Published in final edited form as:

Urban For Urban Green. 2019 May ; 41: 104–107. doi:10.1016/j.ufug.2019.03.011.

Associations between types of greenery along neighborhood roads and weight status in different climates

Wei-Lun Tsai[1], **Amy J.S. Davis**[2], and **Laura E. Jackson**[3,*]

[1]Oak Ridge Institute for Science and Education (ORISE) participant at the Office of Research and Development, U.S. Environmental Protection Agency, Research Triangle Park, NC, USA

[2]Department of Biology, Ghent University, Ghent, Belgium

[3]Office of Research and Development, U.S. Environmental Protection Agency, Research Triangle Park, NC, USA

Abstract

Obesity is a major international health concern. Neighborhood greenery has been identified as a critical factor for promoting health in urban areas, due in part to its apparent role in facilitating healthy weight by promoting physical activity. However, studies have used diverse greenery measures and spatial analysis units to ascertain this relationship. This study examined associations between street greenery and weight status at the residential address level across 500 to 2000m buffers in two climatically distinct communities, Phoenix, AZ, and Portland, OR. Greenery was measured using one-meter landcover data. Street greenery measures were designed to quantify the pedestrian environment along a gradient of suitability for promoting physical exercise. Weight status was defined by body mass index (BMI) calculated from weight and height information on driver's license records. BMI values were dichotomized at 25 into overweight or obese vs. neither. Approximately 500,000 BMI values in Phoenix and 225,000 in Portland were modelled by community using logistic regression. Street tree cover was consistently protective for healthy weight status across all buffer sizes after adjusting for potential confounders. Herbaceous street cover showed protective associations in Phoenix but harmful associations in Portland. Every 10% increase in street tree cover within 2000m was associated with 18% lower odds of being overweight or obese (adjusted odds ratio [AOR]: 0.82, 95% CI: 0.81 – 0.84 in Phoenix; 0.82, 95% CI: 0.81 – 0.83 in Portland). When compared to residents with less than 10% street tree cover within 2000m, those with greater than 10% tree cover had at least 13% (AOR for Portland: 0.87, 95% CI: 0.81 – 0.92) lower odds of being overweight or obese. Findings support the importance of urban street trees in very different climates for facilitating healthy weight status. They can inform greenery management to prioritize vegetation type and allocation decisions in limited urban spaces.

[*]Corresponding Author: jackson.laura@epa.gov, Phone: +1 (919) 541-3088.

CRediT authorship contribution statement

Wei-Lun Tsai: Formal analysis, Investigation, Methodology, Validation, Visualization, Writing - original draft. **Amy J.S. Davis:** Methodology, Writing - review & editing. **Laura E. Jackson:** Data curation, Funding acquisition, Investigation, Project administration, Resources, Software, Supervision, Writing - review & editing.

Keywords

Street greenery; Obesity; Eco-health; Urban green space; EnviroAtlas

1. Introduction

Global prevalence of obesity has almost tripled during the past four decades, becoming a major public health concern (WHO, 2017). In the United States, a recent estimate from 2015 – 2016 indicates that nearly 40% of the adult population aged 20 or over is obese (Hales et al., 2017). Obesity is a major risk for many non-communicable diseases, including cardiovascular diseases, stroke, diabetes, cancers, and asthma, as well as mental disorders (Beuther and Sutherland, 2007; Luppino et al., 2010; WHO, 2017). It is also ranked as the sixth cause of disability-adjusted life years worldwide (Ford et al., 2017). The prevalence of obesity is an enormous burden of healthcare expenditure for governments, health agencies, and individuals. Obesity prevention remains a great challenge for health practitioners, researchers, and policy makers.

A growing body of research recognizes that obesity prevalence is driven in part by societal and environmental factors (Ellaway et al., 2005; Ford et al., 2017; Frank et al., 2004; Mackenbach et al., 2014). Urban design features may contribute to a more obesogenic environment by limiting opportunities for physical activity (Lake and Townshend, 2006; Mackenbach et al., 2014). Greenery in urban areas has been identified as a critical factor for promoting human health, including facilitating healthy weight status (James et al., 2015; Lachowycz and Jones, 2011). This effect may be achieved through a broad range of ecosystem services (James et al., 2015; Maas et al., 2006; Tzoulas et al., 2007). Although associations between urban greenery and weight status are not always consistent, particularly by gender and also due to the use of different greenery definitions and measures (e.g., Cummins and Fagg, 2012; Prince et al., 2012), it remains conceivable that accessible greenery facilitates healthy weight status.

Taking advantage of remote sensing data, researchers commonly use amount of vegetative cover (e.g., percent tree or greenspace, tree density, or greenspace per capita) as a greenery measure in health studies. Lower body mass index (BMI) or the odds of normal weight have been associated with higher percentages of residential greenspace (Ellaway et al., 2005; Schalkwijk et al., 2017; Villeneuve et al., 2018) and neighborhoods with higher tree or greenspace density (Lovasi et al., 2012). Also based on remote sensing data, in this case how vegetation differentially reflects light wavelengths, the Normalized Difference Vegetation Index (NDVI) is frequently used as a measure of overall greenery. NDVI ranges from −1.0 to 1.0, where a lower positive value (<0.2) or a negative value usually represents abiotic materials (water, soil, rock) and a higher value (>0.3) represents vegetation cover. Studies have reported that urban residents in areas with higher NDVI values tended to have healthy weight status (Bell et al., 2008; Dadvand et al., 2014; Klompmaker et al., 2018; Sarkar, 2017). Proximity to parks or natural areas has also been used as a greenery measure in many studies. Living closer or within certain distances to parks or natural areas was found to associate with lower risk of being overweight or obese (Coombes et al., 2010; Dadvand, 2014; Halonen et al., 2014; Klompmaker et al., 2018; Rundle et al., 2009). Other forms of greenery measures used to explore links with weight status include number of green areas (Potestio et al., 2009), park size and cleanliness (Rundle et al., 2013; Stark et al., 2014), total area of parkland (Wolch et al., 2011), park quality (Hobbs et al., 2017), and presence of other environmental and natural amenities (Ghimire et al., 2017). While findings are not entirely consistent, the majority of studies have reported positive associations between higher greenery and greater odds of having healthy weight status.

Different vegetation classes may provide different levels and types of ecosystem services. Some studies have found that trees alleviate thermal discomfort during daytime more than grass (Kim et al., 2018; Shashua-Bar et al., 2011). Certainly grass, shrubs, and other low cover do not provide pedestrian shade, although they may otherwise enhance or even provide a venue for activities. It is possible that multiple vegetation classes may not have the same effects on health outcomes. Beyond a growing understanding of how urban greenery in general may benefit human health, several studies further examine the effects of specific vegetation classes and their distributions on health outcomes. A study that examined the effects of trees and grass both alone and combined on mental health reported that percent tree cover was associated with fewer days of mental health complaints but aggregated vegetative cover was not (Akpinar et al., 2016). Similarly, Reid et al. (2017) found a 23% increase in reporting very good or excellent health status for subjects residing in the highest quartile of tree density but not grass density. Another study examined the relationships between ten land cover classes and general health across Great Britain; their findings included that only broadleaf trees and managed herbaceous cover (e.g., for recreation and amenity purposes) were associated with better general health (Wheeler et al., 2015).

In addition to class of vegetative cover, distribution may also be an important factor in health outcomes. An ecological study examined the effects of landcover pattern on BMI at the county level (Tsai et al., 2016). Findings suggested that more edges between forest cover and developed area (indicating potential access to the forest) were positively associated with being of normal weight, but edge characteristics of other vegetation were not significantly associated with weight status. In addition, many studies indicated that road-based network buffers reflect the spatial extent of an individual’s activity area more precisely than simple radial (Euclidean) buffers (Boruff et al., 2012; James et al., 2014; Oliver et al., 2007) when examining the relationships between neighborhood environments and health outcomes at the individual level. Furthermore, studies on the built environment report that the street network is a critical factor for active living (Ewing and Cervero, 2010; Grasser et al., 2013; Troped et al., 2014). These studies suggest that certain classes and patterns of urban greenery contribute more to health than others.

Based on previous studies (Coombes et al., 2010; Dadvand et al., 2014; Halonen et al., 2014; Klompmaker et al., 2018; Rundle et al., 2009), we hypothesized that accessible urban greenery is positively associated with odds of healthy weight status. As demonstrated by others (Akpinar et al., 2016; Reid et al., 2017; Tsai et al., 2016; Wheeler et al., 2015), different classes of urban greenery may not have the same effects on weight status. We sought to better understand which classes of urban greenery, either individual or aggregated, are associated with healthy weight status and if the effects are similar in different climatic conditions. In addition to the class and distribution of greenery, we also sought to measure urban greenery using fine-resolution landcover data. While commonly used due to greater availability, coarse-resolution landcover data (e.g., 30m resolution or below from satellite imagery) do not capture many small but potentially critical patches of greenery (e.g., street trees, small lawns) within the built environment. Finally, we sought to test previously-documented relationships by analyzing data from large numbers of participants.

2. Methods

2.1 Data collection

Driver's license databases in the United States are a source to obtain large sample sizes to address public health issues (Walsh et al., 2011). Although the data on driver's licenses vary across states, records in many states include information (height and weight) necessary for weight status calculation, demographic information (date of birth and gender), and information (residential address) to identify the home environment at the individual level. Although access to driver's licenses is restricted by the 1994 Federal Driver's Privacy Protection Act as well as state laws and regulations (Littenberg and Lubetkin, 2016), there are fourteen categories for permissible use. Category 5 applies to research purposes:

> *Category 5: For use in research activities, and for use in producing statistical reports, so long as the personal information is not published, re-disclosed, or used to contact individuals.* (U.S. Government of Publishing Office, 2011)

Though height and weight information in driver's license databases is mostly self-reported, much supportive evidence behind the positive associations between urban greenery and healthy weight status is based on self-reported variables (Akpinar, 2017; Astell-Burt, 2014; Coombes et al., 2010; Ellaway et al., 2005; Ghimire et al., 2017; Nielsen and Hansen, 2007; Pereira et al., 2013; West et al., 2012). Despite the tendency for males to over-estimate height and females to under-estimate weight (Connor Gorber et al., 2007), many studies have found that driver's license data were a reliable source of height and weight information for BMI calculation (Brown et al., 2009; Fan et al., 2014; Littenberg et al., 2015; Ossiander et al., 2004). In addition, one study found that self-reported and measured weight categories had more than an 85% matching rate in North America (Krul et al., 2010). Therefore, driver's license databases offer great potential for understanding the relationships between weight status and environments at the individual level.

An initial data request was mailed in January, 2017. Data request letters were sent to the relevant agencies for driver's license records in fifteen states and the District of Columbia, where the U.S. Environmental Protection Agency's EnviroAtlas project (EnviroAtlas hereafter, https://www.epa.gov/enviroatlas/) featured communities are located (Supplemental Figure 1). The geographic areas requested were counties within or intersecting EnviroAtlas community boundaries. Requested information included height, weight, age (date of birth or year of birth), gender, and residential address in years 2009 to 2013; these dates were within five years of those for the fine-resolution landcover data developed for EnviroAtlas communities (Pickard et al., 2015). Responses were received from ten states by the end of February, 2017. Legal documents were examined and negotiated by requesting (Federal) and responding (State) agencies from March to September, 2017. There were irreconcilable differences in the legal terms of data use in four instances; in addition, two state agencies could provide data only for the most current year, and two state agencies either could provide addresses only to zip code or did not release data for research. Therefore, driver's license data were received from only two states, Arizona and Oregon, corresponding to two EnviroAtlas communities, Phoenix, AZ and Portland, OR. These responses resulted in an analysis of two U.S. climatic extremes—the desert Southwest and the forested Northwest. Physical activity around the home in each community may be seasonally constrained due to extreme heat in Phoenix and extreme rain in Portland.

2.2 Study population

The total driver's license records received for the Phoenix, AZ, county (Maricopa) and the Portland, OR, counties (Clackamas, Multnomah and Washington) were 4,394,096 and 1,296,952, respectively. We first assigned a unique ID number to each record. This study included only subjects aged 25 to 55 in year 2011, to exclude potentially recent residents who may have relocated for post-secondary school or retirement. Additionally, subjects residing outside of these two states, with missing information, or without an identifiable physical address (e.g., Tribal chapter house or recreational-vehicle park) were excluded. Remaining addresses were standardized; for instance, "*street*" was standardized to "*st.*" As multiple records in the same location will increase the chances of spatial autocorrelation (Getis, 2010; Lee, 2017; Ripley, 2005), multiple records at the same street address (e.g., house, apartment complex) were detected and only the first (the smallest unique ID number) was selected for inclusion in the analysis. These processes reduced the total records to 1,118,391 for Phoenix and 311,555 for Portland. These records were then geocoded using ESRI ArcGIS 10.4.1 Geocode Addresses function (ESRI ArcGIS Desktop Help 10.4 GeocodingToolbox). Only records within the EnviroAtlas community boundaries, and with a matching score of 100 (maximum score) and a matching status of "M(atched)" were included for this analysis. The total record count after geocoding was 536,332 for Phoenix and 242,357 for Portland.

After finalizing the records through geoprocessing, potential outliers were explored. The determination as to whether an outlier should be removed is important, as the presence of outliers can lead to increased error variance and reduced power of statistical tests (Osborne and Overbay, 2004). Several studies that used self-reported height and weight information as measures or to derive another measure (e.g., body mass index) removed outliers by excluding height, weight, or BMI outside of a certain range. For instance, Littenberg and Lubetkin (2016) defined outliers as height outside of the range of 91.4 to 229 cm, weight outside of the range of 22.7 to 271.7 kg, height equal to weight, and calculated BMI outside of the range of 8 to 100. Some studies removed outliers by excluding height and weight above or below *n*-standard deviation(s) from the mean. For instance, Yang and Hutcheon (2016) defined outliers as 4 standard deviations above or below the conditional mean. Though identifying outliers using height and weight distribution separately is sound, it does not account for their distributions as paired factors. A commonly used multivariate approach for detecting outliers in correlated variables is the Minimum Covariance Determinant (MCD), which is a highly robust estimator of multivariate location and scatter (Rousseeuw and Driessen, 1999). Therefore, the MCD approach was employed in this study to detect outliers by height and weight, using the covMcd function in the R robustbase package (Martin Maechler et al., 2016). In total, 38,902 (7.25%) and 17,635 (7.28%) outliers (Supplemental Figure 2) were detected for Phoenix and Portland, respectively, resulting in total numbers for analysis of 497,430 and 224,722. These numbers were further adjusted by the availability of covariates and full extents of the walkable road network.

This study was approved by the Institutional Review Board of the University of North Carolina, Chapel Hill (IRB#16–2688) and by Human Subject Research Review through the U.S. Environmental Protection Agency (HSR-000745).

2.3 Weight status

The body mass index (BMI) for each subject was calculated based on the height and weight information in the driver's license record using the equation:

$$Body\ Mass\ Index = 703 * Weight\ (lb)/Height\ (in)^2$$

Weight status was then classified as underweight (< 18.5), normal weight (18.5 – 24.9), overweight (25 – 29.9), or obese (>=30) (CDC, 2018). As the underweight population was very small, weight status was further dichotomized into “Neither overweight nor obese” (underweight and normal weight) as the referent group and “Overweight or obese” for analysis.

2.4 Greenery measures

EnviroAtlas provides Meter-scale Urban Land Cover (MULC) data for featured communities; the U.S. Environmental Agency (EPA) develops the MULC in-house or processes MULC developed by others for consistent classification. The landcover map for Phoenix was developed by Arizona State University as part of the National Science Foundation's urban Long-term Ecological Research site; the Portland MULC was developed by EPA. Both were classified based on USDA National Agriculture Imagery Program data for the years 2010 and 2012, respectively, and supplemental information including Light Detection and Ranging (LiDAR) data. The classes of the EnviroAtlas MULC include tree and forest (tree hereafter), grass and herbaceous (herbaceous hereafter), shrub, woody wetland, emergent wetland, impervious surface, water, soil and barren, agriculture, and orchard where applicable. The amount of shrub cover in most of the EnviroAtlas communities (but not Phoenix) is combined into tree cover if >2m or included in herbaceous cover if shorter. The overall accuracies for the MULC datasets are 75.4% for Phoenix (EPA, 2010) and 91.4% for Portland (EPA, 2012). Lower accuracy in Phoenix is due largely to the common difficulty in distinguishing impervious cover from soil/barren cover in desert environments.

Greenery measures were based on an existing EnviroAtlas community metric, Percent Green Space Along Walkable Roads (EPA, 2016b). Here, walkable roads refer to road segments with a speed limit of less than 88 kilometers (55 miles) per hour, and with pedestrian access as attributed in the NavTEQ Street database (Nokia-HERE, 2011). The analysis area for percent greenspace was delineated by creating a 25m analysis zone on each side of the road centerlines. This 50-m catchment area is used to capture potential greenery along sidewalks and visible in front yards (Figure 1). To address our interest in the effects of different classes of greenery on weight status, we extracted from the MULC datasets the total counts for all classes of vegetation along walkable roads. Then we calculated the percentage of each vegetation class by dividing its area by the total area of the 50m analysis zone at the various buffer sizes along walkable roads. Shrub cover in Phoenix was minimal (<2%) along walkable roads, so it was combined with herbaceous cover since it was mostly short. Woody and emergent wetlands were also barely present along walkable roads; they were combined into tree and herbaceous cover, respectively. Percent aggregate greenery was calculated by combining all of the individual classes of vegetation.

Geospatial neighborhood analyses at the individual level typically use radial or network buffers. A radial buffer is created by drawing a circle of a given radius around an individual's address; however, it may not represent the true physically accessible area (James et al., 2014; Oliver et al., 2007). A network buffer is created based on the street network and is considered a better approach to representing the real spatial extent of the physically accessible area (Boruff et al., 2012; Oliver et al., 2007). Therefore, the network buffer was selected to create neighborhood extents in this study. The distance (buffer size) used to define neighborhood extent also varies across studies on greenery and weight status. Buffer sizes used in the past range from 100, 250, and 300m (Dadvand et al., 2014; Klompmaker et al., 2018; Villeneuve et al., 2018), to 1000, 2000, 3000, and 5000m (Astell-Burt, 2014; Bell et al., 2008; Dadvand, 2014; Klompmaker et al., 2018; Liu et al., 2007; Villeneuve et al., 2018; Wilhelmsen et al., 2017). A buffer of 500m is commonly used to define neighborhood extent in studies on greenery and weight status (Dadvand et al., 2014; Klompmaker et al., 2018; Sarkar, 2017; Villeneuve et al., 2018; Wolch et al., 2011). A review on buffer sizes and health outcomes found that relationships between neighborhood greenery and individual physical activity formed an inverse U-shape from 250 to 1999m buffers (Browning and Lee, 2017). Twenty-six percent of the findings were reported to have positive associations between greenery and health outcomes when using buffers less than 250m; 38% were positive when using buffers between 500 – 999m, and 33% were positive when using buffers between 1000 – 1999meters. Neighborhood greenery in this study was therefore generated at four network buffer sizes, 500, 1000, 1500, and 2000m, to examine the relationships between greenery and weight status. Buffer sizes greater than 2000m were considered to exceed common walking distances and thus not examined.

In addition to treating greenery as a continuous measure, we also developed categorical greenery measures to represent four levels of greenery. Categorical greenery may yield a potential dose of greenery for promoting healthy weight status. It is always challenging to determine threshold values to classify greenery levels. Percentile breaks (e.g., tertile, quartile, and quintile) are commonly used in health studies (Almanza et al., 2012; Dadvand, 2014; Lovasi et al., 2013; Richardson et al., 2013; Villeneuve et al., 2018). Though this approach ensures that the numbers of observations are equally distributed in each category, outliers may unduly influence threshold values and result in large variances within lower and upper categories. Alternatively, K-means clustering splits observations into a given number of groups by finding the breaks that minimize the within-group and maximize the between-group variance (Kriegel et al., 2017; Madhulatha, 2012). Therefore, K-means clustering was used in this study to categorize vegetation values into four levels for each buffer size.

As climatic conditions in these two communities are distinct, great differences in break values of greenery levels were expected. Under our methods, any potential threshold amount of greenery for protective effects on healthy weight status across climates would be unknown. Therefore, we also applied a range of fixed greenery thresholds from 10% to 20% to both communities to explore any general greenery threshold effects on weight status.

2.5 Confounding factors

We acquired the best available data for potential confounding factors including age, gender, density of built infrastructure, and park proximity (individual level), and income and race (census block group level). Age and gender were obtained from the driver's license datasets for each participant. Age was calculated by subtracting the four digits of an individual's birth year from 2011 (age at year 2011). Age was categorized into 6 groups by an interval of 5 years with an exception of 6 years in the last group (i.e., 25 – 29, 30 −34, 35 – 39, 40 – 44, 45 – 49, and 50 – 55). Income and race were represented at the census block group (CBG) level by Percent Household below the Adjusted Threshold for Quality of Life (QOL index) (EPA, 2017) and Percent Population that is not "white non-Hispanic" (EPA, 2013; EPA, 2015 for Phoenix and Portland, respectively).

Quality of life is indicated by meeting or exceeding a threshold value for annual household income, which is an estimated minimum required for healthy emotional well-being. Kahneman and Deaton (2010) conducted an analysis on household income and its relation to life evaluation and emotional well-being with a sample size of 450,000 U.S. residents. The authors reported that life evaluation and emotional well-being increased steadily with annual household income up to $75,000, with no further increase in emotional well-being beyond that amount. However, cost of living varies significantly across the United States (Short, 2016); therefore, the threshold of $75,000 for quality of life must be adjusted by locality. The EnviroAtlas QOL index was created based on U.S. Census Table B19001: Household Income In The Past 12 Months (In 2012 Inflation-Adjusted Dollars), and the cost of living index at the county level developed by the Council for Community and Economic Research (C2ER). The adjusted threshold for quality of life was calculated as $75,000 * county-level cost of living index. Then the QOL index value for each CBG was generated using the number of households below the adjusted QOL threshold, divided by the total number of households. Percent other than White, non-Hispanic population per CBG was calculated based on the 2010 U.S. Census Table P0050002: Not Hispanic or Latino. The variable was created using the number of individuals other than White, non-Hispanic, divided by the total population. Both variables were categorized into quartiles for analysis.

The EnviroAtlas metrics, Estimated Walking Distance to a Park Entrance (EPA, 2016c) and Estimated Intersection Density of Walkable Roads (EPA, 2016a), were used to indicate park proximity and the density of built infrastructure at the individual level.

Nearby parks may represent a discrete pathway for physical activity, and investment in neighborhood parks may lead to more greenery along streets. Therefore, park proximity was considered as a confounding factor to distinguish the effects of street greenery. Estimated walking distance to a park entrance was created by the EnviroAtlas program based on two layers – park entrances and the walkable road network. Park information was obtained from multiple sources including PADUS (Protected Areas Database of the United States, USGS, 2016) and county and municipal parks and recreation departments; park entrances were identified based on available local information and Google maps. The walkable road network was based on the NavTEQ Street database (Nokia-HERE, 2011). Walking distance to the nearest park entrance was then calculated at 10m resolution from every point along the roads using the Cost Distance function, and then interpolated for an extended 5km border beyond the EnviroAtlas community boundary using the Natural Neighbor function (ESRI ArcGIS Desktop Help 10.4 Spatial Analyst Toolbox). The nearest distance to a park entrance was classified into 9 categories: ≤250, 250 – 500, 500 – 750, 750 – 1000, 1000 – 2000, 2000 – 3000, 3000 – 4000, 4000 – 5000, and ≥5000meters. This study combined the categories greater than 2000 into one category, ≥2000m, resulting in six categories of estimated walking distance to a park entrance for this analysis. Data values for participants were identified by their residential addresses.

Estimated intersection density of walkable roads was interpolated across each community at 10m resolution using the NavTEQ roads data and the Kernel Density function (ESRI ArcGIS Desktop Help 10.4 Spatial Analyst Toolbox). Multiple moving-window analysis areas were set to correspond to the network buffer sizes (i.e., 500, 1000, 1500, and 2000m). Intersection density values for each buffer size were extracted for each residential address and categorized by quartile.

2.6 Statistical analysis

Moran's I was calculated using residuals from the models for all buffer sizes. Moran's I ranges from −1 (spatially dispersed) to +1 (spatially clustered), with a value of zero indicating spatially random distribution. The respective observed value of Moran's I at 500, 1000, 1500, and 2000m was 0.0151, 0.0149, 0.0148, and 0.0148 in Phoenix, and 0.017, 0.0152, 0.0143, and 0.0137 in Portland. The results indicated that spatial autocorrelations were weak in both communities. Therefore, spatial autocorrelation was not considered in the models in this study.

Logistic regression was applied to examine associations between weight status and neighborhood greenery at the four buffer sizes, controlling for the aforementioned confounding factors. Potential multicollinearity was tested by the generalized variance inflation factor (GVIF). Variables with a GVIF value greater than two would be removed. Effect modification by each confounding factor was examined by multiplicative terms. Any significant interaction was considered if the model was significantly improved by 10 percent, as evaluated by McFadden's pseudo R-squared (McFadden, 1973). We conducted sensitivity analyses to investigate the effect of using overlapping vs non-overlapping buffers sizes, and using the QOL index vs. the Census income variable, Percent Population with Income below Twice the Poverty Level. No significant differences were detected (Supplemental – Sensitivity analysis)

EPA Author Manuscript

EPA Author Manuscript

3. Results

3.1 Descriptive statistics for the study population

The study population in both Phoenix and Portland was aged 25 to 55, with a mean age of approximately 39, and evenly split between females and males (Table 1). According to self-reported height and weight, about half of the population was overweight or obese (53% in Phoenix and 49% in Portland). In Phoenix, 58% of the population resided in census block groups with average annual household incomes below the Adjusted Threshold for Quality of Life. This figure was slightly higher in Portland (59%). Percent non-White population by block group in Phoenix and Portland was 39% and 26%, respectively. The closest park entrance along walkable roads for 29% of the Phoenix study population was between 1 and 2 kilometers, but around 70% of the Portland study population resided within 750m of a walkable park entrance. Mean values of Estimated Intersection Density of Walkable Roads showed that Portland also had better street connectivity than Phoenix across all the buffer sizes. Values for this metric decreased with increasing buffer sizes, from 66 to 52 and from 70 to 59 per square kilometer as buffers increased from 500 to 2000m in Phoenix and Portland, respectively.

3.2 Greenery measures

From the Meter-scale Urban Land Cover data, the percent tree and herbaceous cover along walkable roads in Phoenix was 8.5% and 6.9%, respectively. In Portland, the values for tree and herbaceous cover were much higher (20.9% and 28.8%, respectively) (Figure 2). Mean tree cover along walkable roads across all buffer sizes was around 9% in Phoenix and 20% in Portland (Table 2). Mean herbaceous cover across all buffer sizes in Portland (around 25%) was four times more than the average amount in Phoenix (around 6%). The range of values for both tree and herbaceous cover in Phoenix substantially declined with increasing distance from home (e.g., upper range of tree cover was 54.8% at 500m and 30.6% at 2000m), whereas the range of values for both cover types showed only a small decline with increasing buffer size in Portland (e.g., upper range of tree cover was 99.9% at 500m and 90.1% at 2000m).

For the four-level categorical greenery measures determined by K-means clustering, the first break values for tree cover along walkable roads were 5.5 to 5.8% across all the buffers in Phoenix, and 15 to 17% in Portland (Table 2). The first break values for herbaceous cover were around 5% in Phoenix and 20% in Portland. For aggregate greenery, the first break values were 11% in Phoenix and 40% in Portland.

3.3 Relationships between urban greenery and weight status

None of the independent variables in the models had a GVIF greater than two, after controlling for confounding factors; therefore, none of these variables was removed. The adjusted odds ratios (AORs) using continuous greenery measures along walkable roads showed that every 10% increase in tree cover across all buffer sizes in both communities was significantly associated with at least 11% lower odds of being overweight or obese (Table 3). In addition, the relationships were stronger with increasing buffer sizes. For instance, every 10% increase in tree cover at 500, 1000, 1500, and 2000m in Portland was associated with

11% (AOR=0.89, 95% CI: 0.88–0.9), 14% (AOR=0.86, 95% CI: 0.85–0.87), 16% (AOR=0.84, 95% CI: 0.82–0.85), and 18% (AOR=0.82, 95% CI: 0.81–0.83) lower odds of being overweight or obese. For herbaceous cover, a 10% increase across buffer sizes in Phoenix was associated with lower odds of being overweight or obese (e.g., AOR at 500m = 0.83, 95% CI: 0.81 – 0.84). However, the same increment in Portland was associated with higher odds of being overweight or obese (e.g., AOR at 500m = 1.16, 95% CI: 1.15 – 1.18). The effect of aggregate greenery in Phoenix was weaker than either tree or herbaceous cover alone at all buffer sizes, while the effect in Portland was between those of tree and herbaceous cover.

According to models using the categorical greenery measures, living in Phoenix with at least 5.7% tree cover (reference threshold) along walkable roads within a 500m network buffer was associated with at least 5% lower odds of being overweight or obese; AORs were lower with greater tree cover (AOR at 500m = 0.95, 95% CI: 0.94 – 0.97; 0.87, 95% CI: 0.85 – 0.88; and 0.78, 95% CI: 0.77 – 0.8 for tree cover Levels II, III, and IV). The effects were similar across all buffer sizes (Table 3). Living in Portland with at least 15.1% tree cover (reference threshold) within 500m from home was associated with at least 7% lower odds of being overweight or obese. As in Phoenix, stronger effects were observed with increasing tree cover (AOR at 500m = 0.93, 95% CI: 0.91 – 0.95; 0.80, 95% CI: 0.78 – 0.82; and 0.65, 95% CI: 0.62 – 0.68 for tree cover Level II, III, and IV). The effects at different levels of tree cover were similar across all buffer sizes when using categorical measures.

In Phoenix, compared to residents with less than 4.8% herbaceous cover (referent) within 500m, greater herbaceous cover was associated with at least 6% lower odds of being overweight or obese (AOR at 500m = 0.94, 95% CI: 0.93 – 0.96; 0.87, 95% CI: 0.86 – 0.89; and 0.80, 95% CI: 0.77 – 0.82 for herbaceous cover Levels II, II, and IV), with similar effects across all buffer sizes. In Portland, compared to those with less than 20.4% herbaceous cover (referent) within 500m, greater herbaceous cover was associated with at least 12% higher odds of being overweight or obese (AOR at 500m = 1.12, 95% CI: 1.09 – 1.15; 1.25, 95% CI: 1.22 – 1.28; and 1.36, 95% CI: 1.30 – 1.42 for herbaceous cover Levels II, III, and IV); these effects were also similar across all buffer sizes.

In Phoenix, compared to those with less than 10.68% aggregate greenery (referent), participants with greater aggregate greenery were associated with at least 3% lower odds of being overweight or obese (AOR at 500m = 0.97, 95% CI: 0.95 – 0.98; 0.84, 95% CI: 0.83 – 0.86; and 0.75, 95% CI: 0.73 – 0.76 for aggregate greenery Levels II, III, and IV). The effects were similar across all buffer sizes. However, the effects of aggregate greenery were not protective for 500m buffers in Portland (AOR=1.03, 95% CI: 1.01 – 1.05). Aggregate greenery starting at approximately 49% was associated in Portland with at least 6% lower odds of being overweight or obese when comparing to those with less than 39.2% aggregate greenery (referent) (AOR at 500m = 0.94, 95% CI: 0.91 – 0.96 and 0.78, 95% CI: 0.74 – 0.81; at 1000m = 0.87, 95% CI: 0.85 – 0.90 and 0.72, 95% CI: 0.69 – 0.46; at 1500m = 0.85, 95% CI: 0.83 – 0.88 and 0.70, 95% CI: 0.66 – 0.74; and at 2000m = 0.85, 95% CI: 0.82 – 0.87 and 0.70, 95% CI: 0.67 – 0.74 for Levels III and IV of aggregate greenery, respectively). Most of the effect modifications by confounding factors changed model performance by less than 1%; therefore, none of the effect modification terms was included in the final model (Supplemental Table 1).

Lower and higher levels of greenery determined by a range of fixed thresholds from 10 to 20 percent were applied only to tree cover in both communities, as herbaceous cover showed divergent effects on weight status. In general, adjusted odds ratios of being overweight or obese dropped by similar amounts in both communities at the same fixed thresholds (Figure 3). In Phoenix, people with higher levels of street tree cover had lower odds with increasing value of the fixed threshold. In Portland, the consistency of having lower odds with increasing threshold was observed only at the 500m buffer. At the other buffer sizes, this trend was detected only between 10 to 12% and 17 to 20 percent.

4. Discussion

Much evidence supports greenery benefits to human health through a broad range of ecosystem services (James et al., 2015; Maas et al., 2006; Tzoulas et al., 2007). Questions about whether different classes, extents, and distributions of greenery have varying effects on human health outcomes are still under-explored. This study addressed these research gaps by examining effects of greenery at the individual level for more than 700,000 participants, using a gradient of extents from 500 to 2000m residential buffers and fine-resolution land cover data. In addition, the distribution of greenery was defined as only that along walkable roads, where people have continuous physical access.

4.1 Greenery class and weight status

Tree cover along walkable roads was consistently inversely associated with odds of being overweight or obese in both Phoenix AZ, and Portland OR, across four residential buffer extents from 500m to 2000 meters. Effects were slightly stronger with increasing buffer size in both communities and similar or identical between communities.

Models using categorical tree cover values also showed protective effects that were stronger with increasing buffer size. The lowest tree-cover threshold for which we observed a protective effect on odds of being overweight or obese was around 6% for Phoenix and 16% for Portland. This difference in the lower threshold values likely reflects the large climatic difference between the two study communities. Findings suggest that even very low levels of street tree cover in an arid community may make a significant difference in facilitating physical activity.

Nevertheless, an increasing magnitude of effect was observed in Phoenix at increasing tree-cover thresholds that were fixed at 10 to 20 percent. In Portland, the trend was not smooth, but the odds at all buffer sizes decreased at least 5% from the 10 to the 20% threshold. Within the parameters of this study, increasing tree cover, even by relatively small amounts, up to 2000m from homes along walkable roads is linked to reduced odds of being overweight or obese. More tree cover and longer extents are associated with lower odds. This observation holds in two U.S. climatic extremes.

Modelled relationships between herbaceous cover and odds of overweight/obesity were in opposing directions for Phoenix (protective) and Portland (harmful). These results suggest that herbaceous vegetation may provide different ecosystem services in different climates. In a study on aesthetic preferences for street-tree density (Jiang et al., 2015), amount of herbaceous cover had no effect on preference across four U.S. midwestern cities in temperate climate zones. With abundant tree cover in Portland, increasing herbaceous cover may likewise not increase aesthetic appeal, but instead signify larger parcels and longer distances between destinations. In Phoenix, with little greenery overall, it is possible that both herbaceous and tree cover provide aesthetic appeal to promote outdoor physical activity. Additionally, a review of greenery effects on temperature reduction indicated that, although trees generally produced better cooling effects than short vegetation, grass still had significantly lower surface temperatures than impervious cover (Bowler et al., 2010). It is possible that the heat reduction provided by herbaceous cover in an arid climate is relatively greater and more noticeable when compared to a temperate forested climate.

Due to limitations in available landcover data, many studies have treated multiple vegetation types as aggregate greenery, or overall greenness, to examine its relationships with human health outcomes. Our findings from highly-resolved landcover data showed distinctions among the effects of tree cover, herbaceous cover, and aggregate greenery along walkable roads, particularly in Portland. There, the effects of aggregate greenery reflected the opposing effects of the discrete vegetation classes. The results were consistent for both continuous and categorical greenery values. In Phoenix, the protective effects of herbaceous cover were similar to those of trees. These findings provide direction on which class(es) of vegetation may be most effective to reduce the odds of being overweight or obese in the two study communities.

4.2 Neighborhood extent of greenery and weight status

Many studies have reported beneficial associations between healthy weight status and greenery within 500m from home (Dadvand et al., 2014; Klompmaker et al., 2018; Sarkar, 2017; Villeneuve et al., 2018; Wolch et al., 2011). A review of buffer distances in greenery-health studies recommended larger, non-overlapping buffer sizes (e.g., 1000 – 2000m) to examine relationships with physical activity-related health outcomes (Browning and Lee, 2017). In this study, similar effects on weight status were observed across 500 to 2000m residential network buffers in each community. The effects from using overlapping versus non-overlapping buffers were also similar (Supplemental – Sensitivity Analysis), suggesting that the potential influence of greenery on behavior is continuous at increasing distances from home, rather than discrete. One implication is that greenery, especially tree cover, along walkable roads may encourage people to extend their home-based physical activity range.

4.3 Limitations and implications

Several limitations must be acknowledged in this study. First, this is an observational, cross-sectional analysis, so casual inference cannot be drawn from our findings. Second, we were able to obtain data from only two communities, which were distinct in many aspects including climate. Human perceptions of vegetation may differ across climate gradients, resulting in differential utilization and value. This issue is beyond the scope of our analysis. Third, self-selection may influence the streetscapes in which people choose to live.

We did not have data on individual physical activity levels or locations. We assumed physical activity around the home, but did not consider the workplace as these locations were unknown. We also did not have individual-level information on income or race. Therefore, variations in these factors below the block-group level have been generalized and results may have been affected by the ecological fallacy whereby mean attributes of a group are incorrectly ascribed to individuals (Blakely and Woodward, 2000). However, in delineating block groups, the U.S. Census Bureau strives to maximize within-group homogeneity and between-group heterogeneity (U.S. Census Bureau, 1994).

In addition, data on length of residency were not available; however, potentially recent arrivals (college students and retirees) were removed by narrowing the age group from 25 to 55 years old. Data were also unavailable on environmental stressors such as air pollution and crime rate, and on infrastructure such as greenways and bike routes, all of which can modify relationships between greenery and health outcomes.

The removal of records without complete street addresses may have resulted in exclusion bias, particularly for residents in rural and Tribal lands where location information other than a street address is listed on driver's licenses. Findings from this study are likely not applicable to areas beyond the urban/suburban landscape. There may also be exclusion bias associated with the removal of one or more records per street address, as different exclusion criteria may result in divergent samples. However, by limiting the number of records to one per address, we decreased the amount of spatial autocorrelation in our data resulting from duplicate information to non-statistically significant levels, and thus avoided an inflated Type I error rate (Griffith, 2005).

Finally, only logistic regression was employed to examine the relationships between dichotomous weight status and street greenery in both continuous and categorical forms. Other statistical approaches (e.g., spline and loess models) could be tested to explore potential non-linearities in these relationships throughout the street greenery continuum.

Despite several limitations of this analysis, driver's license records provided us with a large study population that included most households. The greenery measures were based on high-resolution and finely-classified landcover data. The measures were designed specifically to capture potential ecosystem services (e.g., shade, cooling effect, and aesthetics) that promote physical activity in publicly accessible areas. In addition, greenery measures included not only individual vegetative classes but also aggregate vegetation. The neighborhood extents cover a range of distances for localized physical activities, including a short walk (within 500m), run, or bike ride (1 to 2km). The results are drawn from large populations, providing strong statistical power. Findings from this study support the importance of urban street greenery, even in very different climates, for health and well-being. They can help guide urban greenery management to prioritize vegetation class and allocation decisions in limited urban spaces.

5. Conclusion

The recognition of nature as a viable means for promoting human health and well-being has been rapidly growing (e.g., Natural England, 2010; Van den Bosch et al., 2016; WHO Regional Office for Europe, 2016a, b). It is important to understand which types of nature interaction may link to specific health outcomes. For instance, neighborhood greenery within a small buffer around the home, school, or workplace may be important for mental health, since visual contact with nature has been linked repeatedly with mental well-being (Brown et al., 2013; Kaplan, 2001; Ulrich, 1984) sometimes by mediating neighbor interaction (Kuo et al., 1998). Numerous studies also report beneficial effects of highly localized greenery (e.g., window views) on academic performance (Matsuoka 2010; Benfield et al., 2015; Donovan et al., 2018). Larger buffers targeting physically accessible areas capture nature that may influence physical activity-related health outcomes. Findings from this study suggest that different classes of greenery can have varying associations with the same fitness measure, and the results may differ by climate. More trees along walkable roads were consistently associated with lower odds of overweight/obesity across smaller (less than or equal to 1 km) and larger (greater than 1 km) neighborhood extents. Further research should consider extending analyses across additional climatic conditions to test variation in effects of greenery by class and allocation on health outcomes. Longitudinal studies, such as interventions and before versus after relocations, would address causal relationships between greenery and human health.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgements

We would like to express our gratitude to states that offered tremendous assistance in our data requests, with special thanks to the Oregon State Department of Transportation's Driver and Motor Vehicle Services, the Arizona State Department of Transportation Research Center, the Washington State Department of Licensing, the Indiana Bureau of Motor Vehicles, and the Iowa Department of Transportation's Office of Driver Services. We would like to thank the Office of General Counsel at the U.S. Environmental Protection Agency for ensuring the legal use of state data, and the chief of the Epidemiology Branch, Dr. Timothy Wade, for his support in data requests. We also appreciate our internal reviewer, Dr. Kim Lichtveld, for her time in providing us with valuable comments. We are grateful to the EnviroAtlas Meter-scale Urban Land Cover team, led by Dr. Andrew Pilant, for creating the high-accuracy land cover data. Finally, we thank former EnviroAtlas team members: Ms. Alexandra Sears, Ms. Leah Yngve, and Dr. Yan Jiang, who carefully designed and created geospatial metrics for fostering research on the role of urban ecosystem services in public health.

Drs. Tsai and Davis were funded through interagency agreement DW-89-92429801 between the U.S. Environmental Protection Agency and the U.S. Department of Energy. This paper has been reviewed by the National Health and Environmental Effects Research Laboratory, U.S. Environmental Protection Agency, and approved for publication. Approval does not signify that the contents reflect the views and policies of the Agency, nor does the mention of trade names of commercial products constitute endorsement or recommendation for use.

References

Akpinar A, 2017 Urban green spaces for children: A cross-sectional study of associations with distance, physical activity, screen time, general health, and overweight. Urban For. Urban Gree 25, 66–73.

Akpinar A, Barbosa-Leiker C, Brooks KR, 2016 Does green space matter? Exploring relationships between green space type and health indicators. Urban For. Urban Gree 20, 407–418.

Almanza E, Jerrett M, Dunto G, 2012 A study of community design, greenness, and physical activity in children using satellite, GPS and accelerometer data. Health Place 18, 46–54. [PubMed: 22243906]

Astell-Burt, 2014 Greener neighborhoods, slimmer people? Evidence from 246,920 Australians". Int. J. Obes. (Lond.).

Bell JF, Wilson JS, Liu GC, 2008 Neighborhood greenness and 2-year changes in body mass index of children and youth. Am. J. Prev. Med 35, 547–553. [PubMed: 19000844]

Benfield JA, Rainbolt GN, Bell PA, Donovan GH, 2015 Classrooms With Nature Views: Evidence of Differing Student Perceptions and Behaviors. Environ. Behav 47, 140–157.

Beuther DA, Sutherland ER, 2007 Overweight, Obesity, and Incident Asthma. Am. J. Respir. Crit. Care Med 175, 661–666. [PubMed: 17234901]

Blakely TA, Woodward AJ, 2000 Ecological effects in multi-level studies. Journal of Epidemiology and Community Health 54, 367–374. [PubMed: 10814658]

Boruff BJ, Nathan A, Nijenstein S, 2012 Using GPS technology to (re)-examine operational definitions of 'neighbourhood' in place-based health research. Int J Health Geogr 11, 22. [PubMed: 22738807]

Bowler DE, Buyung-Ali L, Knight TM, Pullin AS, 2010 Urban greening to cool towns and cities: A systematic review of the empirical evidence. Landsc. Urban Plan 97, 147–155.

Brown BB, Yamada I, Smith KR, Zick CD, Kowaleski-Jones L, Fan JX, 2009 Mixed land use and walkability: Variations in land use measures and relationships with BMI, overweight, and obesity. Health Place 15, 1130–1141. [PubMed: 19632875]

Brown DK, Barton JL, Gladwell VF, 2013 Viewing Nature Scenes Positively Affects Recovery of Autonomic Function Following Acute-Mental Stress. Environ. Sci. Technol 47, 5562–5569. [PubMed: 23590163]

Browning M, Lee K, 2017 Within What Distance Does "Greenness" Best Predict Physical Health? A Systematic Review of Articles with GIS Buffer Analyses across the Lifespan. Int. J. Env. Res. Public Health 14, 675.

C2ER, Products & Services: Cost of Living Index, https://www.c2er.org/products/. The Council for Community and Economic Research.

[CDC] U.S. Centers for Disease Control and Prevention, 2018 About Adult BMI, https://www.cdc.gov/healthyweight/assessing/bmi/adult_bmi/index.html Date Accessed: January 22, 2018.

Connor Gorber S, Tremblay M, Moher D, Gorber B, 2007 A comparison of direct vs. self-report measures for assessing height, weight and body mass index: a systematic review. Obes Rev 8, 307–326. [PubMed: 17578381]

Coombes E, Jones AP, Hillsdon M, 2010 The relationship of physical activity and overweight to objectively measured green space accessibility and use. Social Science & Medicine 70, 816–822. [PubMed: 20060635]

Cummins S, Fagg J, 2012 Does greener mean thinner? Associations between neighbourhood greenspace and weight status among adults in England. Int. J. Obes. (Lond.) 36, 1108–1113. [PubMed: 21986707]

Dadvand P, Villanueva CM, Font-Ribera L, Martinez D, Basagana X, Belmonte J, Vrijheid M, Grazuleviciene R, Kogevinas M, Nieuwenhuijsen MJ, 2014 Risks and benefits of green spaces for children: a cross-sectional study of associations with sedentary behavior, obesity, asthma, and allergy. Environ Health Perspect 122, 1329–1335. [PubMed: 25157960]

Dadvand PV, Cristina M;Font-Ribera Laia;Martinez David;Basagaña Xavier;Belmonte Jordina;Vrijheid Martine;Gražulevičienė Regina;Kogevinas Manolis;Nieuwenhuijsen Mark J., 2014 Risks and Benefits of Green Spaces for Children: A Cross-Sectional Study of Associations with Sedentary Behavior, Obesity, Asthma, and Allergy. Environ Health Persp 122, 1329–1335.

Donovan GH, Michael YL, Gatziolis D, Hoyer RW, 2018 The Relationship Between the Natural Environment and Individual-Level Academic Performance in Portland, Oregon. Environ. Behav, 0013916518796885.

Ellaway A, Macintyre S, Bonnefoy X, 2005 Graffiti, greenery, and obesity in adults: Secondary analysis of european cross sectional survey. British Medical Journal 331, 611–612. [PubMed: 16113034]

EPA Author Manuscript
EPA Author Manuscript

[EPA] U.S. Environmental Protection Agency, 2010 EnviroAtlas - Phoenix, AZ - Meter-Scale Urban Land Cover (MULC) Data. Metadata: https://edg.epa.gov/metadata/rest/document?id=%7BD556044C-FCCC-4E8B-B157-5E7B8587AEE7%7D&xsl=metadata_to_html_full.

[EPA] U.S. Environmental Protection Agency, 2012 EnviroAtlas - Portland, OR - Meter-Scale Urban Land Cover (MULC) Data (2012). Metadata: https://edg.epa.gov/metadata/rest/document?id=%7B65A8193B-0652-4748-AE8E-FD328CCC448D%7D&xsl=metadata_to_html_full.

[EPA] U.S. Environmental Protection Agency, 2013 EnviroAtlas - Phoenix, AZ - Demographics by Block Group. Metadata: https://edg.epa.gov/metadata/rest/document?id=%7BAA13D671-AEEE-4B01-BBC5-5A7B6D64B1A9%7D&xsl=metadata_to_html_full.

[EPA] U.S. Environmental Protection Agency, 2015 EnviroAtlas - Portland, OR - Demographics by Block Group. Metadata: https://edg.epa.gov/metadata/rest/document?id=%7B24158D84-8EE2-4887-B5E6-F3CAFFD76AAA%7D.

[EPA] U.S. Environmental Protection Agency, 2016a EnviroAtlas Estimated Intersection Density of Walkable Roads Web Service. Details: https://edg.epa.gov/metadata/catalog/search/resource/details.page?uuid=%7B4a7dad9e-a242-42d7-b851-36654d12c220%7D.

[EPA] U.S. Environmental Protection Agency, 2016b EnviroAtlas Estimated Percent Green Space Along Walkable Roads Web Service. Details: https://edg.epa.gov/metadata/rest/document?id=%7B3275e906-3d2b-422c-8747-9d53d288be56%7D&xsl=metadata_to_html_full.

[EPA] U.S. Environmental Protection Agency, 2016c EnviroAtlas Proximity to Parks Web Service. Details: https://edg.epa.gov/metadata/catalog/search/resource/details.page?uuid=%7B8e728fbb-dc7b-46b1-aa49-7861032f8f03%7D.

[EPA] U.S. Environmental Protection Agency, 2017 EnviroAtlas - Household income metrics related to emotional well-being by Census Block Group for the Conterminous United States. Metadata: https://edg.epa.gov/metadata/rest/document?id=%7Bb188b882-f130-43c6-9000-cd1e6f871a6d%7D&xsl=metadata_to_html_full.

ESRI ArcGIS Desktop Help 10.4 GeocodingToolbox, http:/desktop.arcgis.com/en/arcmpa/10.4/tools/geocoding-toolbox/an-overview-of-the-geocoding-toolbox.htm.

ESRI ArcGIS Desktop Help 10.4 Spatial Analyst Toolbox, http:/desktop.arcgis.com/en/arcmpa/10.4/tools/spatial-analyst-toolbox/an-overview-of-the-spatial-analyst-toolbox.htm.

Ewing R, Cervero R, 2010 Travel and the Built Environment. J. Am. Plan. Assoc 76, 265–294.

Fan JX, Hanson HA, Zick CD, Brown BB, Kowaleski-Jones L, Smith KR, 2014 Geographic scale matters in detecting the relationship between neighbourhood food environments and obesity risk: an analysis of driver license records in Salt Lake County, Utah. BMJ Open 4.

Ford ND, Patel SA, Narayan KV, 2017 Obesity in low-and middle-income countries: burden, drivers, and emerging challenges. Annu. Rev. Public Health 38, 145–164. [PubMed: 28068485]

Frank LD, Andresen MA, Schmid TL, 2004 Obesity relationships with community design, physical activity, and time spent in cars. Am. J. Prev. Med 27, 87–96. [PubMed: 15261894]

Getis A, 2010 Spatial autocorrelation, Handbook of applied spatial analysis. Springer, pp. 255–278.

Ghimire R, Ferreira S, Green GT, Poudyal NC, Cordell HK, Thapa JR, 2017 Green Space and Adult Obesity in the United States. Ecological Economics 136, 201–212.

Grasser G, Van Dyck D, Titze S, Stronegger W, 2013 Objectively measured walkability and active transport and weight-related outcomes in adults: a systematic review. Int J Public Health 58, 615–625. [PubMed: 23224518]

Griffith DA, 2005 Effective geographic sample size in the presence of spatial autocorrelation. Ann. Assoc. Am. Geogr 95, 740–760.

Hales CM, Carroll MD, Fryar CD, Ogden CL, 2017 Prevalence of obesity among adults and youth: United States, 2015–2016. NCHS data brief, 1–8.

Halonen JI, Kivimäki M, Pentti J, Stenholm S, Kawachi I, Subramanian SV, Vahtera J, 2014 Green and blue areas as predictors of overweight and obesity in an 8-year follow-up study. Obesity 22, 1910–1917. [PubMed: 24771608]

Hobbs M, Green MA, Griffiths C, Jordan H, Saunders J, Grimmer H, McKenna J, 2017 Access and quality of parks and associations with obesity: A cross-sectional study. SSM - Population Health 3, 722–729. [PubMed: 29349259]

James P, Banay RF, Hart JE, Laden F, 2015 A Review of the Health Benefits of Greenness. Current Epidemiology Reports 2, 131–142. [PubMed: 26185745]

James P, Berrigan D, Hart JE, Hipp JA, Hoehner CM, Kerr J, Major JM, Oka M, Laden F, 2014 Effects of Buffer Size and Shape on Associations between the Built Environment and Energy Balance. Health Place 27, 162–170. [PubMed: 24607875]

Jiang B, Larsen L, Deal B, Sullivan WC, 2015 A dose–response curve describing the relationship between tree cover density and landscape preference. Landsc. Urban Plan 139, 16–25.

Kahneman D, Deaton A, 2010 High income improves evaluation of life but not emotional well-being. Proceedings of the National Academy of Sciences 107, 16489.

Kaplan R, 2001 The Nature of the View from Home:Psychological Benefits. Environ. Behav 33, 507–542.

Kim Y-J, Lee C, Kim J-H, 2018 Sidewalk Landscape Structure and Thermal Conditions for Child and Adult Pedestrians. Int. J. Env. Res. Public Health 15, 148.

Klompmaker JO, Hoek G, Bloemsma LD, Gehring U, Strak M, Wijga AH, van den Brink C, Brunekreef B, Lebret E, Janssen NAH, 2018 Green space definition affects associations of green space with overweight and physical activity. Environ. Res. 160, 531–540. [PubMed: 29106952]

Kriegel H-P, Schubert E, Zimek A, 2017 The (black) art of runtime evaluation: Are we comparing algorithms or implementations? Knowledge and Information Systems 52, 341–378.

Krul AJ, Daanen HA, Choi H, 2010 Self-reported and measured weight, height and body mass index (BMI) in Italy, the Netherlands and North America. The European Journal of Public Health 21, 414–419. [PubMed: 20089678]

Kuo FE, Bacaicoa M, Sullivan WC, 1998 Transforming inner-city landscapes: Trees, sense of safety, and preference. Environ. Behav 30, 28–59.

Lachowycz K, Jones AP, 2011 Greenspace and obesity: a systematic review of the evidence. Obes Rev 12.

Lake A, Townshend T, 2006 Obesogenic environments: exploring the built and food environments. The journal of the Royal Society for the Promotion of Health 126, 262–267. [PubMed: 17152319]

Lee S-I, 2017 Correlation and Spatial Autocorrelation, in: Shekhar S, Xiong H, Zhou X (Eds.), Encyclopedia of GIS. Springer International Publishing, Cham, pp. 360–368.

Littenberg B, Bonnell LN, LeBruin AS, Lubetkin DA, Troy AR, Zia A, 2015 The Relationship Between Access to Natural Environmental Amenities and Obesity. Cureus 7, e377. [PubMed: 26719821]

Littenberg B, Lubetkin D, 2016 Availability, Strengths and Limitations of US State Driver's License Data for Obesity Research. Cureus 8, e518. [PubMed: 27054053]

Liu GC, Wilson JS, Qi R, Ying J, 2007 Green neighborhoods, food retail and childhood overweight: Differences by population density. American Journal of Health Promotion 21, 317–325. [PubMed: 17465177]

Lovasi GS, Bader MD, Quinn J, Neckerman K, Weiss C, Rundle A, 2012 Body mass index, safety hazards, and neighborhood attractiveness. Am J Prev Med 43, 378–384. [PubMed: 22992355]

Lovasi GS, Schwartz-Soicher O, Quinn JW, Berger DK, Neckerman KM, Jaslow R, Lee KK, Rundle A, 2013 Neighborhood safety and green space as predictors of obesity among preschool children from low-income families in new york city. Prev Med 57, 189–193. [PubMed: 23732240]

Luppino FS, de Wit LM, Bouvy PF, Stijnen T, Cuijpers P, Penninx BW, Zitman FG, 2010 Overweight, obesity, and depression: a systematic review and meta-analysis of longitudinal studies. Arch. Gen. Psychiatry 67, 220–229. [PubMed: 20194822]

Maas J, Verheij R, Groenewegen P, de Vries S, Spreeuwenberg P, 2006 Green space, urbanity and health: How strong is the relation? J Epidemiol Community Health 60, 587–592. [PubMed: 16790830]

Mackenbach JD, Rutter H, Compernolle S, Glonti K, Oppert J-M, Charreire H, De Bourdeaudhuij I, Brug J, Nijpels G, Lakerveld J, 2014 Obesogenic environments: a systematic review of the association between the physical environment and adult weight status, the SPOTLIGHT project. BMC Public Health 14, 233–233. [PubMed: 24602291]

Madhulatha TS, 2012 An overview on clustering methods. arXiv preprint arXiv:1205.1117.

Maechler Martin, Rousseeuw Peter, Croux Christophe, Todorov Valentin, Ruckstuhl Andreas, Matias Salibian-Barrera Tobias Verbeke, Koller Manuel, Conceicao Eduardo L. T., Palma M.A.d., 2016 robustbase: Basic Robust Statistics R package version 0.92–7. URL http://CRAN.R-project.org/package=robustbase.

Matsuoka RH, 2010 Student performance and high school landscapes: Examining the links. Landsc. Urban Plan. 97, 273–282.

McFadden D, 1973 Conditional logit analysis of qualitative choice behavior.

Natural England, 2010 ‘Nature Nearby’ - Accessible Natural Greensapce Guidance, in: England, U.K.N. (Ed.).

Nielsen TS, Hansen KB, 2007 Do green areas affect health? Results from a Danish survey on the use of green areas and health indicators. Health Place 13, 839–850. [PubMed: 17392016]

Nokia-HERE, 2011 NavTEQ Streets [Esri File Geodatabase], in: HERE N (Ed.),. [Obtained from US EPA’s Office of Environmental Information, 201x.] ed, Chicago, IL.

Oliver LN, Schuurman N, Hall AW, 2007 Comparing circular and network buffers to examine the influence of land use on walking for leisure and errands. International journal of health geographics 6, 1. [PubMed: 17214903]

Osborne JW, Overbay A, 2004 The power of outliers (and why researchers should always check for them). Practical assessment, research & evaluation 9, 1–12.

Ossiander EM, Emanuel I, O’Brien W, Malone K, 2004 Driver’s licenses as a source of data on height and weight. Econ. Hum. Biol 2, 219–227. [PubMed: 15464003]

Pereira G, Christian H, Foster S, Boruff BJ, Bull F, Knuiman M, Giles-Corti B, 2013 The association between neighborhood greenness and weight status: an observational study in Perth Western Australia. Environ. Health 12, 49. [PubMed: 23783002]

Pickard BR, Daniel J, Mehaffey M, Jackson LE, Neale A, 2015 EnviroAtlas: A new geospatial tool to foster ecosystem services science and resource management. Ecosystem Services 14, 45–55.

Potestio M, Patel A, Powell C, McNeil D, Jacobson RD, McLaren L, 2009 Is there an association between spatial access to parks/green space and childhood overweight/obesity in calgary, canada? International Journal of Behavioral Nutrition and Physical Activity 6, 77. [PubMed: 19930567]

Prince SA, Kristjansson EA, Russell K, Billette J-M, Sawada MC, Ali A, Tremblay MS, Prud’homme D, 2012 Relationships Between Neighborhoods, Physical Activity, and Obesity: A Multilevel Analysis of a Large Canadian City. Obesity 20, 2093–2100. [PubMed: 22262164]

Reid C, Clougherty J, Shmool J, Kubzansky L, 2017 Is All Urban Green Space the Same? A Comparison of the Health Benefits of Trees and Grass in New York City. Int. J. Env. Res. Public Health 14, 1411.

Richardson EA, Pearce J, Mitchell R, Kingham S, 2013 Role of physical activity in the relationship between urban green space and health. Public Health 127, 318–324. [PubMed: 23587672]

Ripley BD, 2005 Spatial statistics. John Wiley & Sons.

Rousseeuw PJ, Driessen KV, 1999 A Fast Algorithm for the Minimum Covariance Determinant Estimator. Technometrics 41, 212–223.

Rundle A, Neckerman KM, Freeman L, Lovasi GS, Purciel M, Quinn J, 2009 Neighborhood food environment and walkability predict obesity in New York City. Environ Health Perspect 117.

Rundle A, Quinn J, Lovasi G, Bader MD, Yousefzadeh P, Weiss C, Neckerman K, 2013 Associations between body mass index and park proximity, size, cleanliness, and recreational facilities. Am J Health Promot 27, 262–269. [PubMed: 23448416]

Sarkar C, 2017 Residential greenness and adiposity: Findings from the UK Biobank. Environ. Int 106, 1–10. [PubMed: 28551493]

Schalkwijk AAH, van der Zwaard BC, Nijpels G, Elders PJM, Platt L, 2017 The impact of greenspace and condition of the neighbourhood on child overweight. European Journal of Public Health, ckx037–ckx037.

Shashua-Bar L, Pearlmutter D, Erell E, 2011 The influence of trees and grass on outdoor thermal comfort in a hot-arid environment. International Journal of Climatology 31, 1498–1506.

Short D, 2016 Happiness Revisited: A Household Income of $75K? https://www.advisorperspectives.com/dshort/commentaries/2016/10/21/happiness-revisited-a-household-income-of-75k. Advisor Perspectives

Stark JH, Neckerman K, Lovasi GS, Quinn J, Weiss CC, Bader MDM, Konty K, Harris TG, Rundle A, 2014 The impact of neighborhood park access and quality on body mass index among adults in New York City. Preventive Medicine 64, 63–68. [PubMed: 24704504]

Troped PJ, Starnes HA, Puett RC, Tamura K, Cromley EK, James P, Ben-Joseph E, Melly SJ, Laden F, 2014 Relationships between the built environment and walking and weight status among older women in three U.S. States. J Aging Phys Act 22, 114–125. [PubMed: 23538637]

Tsai WL, Floyd MF, Leung YF, McHale MR, Reich BJ, 2016 Urban Vegetative Cover Fragmentation in the US Associations With Physical Activity and BMI. Am. J. Prev. Med 50, 509–517. [PubMed: 26597506]

Tzoulas K, Korpela K, Venn S, Yli-Pelkonen V, Kaźmierczak A, Niemela J, 2007 Promoting ecosystem and human health in urban areas using Green Infrastructure: a literature review. Landscape Urban Plann 81.

U.S. Census Bureau, 1994 Geographic areas reference manual. U.S. Dept. of Commerce, Economics and Statistics Administration, Bureau of the Census, Washington, D.C.

Ulrich RS, 1984 View through a window may influence recovery from surgery. sCIENCE 224, 420–421. [PubMed: 6143402]

U.S. Government Publishing Office, 2011 18 U.S.C. 2721 - Prohibition on release and use of certain personal information from state motor vehicle records.

[USGS] U.S. Geological Survey, 2016 Protected Areas Database of the United States (PAD-US). Metadata: https://gapanalysis.usgs.gov/padus/data/metadata/.

Van den Bosch MA, Mudu P, Uscila V, Barrdahl M, Kulinkina A, Staatsen B, Swart W, Kruize H, Zurlyte I, Egorov AI, 2016 Development of an urban green space indicator and the public health rationale. Scand. J. Public Health 44, 159–167. [PubMed: 26573907]

Villeneuve PJ, Jerrett M, Su JG, Weichenthal S, Sandler DP, 2018 Association of residential greenness with obesity and physical activity in a US cohort of women. Environ. Res 160, 372–384. [PubMed: 29059619]

Walsh MC, Trentham-Dietz A, Palta M, 2011 Availability of Driver's License Master Lists for Use in Government-Sponsored Public Health Research. American Journal of Epidemiology 173, 1414–1418. [PubMed: 21571870]

West ST, Shores KA, Mudd LM, 2012 Association of available parkland, physical activity, and overweight in America's largest cities. J. Public Health Manag. Pract 18, 423–430. [PubMed: 22836533]

Wheeler BW, Lovell R, Higgins SL, White MP, Alcock I, Osborne NJ, Husk K, Sabel CE, Depledge MH, 2015 Beyond greenspace: an ecological study of population general health and indicators of natural environment type and quality. Int J Health Geogr 14, 17. [PubMed: 25924685]

WHO, 2017 Obesity and Overweight factsheet from the World Health Organization. Health (N. Y.).

WHO Regional Office for Europe, 2016a Urban Gree Space and Health: Intervention Impacts and Effectiveness. WHO Regional Office for Europe Germany.

WHO Regional Office for Europe, 2016b Urban Green Spaces and Health. A Review of Evidence. WHO Regional Office for Europe Copenhagen.

Wilhelmsen CK, Skalleberg K, Raanaas RK, Tveite H, Aamodt G, 2017 Associations between green area in school neighbourhoods and overweight and obesity among Norwegian adolescents. Preventive Medicine Reports 7, 99–105. [PubMed: 28593129]

Wolch J, Jerrett M, Reynolds K, McConnell R, Chang R, Dahmann N, Brady K, Gilliland F, Su JG, Berhane K, 2011 Childhood obesity and proximity to urban parks and recreational resources: a longitudinal cohort study. Health Place 17, 207–214. [PubMed: 21075670]

Yang S, Hutcheon JA, 2016 Identifying outliers and implausible values in growth trajectory data. Ann. Epidemiol 26, 77–80.e72. [PubMed: 26590476]

EPA Author Manuscript

EPA Author Manuscript

Highlights

- Types of greenery can have different associations with weight status.
- Higher levels of tree cover across tested thresholds were consistently protective.
- Greenery effects were greater in larger buffers.

Figure 1.

A) 10% tree cover and 3% herbaceous cover in Meter-scale Urban Land Cover (MULC) view and the corresponding view in Google Earth (A'). B) 15% tree cover and 4% herbaceous cover in MULC view and the corresponding view in Google Earth (B'). C) 20% tree cover and 6% herbaceous cover in MULC view and the corresponding view in Google Earth (C').

EPA Author Manuscript

EPA Author Manuscript

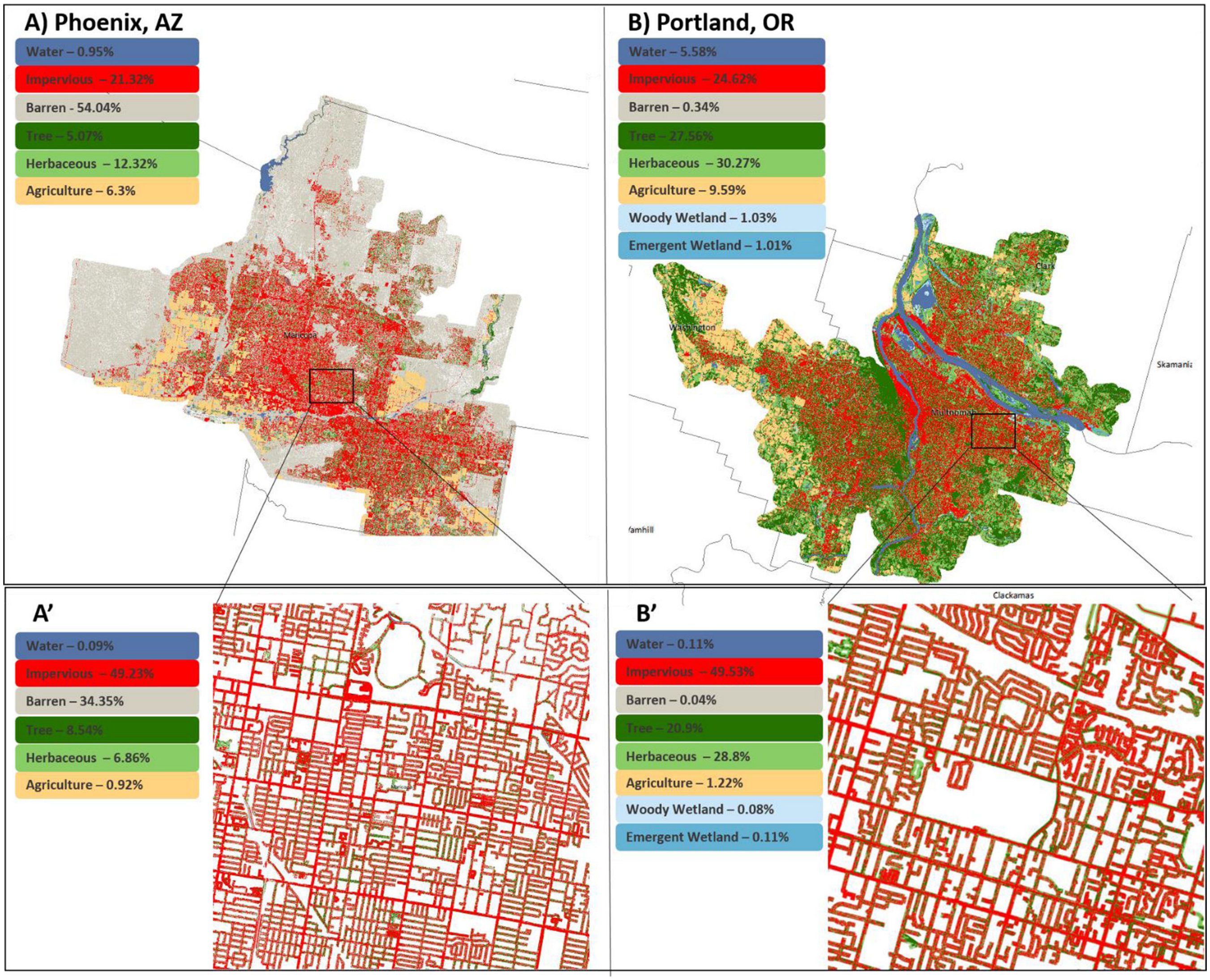

Figure 2.

Meter-scale Urban Land Cover in Phoenix, AZ (A) and Portland, OR (B). Details of the landcover catchment area along walkable roads (A': Phoenix, AZ and B': Portland).

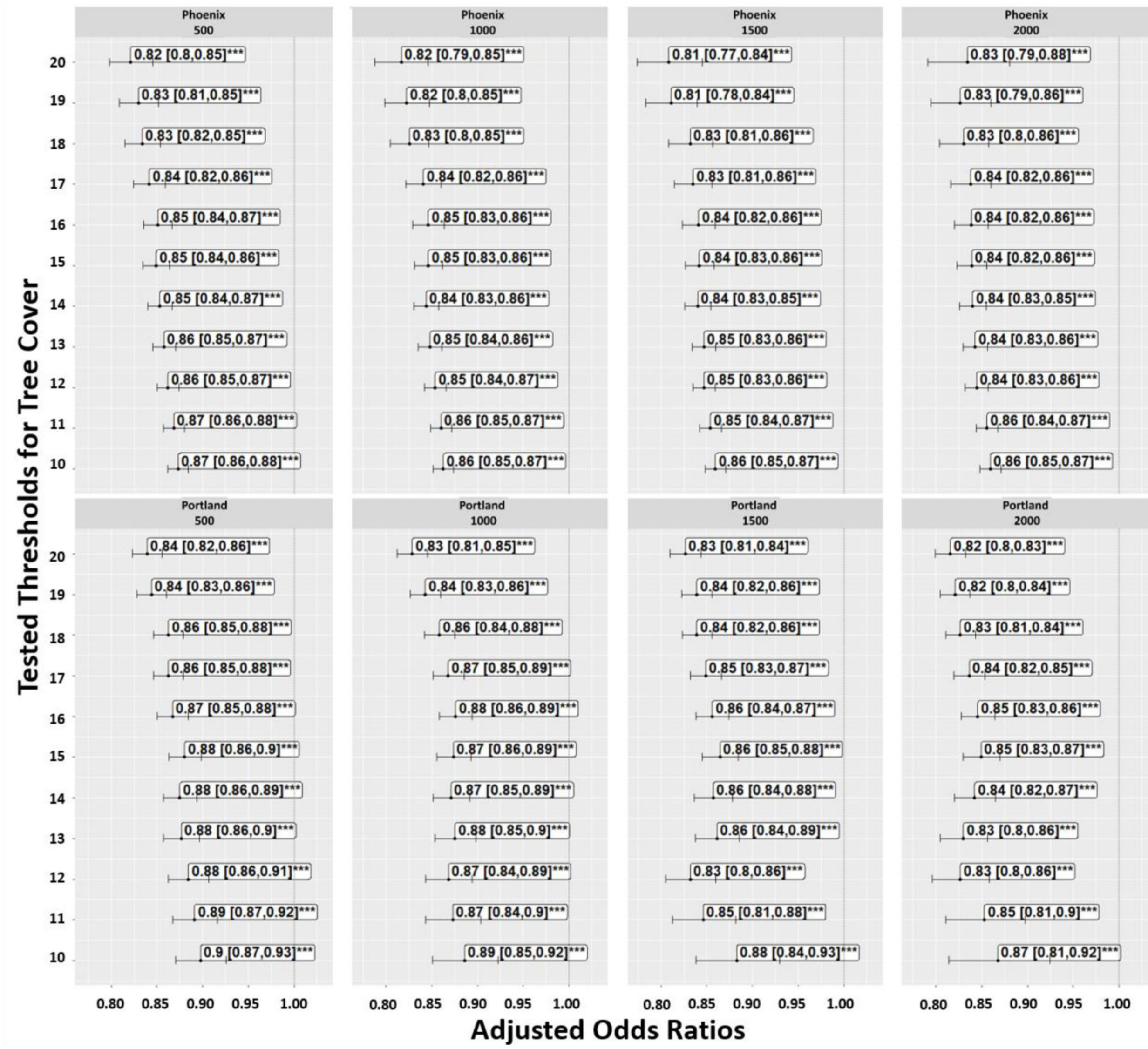

Figure 3.

Adjusted odds ratios with 95% confidence intervals at a range of thresholds from 10% to 20% of tree cover along walkable roads.

Table 1

Descriptive statistics for the study population

	Phoenix, AZ		Portland, OR	
Total Population [†]	**497,311**		**224,718**	
Female	236,224 (47.5%)		113,438 (50.48%)	
Male	261,087 (52.5%)		111,280 (49.52%)	
Mean Age at Year 2011	**39.38 (sd = 8.91)**		**38.9 (sd = 8.93)**	
25 – 29	89,259 (17.95%)		42,813 (19.05%)	
30 – 34	83,766 (16.84%)		41,019 (18.25%)	
35 – 39	79,619 (16.01%)		34,850 (15.51%)	
40 – 44	81,737 (16.44%)		37,774 (16.81%)	
45 – 49	76,860 (15.46%)		31,089 (13.83%)	
50 – 55	86,070 (17.31%)		37,177 (16.54%)	
Mean BMI	**25.9 (sd = 4.28)**		**24.92 (sd =3.8)**	
Neither Overweight nor Obese (Referent)				
Underweight	89,23 (1.79%)		38,78 (1.73%)	
Normal Weight	205,937 (41.41%)		114,717 (51.05%)	
Overweight or Obese				
Overweight	191,374 (38.48%)		80,188 (35.68%)	
Obese	91,077 (18.31%)		25,939 (11.54%)	
Park Proximity				
No access within 2km (Referent)	48,069 (9.67%)		41,90 (1.86%)	
Within 250m	55,508 (11.16%)		42,414 (18.87%)	
>250 and <=500m	68,098 (13.69%)		60,135 (26.76%)	
>500 and <=750m	69,176 (13.91%)		52,918 (23.55%)	
>750 and <=1000m	60,873 (12.24%)		32,589 (14.5%)	
>1000 and <=2000m	144,351 (29.03%)		32,472 (14.45%)	
Mean Quality of Life (QOL index)	**57.98 (sd = 21.78)**		**59.07 (sd = 19.23)**	
4-Level	**Range**	**Total Pop (%)**	**Range**	**Total Pop (%)**
Referent	0 – 40.62	124,429 (25.02%)	7.74 – 45.74	56,406 (25.10%)
Level II	40.63 – 58.38	124,282 (24.99%)	45.75 – 61.18	56,002 (24.92%)
Level III	58.39 – 75.59	124,306 (25.00%)	61.19 – 74.63	56,185 (25.00%)
Level IV	75.6 – 100.00	124,429 (25.02%)	74.64 – 100.00	56,125 (24.98%)
Mean Percent Non-White Population	**39.07 (sd=24.78)**		**26.07 (sd=13.05)**	
Referent	1.35 – 20.63	124,394 (25.01%)	1.53 – 15.38	56,290 (25.05%)
Level II	20.64 – 30.65	124,365 (25.01%)	15.39 – 23.78	56,221 (25.02%)
Level III	30.66 – 54.51	124,232 (24.98%)	23.79 – 34.5	56,056 (24.95%)
Level IV	54.52 – 98.41	124,320 (25.00%)	34.51 – 86.51	56,151 (24.99%)
Estimated Intersection Density of Walkable Roads				

	Phoenix, AZ		**Portland, OR**	
Mean Intersection Density at 500m	**65.91 (sd = 23.55)**		**70.34 (sd = 28.46)**	
Referent	0 – 51.65	124,328 (25%)	0 – 50.48	56,180 (25%)
Level II	51.66 – 65.89	124,328 (25%)	50.49 – 67.25	56,179 (25%)
Level III	65.90 – 80.36	124,327 (25%)	67.26 – 89.15	56,179 (25%)
Level IV	80.37 – 269.19	124,328 (25%)	89.16 – 187.98	56,180 (25%)
Mean Intersection Density at 1000m	**58.76 (sd = 18.04)**		**64.42 (sd = 25.73)**	
Referent	0 – 48.17	124,328 (25%)	0 – 46.84	56,180 (25%)
Level II	48.18 – 59.79	124,329 (25%)	46.85 – 60.20	56,179 (25%)
Level III	59.80 – 70.85	124,326 (25%)	60.21 – 81.35	56,179 (25%)
Level IV	70.86 – 153.87	124,328 (25%)	81.36 – 168.71	56,180 (25%)
Mean Intersection Density at 1500m	**54.79 (sd = 16.48)**		**61.2 (sd = 24.76)**	
Referent	0 – 45.23	124,328 (25%)	0 – 44.70	56,180 (25%)
Level II	45.24 – 56.30	124,328 (25%)	44.71 – 56.75	56,179 (25%)
Level III	56.31 – 65.85	124,327 (25%)	56.76 – 76.44	56,179 (25%)
Level IV	65.86 – 128.87	124,328 (25%)	76.45 – 147.54	56,180 (25%)
Mean Intersection Density at 2000m	**52.07 (sd = 15.27)**		**58.82 (sd = 24.02)**	
Referent	0 – 43.16	124,328 (25%)	0 – 42.95	56,180 (25%)
Level II	43.17 – 53.73	124,328 (25%)	42.96 – 54.19	56,179 (25%)
Level III	53.74 – 62.71	124,327 (25%)	54.20 – 72.59	56,179 (25%)
Level IV	62.72 – 116.42	124,328 (25%)	72.60 – 132.48	56,180 (25%)

[†] Total population was adjusted by the availability of Percent Household below the Adjusted Threshold for Quality of Life (QOL index). The index was not available for 119 and 3 samples in PAZ and POR, respectively.

EPA Author Manuscript

EPA Author Manuscript

Table 2

Descriptive statistics for continuous and categorical greenery measures

Buffer Size	500m		1000m		1500m		2000m	
Phoenix, AZ - Total Population	**497,302**		**496,925**		**496,450**		**495,978**	
Mean Tree Cover	**9.1 (sd=5.8)**		**8.99 (sd=5.28)**		**8.91 (sd=4.96)**		**8.88 (sd=4.75)**	
4-Level	**Range**	**Total Pop (%)**	**Range**	**Total Pop (%)**	**Range**	**Total Pop (%)**	**Range**	**Total Pop (%)**
Referent	0 – 5.74	164,285 (33.04%)	0 – 5.73	154,870 (31.17%)	0 – 5.56	141,891 (28.58%)	0.01 – 5.56	135,673 (27.35%)
Level II	5.75 – 11.15	168,448 (33.87%)	5.74 – 10.71	171,368 (34.49%)	5.57 – 10.12	170,884 (34.42%)	5.57 – 9.90	173,489 (34.98%)
Level III	11.16 – 17.61	122,584 (24.65%)	10.72 – 16.32	122,559 (24.66%)	10.13 – 15.10	120,705 (24.31%)	9.91 – 14.54	116,399 (23.47%)
Level IV	17.62 – 54.76	41,985 (8.44%)	16.33 – 37.00	48,128 (9.69%)	15.11 – 33.20	62,970 (12.68%)	14.55 – 30.58	70,417 (14.2%)
Mean Herbaceous Cover	**6.29 (sd=3.43)**		**6.42 (sd=2.95)**		**6.43 (sd=2.65)**		**6.46 (sd=2.44)**	
Referent	0 – 4.78	185,480 (37.3%)	0 – 4.88	163,527 (32.91%)	0.02 – 5.08	171,694 (34.58%)	0.07 – 5.27	177,132 (35.71%)
Level II	4.79 – 8.03	193,422 (38.89%)	4.89 – 7.61	192,655 (38.77%)	5.09 – 7.56	181,121 (36.48%)	5.28 – 7.62	180,228 (36.34%)
Level III	8.04 – 13.02	95,754 (19.25%)	7.62 – 11.55	112,237 (22.59%)	7.57 – 10.91	114,378 (23.04%)	7.63 – 10.65	112,017 (22.59%)
Level IV	13.03 – 45.35	22,774 (4.58%)	11.56 – 33.34	28,520 (5.74%)	10.92 – 30.60	29,257 (5.89%)	10.66 – 30.07	26,601 (5.36%)
Mean Aggregate Greenery	**15.39 (sd=7.65)**		**15.41 (sd=6.85)**		**15.34 (sd=6.38)**		**15.33 (sd=6.05)**	
Referent	0 – 10.68	148,483 (29.86%)	0 – 10.66	135,073 (27.18%)	0.04 – 10.82	133,733 (26.94%)	0.14 – 10.78	1,244 (25%)
Level II	10.69 – 17.77	181,313 (36.46%)	10.67 – 16.86	172,055 (34.62%)	10.83 – 16.51	168,709 (33.98%)	10.79 – 16.15	169,679 (34.21%)
Level III	17.78 – 26.64	126,430 (25.42%)	16.87 – 24.26	134,624 (27.09%)	16.52 – 23.06	128,172 (25.82%)	16.16 – 22.30	129,358 (26.08%)
Level IV	26.65 – 71.97	41,076 (8.26%)	24.27 – 64.72	55,173 (11.1%)	23.07 – 48.57	65,836 (13.26%)	22.31 – 43.13	72,937 (14.71%)
Portland, OR - Total Population	**224,346**		**223,715**		**223,672**		**223,642**	
Mean Tree Cover	**20.12 (sd=9.7)**		**20.38 (sd=8.54)**		**20.46 (sd=7.83)**		**20.54 (sd=7.32)**	
4-Level	**Range**	**Total Pop (%)**	**Range**	**Total Pop (%)**	**Range**	**Total Pop (%)**	**Range**	**Total Pop (%)**
Referent	0 – 15.10	69,369 (30.92%)	0 – 16.64	79,383 (35.48%)	1.43 – 16.52	69,516 (31.08%)	2.97 – 16.70	67,408 (30.14%)
Level II	15.11 – 24.28	99,705 (44.44%)	16.65 – 25.24	98,895 (44.21%)	16.53 – 24.13	102,563 (45.85%)	16.71 – 23.57	101,189 (45.25%)
Level III	24.29 – 38.23	43,292 (19.3%)	25.25 – 38.71	36,775 (16.44%)	24.14 – 36.11	41,256 (18.44%)	23.58 – 34.31	42,948 (19.2%)
Level IV	38.24 – 99.87	11,980 (5.34%)	38.72 – 93.83	8,662 (3.87%)	36.12 – 90.30	10,337 (4.62%)	34.32 – 90.10	12,097 (5.41%)
Mean Herbaceous Cover	**25.04 (sd=6.45)**		**25.14 (sd=5.89)**		**25.11 (sd=5.57)**		**25.09 (sd=5.35)**	
Referent	0 – 20.43	50,210 (22.38%)	4.03 – 20.10	37,349 (16.69%)	4.88 – 20.02	33,367 (14.92%)	5.39 – 19.92	28,830 (12.89%)
Level II	20.44 – 26.96	95,567 (42.6%)	20.11 – 26.01	94,296 (42.15%)	20.03 – 25.52	90,619 (40.51%)	19.93 – 25.42	95,437 (42.67%)

EPA Author Manuscript

EPA Author Manuscript

Buffer Size	500m		1000m		1500m		2000m	
Level III	26.97 – 35.24	66,901 (29.82%)	26.02 – 33.29	75,502 (33.75%)	25.53 – 32.2	79,444 (35.52%)	25.43 – 31.96	79,568 (35.58%)
Level IV	35.25 – 77.41	11,668 (5.2%)	33.3 – 76.03	16,568 (7.41%)	32.21 – 68.57	20,242 (9.05%)	31.97 – 63.33	19,807 (8.86%)
Mean Aggregate Greenery	**45.16 (sd=9.76)**		**45.51 (sd=8.47)**		**45.58 (sd=7.86)**		**45.62 (sd=7.43)**	
Referent	0 – 39.21	58,252 (25.97%)	9.50 – 41.37	71,679 (32.04%)	12.96 – 41.78	71,803 (32.1%)	16.11 – 41.94	70,813 (31.66%)
Level II	39.22 – 48.58	101,431 (45.21%)	41.38 – 49.59	100,722 (45.02%)	41.79 – 49.36	102,074 (45.64%)	41.95 – 48.94	100,391 (44.89%)
Level III	48.59 – 61.45	50,930 (22.7%)	49.6 – 61.75	40,475 (18.09%)	49.37 – 60.63	38,464 (17.2%)	48.95 – 59.53	40,485 (18.1%)
Level IV	61.46 – 99.90	13,733 (6.12%)	61.76 – 98.37	10,839 (4.85%)	60.64 – 95.90	11,331 (5.07%)	59.54 – 95.93	11,953 (5.34%)

EPA Author Manuscript
EPA Author Manuscript

Table 3

Adjusted odds ratios for being overweight or obese using continuous and categorical greenery measures

	Phoenix, AZ					Portland, OR				
500m	**Percentage Range**	**AOR**[†]	**Lower CI**	**Higher CI**	**p-value**	**Percentage Range**	**AOR**	**Lower CI**	**Higher CI**	**p-value**
Tree (continuous)	every 10% increase	0.87	0.86	0.88	***	every 10% increase	0.89	0.88	0.90	***
Referent	0 – 5.74	-	-	-	-	0 – 15.10	-	-	-	-
Level II	5.75 – 11.15	0.95	0.94	0.97	***	15.11 – 24.28	0.93	0.91	0.95	***
Level III	11.16 – 17.61	0.87	0.85	0.88	***	24.29 – 38.23	0.80	0.78	0.82	***
Level IV	17.62 – 54.76	0.78	0.77	0.80	***	38.24 – 99.87	0.65	0.62	0.68	***
Herbaceous (continuous)	every 10% increase	0.83	0.81	0.84	***	every 10% increase	1.16	1.15	1.18	***
Referent	0 – 4.78	-	-	-	-	0 – 20.43	-	-	-	-
Level II	4.79 – 8.03	0.94	0.93	0.96	***	20.44 – 26.96	1.12	1.09	1.15	***
Level III	8.04 – 13.02	0.87	0.86	0.89	***	26.97 – 35.24	1.25	1.22	1.28	***
Level IV	13.03 – 45.35	0.80	0.77	0.82	***	35.25 – 77.41	1.36	1.30	1.42	***
Aggregate Greenery (continuous)	every 10% increase	0.89	0.88	0.90	***	every 10% increase	0.95	0.94	0.96	***
Referent	0 – 10.68	-	-	-	-	0 – 39.21	-	-	-	-
Level II	10.69 – 17.77	0.97	0.95	0.98	***	39.22 – 48.58	1.03	1.01	1.05	**
Level III	17.78 – 26.64	0.84	0.83	0.86	***	48.59 – 61.45	0.94	0.91	0.96	***
Level IV	26.65 – 71.97	0.75	0.73	0.76	***	61.46 – 99.90	0.78	0.74	0.81	***
1000m										
Tree (continuous)	every 10% increase	0.85	0.84	0.86	***	every 10% increase	0.86	0.85	0.87	***
Referent	0 – 5.73	-	-	-	-	0 – 16.64	-	-	-	-
Level II	5.74 – 10.71	0.95	0.94	0.97	***	16.65 – 25.24	0.91	0.89	0.93	***
Level III	10.72 – 16.32	0.86	0.84	0.87	***	25.25 – 38.71	0.76	0.74	0.78	***
Level IV	16.33 – 37.00	0.78	0.76	0.80	***	38.72 – 93.83	0.62	0.58	0.65	***
Herbaceous (continuous)	every 10% increase	0.78	0.76	0.80	***	every 10% increase	1.19	1.17	1.21	***
Referent	0 – 4.88	-	-	-	-	4.03 – 20.10	-	-	-	-
Level II	4.89 – 7.61	0.93	0.92	0.95	***	20.11 – 26.01	1.12	1.09	1.15	***
Level III	7.62 – 11.55	0.86	0.85	0.88	***	26.02 – 33.29	1.24	1.21	1.28	***

EPA Author Manuscript
EPA Author Manuscript

	Phoenix, AZ					Portland, OR				
500m	**Percentage Range**	**AOR†**	**Lower CI**	**Higher CI**	**p-value**	**Percentage Range**	**AOR**	**Lower CI**	**Higher CI**	**p-value**
Level IV	11.56 – 33.34	0.78	0.76	0.80	***	33.3 – 76.03	1.40	1.34	1.46	***
Aggregate Greenery (continuous)	every 10% increase	0.86	0.86	0.87	***	every 10% increase	0.92	0.91	0.94	***
Referent	0 – 10.66	-	-	-	-	9.5 – 41.37	-	-	-	-
Level II	10.67 – 16.86	0.97	0.96	0.99	***	41.38 – 49.59	1.01	0.99	1.03	
Level III	16.87 – 24.26	0.84	0.82	0.85	***	49.6 – 61.75	0.87	0.85	0.90	***
Level IV	24.27 – 64.72	0.75	0.73	0.76	***	61.76 – 98.37	0.72	0.69	0.76	***
1500m										
Tree (continuous)	every 10% increase	0.84	0.83	0.85	***	every 10% increase	0.84	0.83	0.85	***
Referent	0 – 5.56	-	-	-	-	1.43 – 16.52	-	-	-	-
Level II	5.57 – 10.12	0.96	0.95	0.98	***	16.53 – 24.13	0.90	0.88	0.92	***
Level III	10.13 – 15.10	0.86	0.85	0.88	***	24.14 – 36.11	0.75	0.73	0.77	***
Level IV	15.11 – 33.2	0.79	0.77	0.80	***	36.12 – 90.3	0.61	0.58	0.64	***
Herbaceous (continuous)	every 10% increase	0.75	0.73	0.76	***	every 10% increase	1.21	1.19	1.23	***
Referent	0.02 – 5.08	-	-	-	-	4.88 – 20.02	-	-	-	-
Level II	5.09 – 7.56	0.92	0.91	0.94	***	20.03 – 25.52	1.12	1.09	1.15	***
Level III	7.57 – 10.91	0.86	0.85	0.88	***	25.53 – 32.2	1.26	1.23	1.30	***
Level IV	10.92 – 30.60	0.76	0.74	0.78	***	32.21 – 68.57	1.38	1.32	1.44	***
Aggregate Greenery (continuous)	every 10% increase	0.85	0.84	0.86	***	every 10% increase	0.90	0.88	0.91	***
Referent	0.04 – 10.82	-	-	-	-	12.96 – 41.78	-	-	-	-
Level II	10.83 – 16.51	0.98	0.96	0.99	**	41.79 – 49.36	0.99	0.97	1.01	
Level III	16.52 – 23.06	0.83	0.82	0.85	***	49.37 – 60.63	0.85	0.83	0.88	***
Level IV	23.07 – 48.57	0.75	0.73	0.77	***	60.64 – 95.9	0.70	0.66	0.74	***
2000m										
Tree (continuous)	every 10% increase	0.82	0.81	0.84	***	every 10% increase	0.82	0.81	0.83	***
Referent	0.01 – 5.56	-	-	-	-	2.97 – 16.7	-	-	-	-
Level II	5.57 – 9.90	0.95	0.93	0.96	***	16.71 – 23.57	0.89	0.87	0.91	***
Level III	9.91 – 14.54	0.86	0.85	0.88	***	23.58 – 34.31	0.74	0.72	0.76	***

EPA Author Manuscript

EPA Author Manuscript

	Phoenix, AZ					Portland, OR				
500m	**Percentage Range**	**AOR†**	**Lower CI**	**Higher CI**	**p-value**	**Percentage Range**	**AOR**	**Lower CI**	**Higher CI**	**p-value**
Level IV	14.55 – 30.58	0.78	0.76	0.79	***	34.32 – 90.1	0.61	0.59	0.64	***
Herbaceous (continuous)	every 10% increase	0.71	0.70	0.73	***	every 10% increase	1.24	1.22	1.27	***
Referent	0.07 – 5.27	-	-	-	-	5.39 – 19.92	-	-	-	-
Level II	5.28 – 7.62	0.92	0.90	0.93	***	19.93 – 25.42	1.16	1.12	1.19	***
Level III	7.63 – 10.65	0.84	0.82	0.85	***	25.43 – 31.96	1.31	1.27	1.35	***
Level IV	10.66 – 30.07	0.76	0.74	0.78	***	31.97 – 63.33	1.45	1.39	1.51	***
Aggregate Greenery (continuous)	every 10% increase	0.83	0.83	0.84	***	every 10% increase	0.88	0.87	0.90	***
Referent	0.14 – 10.78	-	-	-	-	16.11 – 41.94	-	-	-	-
Level II	10.79 – 16.15	0.98	0.97	1.00	*	41.95 – 48.94	0.99	0.97	1.01	
Level III	16.16 – 22.3	0.82	0.81	0.84	***	48.95 – 59.53	0.85	0.82	0.87	***
Level IV	22.31 – 43.13	0.74	0.73	0.76	***	59.54 – 95.93	0.70	0.67	0.74	***

†AOR: adjusted odds ratio. Models were controlled for age, sex, percent household below the adjusted threshold for quality of life (QOL index as income factor), percent non-White population, estimated intersection density of walkable roads, and distance to a nearest park entrance.

Significance level:

* <0.05

** <0.01

*** <0.001