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It's not easy assessing greenness: A comparison of NDVI datasets and neighborhood types and their associations with self-rated health in New York City

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ABSTRACT

Growing evidence suggests that exposure to greenness benefits health, but studies assess greenness differently. We hypothesize greenness-health associations vary by exposure assessment method. To test this, we considered four vegetation datasets (three Normalized Difference Vegetation Index datasets with different spatial resolutions and a finely-resolved land cover dataset), and six aggregation units (five radial buffer sizes and self-described neighborhoods) of each dataset. We compared associations of self-rated health and these metrics of greenness among a sample of New York City residents. Associations with self-rated health varied more by aggregation unit than by vegetation dataset; larger buffers and self-described neighborhoods showed more positive associations. Researchers should consider spatial exposure misclassification in future greenness and health research.

1. Introduction

There is a large and growing literature on the associations between green space, also known as greenness or surrounding vegetation, and a variety of health outcomes. For example, studies have found that people who live in areas with more versus less surrounding greenness live longer (Gascon et al., 2016; James et al., 2016), have better mental health (Gascon et al., 2015; James et al., 2015), fewer adverse birth outcomes (Dadvand et al., 2012; Hystad et al., 2014), and better self-rated health (de Vries et al., 2013; Maas et al., 2006; Triguero-Mas et al., 2015). There are numerous review articles on benefits of green space in relation to a variety of health outcomes (de Keijzer et al., 2016; Gascon et al., 2016, 2015; James et al., 2015; Lachowycz and Jones, 2011). While findings have largely been positive, they are not fully consistent and the lack of consistency may be due to the variability in how greenness is measured across studies. Such variation makes it more difficult to compare findings across studies. Limited methodological work to date has sought to evaluate which measures of greenness might be most appropriate for studies of associated health effects, or if indeed greenness measures are largely interchangeable. Such information might permit more rapid advances in research seeking to evaluate the role of greenness in health.

Two key domains of assessing exposure to greenness have not been well studied. These are (1) the spatial resolution of the underlying vegetation data and (2) how that is aggregated into areal units to estimate personal 'exposures' to greenness.

The source of vegetation data for assessing greenness exposures are either land use or land cover databases or measures of the Normalized Difference Vegetation Index (NDVI), a measure of photosynthetic capacity or chlorophyll abundance derived from satellite data (Myneni et al., 1995). Increasingly, studies are using NDVI over land cover maps, particularly if they are studies of larger geographic areas or are investigating exposure over time as NDVI is uniformly calculated from remotely-sensed data such that measures are consistent across time and space. Land cover datasets, on the other hand, capture greenspace at a single time point and are generally updated every few years rather than seasonally or annually. For example, the National Land Cover Database (NLCD) in the US (https://www.mrlc.gov/nlcd2011.php) was assessed

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in 1992, 2001, 2006, and 2011, and the CORINE land cover dataset for Europe (http://land.copernicus.eu/pan-european/corine-land-cover) was assessed in 1990, 2000, 2006, and 2012. Moreover, because different spatial resolutions and classification categories are often used in different geographical locations, it is difficult to compare land cover datasets in different regions of the world. Land use/land cover datasets classify remotely-sensed pixels across the landscape as to their predominant land cover or land use type according to predetermined categories such as forest, water and developed land and can vary in spatial resolution from 30 m spatial resolution for the NLCD, and 250 m resolution for CORINE. To assess exposure to vegetation within a given area, researchers then combine exposures across all categories of the landscape that are mostly covered in vegetation (e.g., forests, grasslands). Variation can arise depending on which land cover/land use categories are used, and pixel size (i.e., the spatial resolution or smallest unit that is uniformly classified into a given type).

In contrast, the method for calculating NDVI has been standardized and can be applied to many remotely sensed data that have retrievals in the infrared section of the electromagnetic spectrum. Many researchers calculate NDVI from Landsat satellite retrievals because of its fine spatial resolution (30 m) and consistency across time: Landsat satellites have been retrieving multispectral imagery since 1982. Additionally, there are NDVI products available since 2000 from the MODIS platform at a 250-m spatial resolution that is pre-calculated by NASA. NDVI data has been available from the AVHRR satellite since 1981, with 1-km spatial resolution. Because of its ready availability compared to Landsat data, MODIS NDVI is being increasingly used in epidemiological investigations of greenness and health, yet, to date, we know of no studies which formally compare the use of the coarser NDVI data products in relation to the Landsat NDVI. Further, we are not aware of any epidemiological studies using the AVHRR NDVI data, despite its long-term availability (since 1981), which could enable longitudinal analysis of changes in NDVI and associated health effects applied to historical cohorts.

Studies also vary significantly in how they assign greenness exposures to individuals. Most studies create circular or radial buffers around an individual's home address or the centroid of their ZIP code or census tract, depending on the geographic information available for study participants. A recent review found there is no consistency as yet among studies comparing across radii as to whether very proximate greenness or greenness at farther distances are more strongly associated with health (Ekkel and de Vries, 2017). While observed differences in the strength of associations depending on buffer size could be due in part to differences in which health outcome were analyzed or in the specific location and populations under study. Issues of the modifiable areal unit problem (MAUP) and the uncertain geographic context problem (UGCoP), however, are likely also at play. The MAUP (Kwan, 2009) states that results of analyses depend on the spatial units of analyses chosen, which can be affected both by the spatial resolution of the underlying dataset as well as how data are spatially aggregated into areal units. A related problem, the UGCoP (Kwan, 2012), states that the results of an analysis using areal units is dependent on the geographic unit of analysis, and that this unit of analysis may often differ from the true geographical unit that is affecting health. The UGCoP has been shown in other studies, notably one on the built environment and energy balance (James et al., 2014), but has not been analyzed in studies of green space, to our knowledge.

Some researchers have been moving away from using radial buffers centered on a person's address to assign exposures because those buffers assume that a person's exposures are spread equally in all directions from their residence and that every person's neighborhood is of equal size (Vallée et al., 2015). To take account of the likelihood that different people conceptualize their neighborhood in different ways, researchers have begun asking research participants to self-define their neighborhood (Shmool et al., 2018). Variously, these neighborhoods are called perceived neighborhoods (Perchoux et al., 2016) or self-described neighborhoods (Colabianchi et al., 2014). Self-described neighborhoods may be more informative than researcher-defined neighborhoods, however these have not been used in greenness and health studies to date. We know of only one study that investigated green space within self-described neighborhoods (Perchoux et al., 2016), but that study did not link to health outcomes. Other researchers have proposed the use of activity spaces, which demarcate the areal units in which individuals spend most or all of their time (Perchoux et al., 2013), but these have been mainly used in studies assessing the role of the built environment on physical activity.

The goal of the present study is to evaluate and compare various greenness exposure estimates, and their observed associations with self-reported health, using multiple vegetation datasets [three different measures of NDVI with different spatial resolution and a high resolution (3-ft) land cover dataset] and several areal aggregation units [five radial buffers (ranging from 100 m to 2000 m), and self-described neighborhoods]. We hypothesized that smaller buffer sizes and finer-resolution greenness data would better predict self-rated health, after adjusting for socio-economic status (SES) and air pollution.

2. Methods

2.1. Study population

Our study population consisted of New York City (NYC) residents completing a survey either in the summer (June – September 2012) or winter (December – March 2012–2013) through random digit dialing (RDD) of landlines and cell phones, or an online survey. Trained staff at the Survey Research Program of the University Center for Social and Urban Research (UCSUR) at the University of Pittsburgh administered the RDD surveys. The online survey was a standing survey panel administered by Survey Sampling International (http://www.surveysampling.com, MyOpinions Pty Ltd., Shelton, CT, USA). All participants provided informed consent before responding to survey questions.

The survey was designed to be geographically representative of the populations in the five NYC boroughs, although response rates by landline RDD, cellular RDD, and online survey differ slightly by borough. Response rates were similar across RDD frames and seasons, and comparable to national survey response rates (The Pew Research Center, 2012). 34% of respondents were from the RDD landline sampling frame, 10% from RDD cellular, and 55% from the online frames. The survey participants represent the geography of NYC, but differ in a few ways from the population of NYC based on statistics from the American Community Survey 2008–2012. Survey participants over-represented individuals with more than a high school education, females, and those with annual incomes < the Federal Poverty Line (FPL). Individuals ages 45–64 were under-represented. Survey protocols were approved by the University of Pittsburgh Institutional Review Board.

We successfully geocoded nearest cross-streets from 1439 of the original 1549 survey participants. Nearest cross-streets were provided by survey participants rather than full addresses for confidentiality. Of the geocoded participants, 52 were removed because their reported nearest cross-street did not geocode to a habitable area within NYC. More specifically, two geocoded to areas outside of NYC, 29 to water areas, and 21 to areas within a large city park. Another 106 were missing values for one or more covariates. This resulted in 1281 survey respondents available for analyses using radial buffers. A comparison of those removed to those retained showed no significant differences by sex, age, or income, although the removed individuals had significantly lower educational attainment, on average. Analyses of self-described neighborhoods used the online survey subset for which we had geocoded self-described neighborhoods (N = 530).

Use of the de-identified survey data was approved by the Institutional Review Boards at the University of Pittsburgh Graduate