational park and conservation land contiguity and BMI for young-adult females (positive) and older-adult females (negative) which may reflect a difference in how these groups use and perceive greenspace. Notably, when included separately in preliminary analyses, recreational park and conservation land contiguity were not significantly related to BMI for any group suggesting that, for some groups, these greenspace types are perceived and used similarly for BMI-reducing activities. Identifying such mechanisms requires individual-level investigation.

We found no significant relationships between conservation lands and mean BMI. Although counter to expectations, this might stem from a lack of infrastructure to support recreation (e.g., trails, bike paths) or the location of these lands so as to limit access. Conservation lands occur largely along the study area margins and are relatively rare in most neighborhoods, particularly in more densely-populated areas (Fig. 1). Individuals may thus access these sites via car or other modes of transit resulting in no impact on local BMI. A regional effect that could not be captured in this study might thus exist for these lands.

Greenspace composition was related to BMI for some groups. Levels of impervious surfaces in greenspace, which typically include paved paths and parking areas as well as buildings and athletic facilities (e.g., basketball, tennis courts), were negatively associated with BMI for middle-adult males and females, suggesting that parks with such infrastructure provide opportunities for exercise (e.g., running, walking, exercise programs) or enhance willingness to exercise. The percentage of greenspaces occupied by open water (e.g., ponds, lakes, streams) was negatively related to BMI for older-adult females and middle-adult males.

Such water bodies may increase a park's attractiveness for physical activity or reduce stress, for example, via paths along waterways or by providing an aesthetically-pleasing setting.

Previous studies found that vegetation enhanced health (Boncinelli et al., 2015, Wheeler et al., 2015, Donovan et al., 2013) and we hypothesized a negative relationship between greenspace vegetation and BMI. However, we found significant relationships between BMI and vegetation for only young-adult males with greenspace canopy coverage, which identifies canopy cover only and not the land-cover type beneath that canopy, and percentage of greenspace in grass cover exhibiting significant, positive relationships to BMI for this group. An opposite relationship existed for greenspace forest coverage for this group. This suggests that young-adult males may use forested areas for relaxation or exercise (e.g., hiking, trail-running, mountain biking), but may prefer forested sites with less-dense canopy given the more open, unobstructed ground and aesthetic environment they provide. Grassy areas (e.g., lawns) may limit such opportunities. These variables were not linked to BMI for other groups possibly due to competing effects of tree cover on park use. For example, although treed areas may be attractive for exercise, higher canopy or forest coverage might lower visibility, reducing perceptions of safety and frequency of park use; might reduce exercise infrastructure (e.g., paved trails, sports facilities); or the seasonal nature of canopy cover might limit effects to warm seasons. Grassy areas may similarly provide few sites for physical activity or stress reduction. Past studies suggest that most individuals prefer less crowded, litter-free, well-manicured and maintained greenspaces with open areas (Arnberger and Eder, 2011 & 2015, Bjerke et al. 2006, Nordh et al. 2011, Schipperjin et al., 2010), but that these preferences vary with use type and among individuals (Arnberger and Eder, 2011 & 2015, Reichhart and Arnberger, 2010, Reynolds et al., 2007) and with the perceived safety of parks (Jansson et al. 2013). It is beyond the scope of this study to speculate as to how these perceptions may impact weight status via effects on greenspace use, but future studies should explore the use and perceptions of greenspaces with different vegetative cover.

Calculating BMI from self-reported height and weight has advantages and disadvantages. First, individuals often underestimate their weight, but trends are consistent and data remain useful for describing spatial patterns (Morris et al., 2015, Gorber et al., 2007). Second, people without state-issued identification (e.g., elderly, undocumented, institutionalized, low-income) are underrepresented (Morris et al., 2015). Statistics for the state of Ohio, however, indicate that most (87.2%) of the state's driving-age population possess driver's licenses in proportions representative of the state's gender composition (US Department of Transportation Federal Highway Administration, 2010). Including data from state identification cards, which are issued only to individuals without driver's licenses, increases coverage, but little data exist regarding this population or the prevalence of such cards in Ohio. Likewise, little information exists about driver's license and identification card prevalence for Cleveland specifically or the distribution of license and card holders within Cleveland (our dataset did not indicate the type of card an individual possessed). We acknowledge that some groups may thus be underrepresented in this dataset, but suggest that using datasets such as this one are more likely to capture characteristics of the overall population than can be gathered using survey approaches that sample lower proportions of populations. Deriving BMI from such data has the additional advantage of producing precise estimates of a population's body weight for small areas (e.g., cities) and estimates from these records can

reveal striking geographic variation. Thus, these data are likely to provide high-level coverage unavailable through surveys with typically low response rates (Ossiander, 2004) and which sample smaller proportions of populations. As such, driver's license data represent a valuable, underused resource in obesity research (Littenberg and Lubetkin, 2016).

This study identifies key relationships between urban greenspace and BMI, but cannot identify all relationships or their mechanisms of operation. First, in using mean BMI and characteristics for block group populations, we cannot identify relationships between individuals and environment or detailed spatial variation. Nevertheless, block group BMI improves upon more aggregated values (e.g., county, city) and, as discussed above, our BMI dataset is comprehensive and representative of Ohio's adult population. Future studies should explore applications of triangulation methods in examining relationships at individual and aggregated levels, of more detailed park attributes (e.g., walkways, playing fields, gathering spaces), and of additional local neighborhood attributes, for example crime rates (Lovasi et al., 2013), waterways, and yard sizes, that might influence relationships between greenspace and BMI. We found variation in relationships between age and BMI for some groups, thus differentiating age groups into smaller classes might better identify how relationships between greenspace and BMI vary with age. Lastly, our study design does not facilitate identification of causal relationships between greenspace and BMI or mechanisms whereby such relationships occur which requires detailed, individual-level analysis.

Conclusions

Urban greenspace may support the health of urban populations by facilitating activities that reduce BMI (e.g., physical activity, stress reduction). Past studies suggest that urban greenspace enhances obesity-related health outcomes for some populations, but results are inconclusive and leave questions related to who benefits from urban greenspace and greenspace attributes linked to health unanswered. This study contributes to the emerging picture of who benefits from urban greenspaces and what greenspace attributes are linked to health, suggesting that the importance of greenspace attributes varies with age and gender, with greater associations for females and younger adults, and that designing greenspace to support health requires tailoring to target populations. Although our findings suggest that we could manipulate greenspace attributes to support health for some groups, future research should identify environmental attributes and mechanisms whereby they influence weight status to facilitate greenspace management to support the health of all populations.

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Highlights

- Relationships among greenspace attributes and BMI varied with age and gender
- Relationships were stronger for female and younger groups
- Greenspace composition and contiguity were related to BMI for some groups
- Conservation lands were not significantly related to BMI
- Greenspace was not related to BMI for men over 50 and men and women over 65 years

Fig. 1.
Distribution of greenspace in Cleveland, OH, USA.

Fig. 2.
Cluster analysis of average BMI at the Census block group level by age and gender.

Fig. 3. Coefficients for greenspace variables for female groups. Only statistically significant variables ($p < 0.05$) are included.

Fig. 4. Coefficients for greenspace variables for male groups. Only statistically significant variables ($p < 0.05$) are included.

Table 1

Descriptive statistics for model variables at Census block-group level.

Variable	Description	Census block group (N=546)*			
		Mean	SD	Min	Max
BMI	mean block-group body mass index	27.87	1.17	21.14	34.72
Age	average age of individuals in age and gender group estimated from Ohio BMV data	43.02	4.37	22	66.85
Black	percentage of block-group identified as Black	57.36	36.67	1.35	99.58
Asian	percentage of block-group identified as Asian	1.78	4.65	0.00	47.17
Hispanic	percentage of block-group of Hispanic or Latino origin	8.98	11.74	0.00	55.73
HHI	median block-group household income (USD)	35,631	10,940	10,688	155,108
NoHSD	percentage of block-group without high school diploma	24.49	9.50	0.00	51.10
Bach	percentage of block-group with bachelor's degree or higher	12.66	10.99	0.00	67.17
Park	Area of recreational park in block group (m ²)	125,268	418,746	0	5,058,000
Cemetery	Area of cemetery in block group (m ²)	41,353	302,249	0	3,805,200
Conservation	Area of conservation lands in block group (m ²)	83,642	684,199	0	10,808,100
Con_rec_cons	Contiguity of recreational park and conservation lands in block group	0.35	0.43	0	0.9897
Con_cem	Contiguity of cemetery in block group	0.04	0.19	0	0.9916
Canopy	Mean greenspace canopy cover in block group	7.30	14.56	0.00	79.69
Impervious	Percentage of greenspace covered by impervious surfaces in block group	10.22	17.68	0	98.85
Forest	Percentage of greenspace covered by forest in block group	12.52	21.40	0	100
H2O	Percentage of greenspace covered by water in block group	0.32	1.66	0.00	14.06
Grass	Percentage of greenspace covered by grass in block group	19.89	26.49	0	96.86

* Not all block groups were included due to sample size restrictions

Table 2

Model results for female groups.

Variable	Young-adult			Middle-adult			Older-adult			Retiree		
	β	SE	t-value	β	SE	t-value	β	SE	t-value	β	SE	t-value
(Intercept)	31.355000	2.570000	12.200	15.120000	2.570400	5.882	24.100000	3.216000	7.494	39.570000	2.596000	15.245
Age	-0.191660	0.107810	-1.778	0.162450	0.049550	3.278	0.081680	0.056980	1.433	-0.158300	0.033150	-4.773
Black	0.020718	0.002563	8.082	0.024832	0.002991	8.302	0.012020	0.001600	7.511	0.017040	0.002711	6.287
Asian	-0.055576	0.015946	-3.485	-0.057932	0.011268	-5.141	0.035550	0.007631	-4.655	-0.061840	0.013320	-4.642
Hispanic	0.013539	0.007475	1.811	0.031210	0.006990	4.465	0.015220	0.004637	3.283	0.006083	0.007998	0.761
HHI	-0.000037	0.000008	-4.480	-0.000042	0.000008	-5.132	-0.000011	0.000006	-2.031	-0.000024	0.000009	-2.549
NoHSD	0.016125	0.009301	1.734	0.002755	0.008338	0.331	-0.006232	0.005702	-1.093	0.023590	0.009771	2.414
Bach	-0.037856	0.006998	-5.410	-0.022352	0.006833	-3.271	-0.021270	0.004385	-4.850	0.003486	0.007771	0.449
Conservation	-0.017015	0.009481	-1.795	-0.001328	0.010644	-0.125	-0.001244	0.008234	-0.151	-0.015850	0.013850	-1.145
Cemetery	-0.009338	0.003346	-2.791	0.017044	0.008380	2.034	0.009936	0.006888	1.443	0.011200	0.011450	0.978
Park	-0.010620	0.007845	-1.354	-0.014588	0.006835	-2.135	-0.000803	0.004885	-0.164	-0.002904	0.009165	-0.317
Con_rec_cons	0.561730	0.259990	2.161	0.185950	0.309710	0.600	-0.508100	0.214300	-2.370	-0.413600	0.368000	-1.124
Con_cem	0.337440	0.319480	1.056	0.497170	0.244330	2.035	-0.025900	0.167100	-0.155	-0.017240	0.297000	-0.058
Canopy	0.012957	0.006989	1.854	0.004894	0.007644	0.640	-0.000656	0.005359	-0.122	0.017880	0.009699	1.843
Impervious	-0.006352	0.003399	-1.869	-0.008703	0.003566	-2.300	-0.000878	0.002445	-0.359	0.005720	0.004343	1.317
Forest	-0.005545	0.005102	-1.087	-0.001522	0.005769	-0.264	0.005601	0.004026	1.391	-0.010420	0.007316	-1.425
H ₂ O	-0.053225	0.049594	-1.073	-0.057076	0.030394	-1.878	-0.045170	0.020090	-2.249	-0.016220	0.043980	-0.369
Grass	-0.005349	0.003110	-1.720	0.000410	0.003458	0.119	0.003806	0.002367	1.608	0.004958	0.004003	1.239

 $p < 0.001$,**
 $p < 0.01$,*
 $p < 0.05$

n 523 523 526 492

Adj R^2 0.6578 0.4475 0.4038

Rho 0.25067

LR test value 20.096***

Log likelihood -756.901

1553.8

0.73898

Nagelkerke pseudo- R^2
AIC SAR (AIC lm)

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Table 3

Model results for male groups (detailed model diagnostics from Table 2 are omitted as they are not relevant for OLS models).

Variable	Young-adult			Middle-adult			Older-adult			Retiree		
	β	SE	t-value	β	SE	t-value	β	SE	t-value	β	SE	t-value
(Intercept)	23.650000	1.434000	16.490	***	23.671000	1.878700	12.599	***	24.891000	3.825000	6.508	***
Age	0.111000	0.058370	1.902	.	0.106320	0.045760	2.323	*	0.070202	0.066762	1.052	
Black	0.003266	0.001712	1.908	.	0.012307	0.001525	8.072	***	-0.003175	0.001741	-1.824	.
Asian	-0.045280	0.008009	-5.654	***	-0.048857	0.008740	-5.590	***	-0.046328	0.012159	-3.810	***
Hispanic	0.008102	0.004811	1.684	.	0.011418	0.004170	2.738	**	0.001371	0.005278	0.260	
HHI	0.000005	0.000006	0.804	.	0.000011	0.000006	1.895	.	0.000004	0.000007	0.628	
NoHSD	-0.001323	0.005832	-0.227		-0.005229	0.005953	-0.878		-0.016890	0.007135	-2.367	*
Bach	-0.023240	0.004722	-4.921	***	-0.028248	0.005023	-5.624	***	-0.022127	0.006350	-3.484	***
Conservation	-0.013490	0.007598	-1.776	.	0.005382	0.003923	1.372		0.006500	0.007241	0.898	
Cemetery	0.006808	0.005928	1.148		0.001067	0.007553	0.141		0.007757	0.015318	0.506	
Park	-0.002613	0.004500	-0.581		-0.009817	0.007986	-1.229		0.000835	0.004770	0.175	
Con_rec_cons	-0.128100	0.219700	-0.583		-0.231150	0.229180	-1.009		-0.471520	0.334140	-1.411	
Con_cem	0.321900	0.173200	1.858	.	0.132150	0.235890	0.560		0.291240	0.212960	1.368	
Canopy	0.016730	0.005375	3.112	**	0.001736	0.005148	0.337		-0.002192	0.007986	-0.275	
Impervious	-0.003341	0.002526	-1.323		-0.005231	0.002364	-2.212	*	0.000978	0.002832	0.345	
Forest	-0.010740	0.004084	-2.631	**	0.004452	0.003698	1.204		0.006836	0.007810	0.875	
H ₂ O	-0.005911	0.021430	-0.276		-0.039734	0.014483	-2.744	**	-0.052660	0.029437	-1.789	.
Grass	0.005776	0.002457	2.351	*	0.003014	0.002455	1.227		0.001933	0.003030	0.638	

p<0.001,

**
p<0.01,

*
p<0.05

n 524 529 515 467
Adj R² 0.2292 0.4817 0.1365 0.0927