PUBLIC HEALTH REPORTS

Public Health Reports
2021, Vol. 136(2) 201-211

DOI: 10.1177/0033354920968799
journals.sagepub.com/home/phr
SAGE

Leveraging 31 Million Google Street View Images to Characterize Built Environments and Examine County Health Outcomes

Quynh C. Nguyen, PhD[1]; Jessica M. Keralis, MPH[1]; Pallavi Dwivedi, MPH[1]; Amanda E. Ng, MPH[1]; Mehran Javanmardi, PhD[2]; Sahil Khanna, MS[3]; Yuru Huang, MHS[1]; Kimberly D. Brunisholz, PhD[4]; Abhinav Kumar, MS[5]; and Tolga Tasdizen, PhD[2]

Abstract

Objectives: Built environments can affect health, but data in many geographic areas are limited. We used a big data source to create national indicators of neighborhood quality and assess their associations with health.

Methods: We leveraged computer vision and Google Street View images accessed from December 15, 2017, through July 17, 2018, to detect features of the built environment (presence of a crosswalk, non–single-family home, single-lane roads, and visible utility wires) for 2916 US counties. We used multivariate linear regression models to determine associations between features of the built environment and county-level health outcomes (prevalence of adult obesity, prevalence of diabetes, physical inactivity, frequent physical and mental distress, poor or fair self-rated health, and premature death [in years of potential life lost]).

Results: Compared with counties with the least number of crosswalks, counties with the most crosswalks were associated with decreases of 1.3%, 2.7%, and 1.3% of adult obesity, physical inactivity, and fair or poor self-rated health, respectively, and 477 fewer years of potential life lost before age 75 (per 100 000 population). The presence of non–single-family homes was associated with lower levels of all health outcomes except for premature death. The presence of single-lane roads was associated with an increase in physical inactivity, frequent physical distress, and fair or poor self-rated health. Visible utility wires were associated with increases in adult obesity, diabetes, physical and mental distress, and fair or poor self-rated health.

Conclusions: The use of computer vision and big data image sources makes possible national studies of the built environment's effects on health, producing data and results that may inform national and local decision-making.

Keywords

built environment, big data, GIS, computer vision, structural determinants of health, machine learning

The built environment refers to the settings in which people live, work, and play, and it is defined by human-built or human-designed spaces and features.[1,2] Factors such as roadway characteristics, building type and condition, access to public transportation, green spaces, and walkability have substantial effects on both physical and mental health outcomes.[3-6] The built environment may influence a person's accessibility and, therefore, likelihood to engage in healthy behaviors such as engaging in regular physical activity,[7,8] obtaining adequate nutrition,[9,10] and regularly visiting a health care provider,[11] all of which may contribute to the improvement of physical and mental health.[12]

The built environment is especially important when addressing location-based health disparities. Rates of obesity,[13-15] all-cause mortality,[16] and fair or poor self-rated health[17] are significantly higher in rural areas than in urban areas in the United States. In the United States, populations in rural areas have an estimated all-cause mortality of 40 201

Corresponding Author:
Quynh C. Nguyen, PhD, University of Maryland School of Public Health, Department of Epidemiology and Biostatistics, 2234B SPH Building, 4200 Valley Dr, College Park, MD 20742, USA.
Email: qtnguyen@umd.edu

excess deaths per 100 000 population per year compared with urban areas, and the average person living in a nonmetropolitan area has 30% higher odds of reporting fair or poor health when compared with the average person living in a metropolitan area.[16,17] These health disparities may be largely explained by the structural disadvantages in rural communities. Because rural environments typically have fewer built features, such as buildings, modes of public transportation, and sidewalks, than urban areas, rural residents may find it more difficult to access health care or other services than residents in urban areas.[18]

In addition, physical disorder in neighborhood environments predicts rates of chronic diseases[19] and poor self-rated health.[20] Physical disorder refers to features of the environment that signal decay, disrepair, and uncleanliness. Examples of neighborhood indicators of physical disorder include vacant or abandoned housing, dilapidated buildings, abandoned cars, graffiti, and litter.[21] Physical disorder is hypothesized to indicate a breakdown of social disorder and control, which reduces personal well-being and increases fear, mistrust, isolation, anger, anxiety, and demoralization because of the daily stress imposed by environments that are deemed unsafe.[22]

Researchers and policy makers are interested in continually monitoring and documenting these associations at the county level. As an administrative and demographic unit, county governments are responsible for many features of the built environment, including roads, crosswalks, and public spaces. County governments are also responsible for providing law enforcement, keeping vital statistics data, and controlling communicable disease, all of which may directly affect population health or the creation of policy.[23] Learning more about the built environment and its relationship with population health at the county level may be pivotal for making informed policy decisions in the future.

Research investigating the built environment and population health has relied on time- and resource-intensive site visits to conduct assessments of community features[24] or manual annotations of street images.[25-27] Given the time and expense of those data, only local studies have been conducted. Other data include self-reported survey data,[28] administrative data,[29] or satellite imaging,[3] each of which brings its own sets of strengths and limitations. Self-reported data provide insights into how a neighborhood is perceived from a resident's point of view but can also be inherently biased or subjective as a result. In addition, satellite imagery provides only views from overhead and, thus, may not allow for examination of some neighborhood features that require ground-level views.

Google Street View (GSV) images provide a unique perspective into the local built environment, with ground-level views not possible with other data sources. These ground-level views can be used to quantify the existence of resources (eg, crosswalks, sidewalks) or risks (eg, dilapidated buildings) in an area. In addition, by using GSV, investigators gain flexibility in assessing various features of the built environment from one data source. GSV images are collected in a standardized, uniform manner and are publicly available to researchers. Collecting millions of images on a large portion of the United States, GSV has the potential to both bridge previous gaps in methodology and reduce time and effort previously spent completing expensive in-person data collection.

Previous research using GSV has found it to be consistent with field assessments[26] and that it can also be used to accurately identify certain features of the built environment, such as crosswalks, commercial buildings, highways, and grasslands.[30,31] Li et al[32] found GSV to be an appropriate tool for assessing street-level urban greenery. Yin and Wang[33] used GSV images to objectively create measures of visual enclosure, which were then significantly inversely associated with pedestrian counts (ie, number of pedestrians passing a sampled street block during a 10-minute observation period) and walk score (ie, a proxy of neighborhood walkability). Using GSV images is comparatively cost-efficient because it leverages an existing data source rather than asking people to assess features of the built environment. GSV also provides near-complete coverage of the US road system.[34]

In a previous study, we demonstrated the feasibility and accuracy of using computer vision to label GSV images from visually distinct areas.[30] Subsequent analyses from our group showed that a greater presence of highways was related to a lower prevalence of chronic diseases and premature mortality on a county level. Compared with urban areas, rural areas, defined as areas with limited infrastructure in GSV images, had higher rates of chronic disease, including obesity, diabetes, and premature mortality, but lower rates of excessive drinking. An examination of the same data at the census-tract level for cities across the United States found that features of the built environment were related to chronic conditions and health behaviors.[19]

The objective of this study was to use GSV images to measure the association between features of the built environment (eg, presence of a crosswalk, building type other than single-family homes, single-lane roads, and visible utility wires) and health behaviors and outcomes at the county level. Unlike census tract–level analyses,[19] which had

[1] Department of Epidemiology and Biostatistics, University of Maryland School of Public Health, College Park, MD, USA
[2] Department of Electrical and Computer Engineering, Scientific Computing and Imaging Institute, University of Utah, Salt Lake City, UT, USA
[3] Electrical and Computer Engineering Department and Robert H. Smith School of Business, University of Maryland, College Park, MD, USA
[4] Intermountain Healthcare Delivery Institute, Intermountain Healthcare, Murray, UT, USA
[5] Department of Computer Science and Engineering, Michigan State University, East Lansing, MI, USA

outcomes available only for urban areas from the 500 Cities Project, we were able to include both urban and rural areas using national data sources for health outcomes and image data.

Methods

Google Street View Image Collection

In the United States, vast, sparsely populated, roadless areas abound, especially mountain ranges and deserts. We chose street intersections because they can represent hubs of activity, where people and traffic gather. Street intersections also provide views of commercial buildings (if present) and residential buildings. As such, our measures are interpreted as the percentage of features of the built environment seen at these intersections. We assessed roadway network files from the 2017 Census Topologically Integrated Geographic Encoding and Referencing data set and downloaded all road types.[35] We identified street intersections using PostgreSQL (an open-source object-relational database system) with the PostGIS plugin, a spatial database extender that enables location queries to be run in SQL.[36]

We retrieved GSV images for street intersections using the corresponding coordinates identified from PostgreSQL. From December 15, 2017, through July 17, 2018, we used Google's Street View Image application programming interface (API) to obtain images. In total, we collected 31 247 167 images from across the United States, excluding Alaska and Hawaii. GSV-derived indicators were available for 93% of counties. Parameters for the API included the following: image size (640 × 640 pixels, the maximum image resolution for nonpremium plan users), geographic location (geographic coordinates or addresses), field of view (zoom level), up or down angle of the camera relative to the Street View vehicle (default is 0), and heading (direction the camera is facing, with 0 = north, 90 = east, 180 = south, and 270 = west). We obtained 4 GSV images (directions: west, east, north, and south) for each pair of coordinates to capture 360-degree views of the environment. GSV API provides the most recent image available for a location. However, areas differ in the rate at which their GSV images are updated. In our data set, image dates ranged from 2007 to 2017, and the median year was 2013.

Neighborhood Characteristics and Image Processing

Details on our methods can be found elsewhere.[30,37] Briefly, we examined the following neighborhood characteristics at each intersection: (1) presence of a crosswalk (yes/no), (2) presence of a non–single-family home (yes/no), (3) presence of a single-lane road (yes/no), and (4) visible utility wires overhead (yes/no). We used crosswalks as an indicator of walkability.[19,38-46] We used the presence of a building that was not a single-family home (eg, schools, stores) as an indicator of mixed land use, which is associated with better health outcomes than having few non–single-family homes.[19,47,48] Images without any buildings received a value of 0 for presence of a non–single-family home. We used single-lane roads as an indicator of low levels of urban development, which is in turn associated with worse health outcomes than having fewer single-lane roads.[47,49,50] Visible utility wires were an indicator of physical disorder, which is correlated with worse health outcomes than having fewer visible utility wires.[19] A study in Brazil that examined utility wires indicated they may also present the risk of electrocution/electrical fire.[51] Studies show an association between visible utility wires and negative health outcomes.[19] Computer vision models were unable to accurately identify other indicators of physical disorder, including litter (too small to be seen), graffiti (rare outside of some urban settings), and poor building condition (large variation in appearance).

We manually annotated images (from Chicago, Illinois; Charleston, West Virginia; and nationally) for neighborhood characteristics from December 1, 2016, through February 28, 2017. We chose few images for manual annotation from these 2 visually distinct and geographically dispersed cities to help ensure that the computer vision models could predict the presence or absence of built-environment features across different landscapes. Chicago and Charleston have small and medium population sizes and vary in population density, demographic characteristics, and visual features. A map of the geographic distribution of GSV-derived features of the built environment in these 2 areas appears elsewhere.[30] We added a national subsample of images to help ensure our training data set could be used to create prediction models for the entire United States. We increased the size of the training data set until prediction models reached accuracies >85%. In total, our investigative team manually labeled 18 700 images. Interrater agreement was >85% for all neighborhood indicators. We randomly divided each labeled image data set into a training set (80%), which we used to calibrate the model, and a test set (20%), which we used to evaluate the trained model's accuracy. We used a deep convolutional network (Visual Geometry Group model) for object recognition. We used Stochastic Gradient Descent with the Adam optimizer, to train the network with cross entropy loss for classification. We trained separate networks for each neighborhood indicator and achieved high accuracies (85%-93%) for the separate recognition tasks.

Demographic and Socioeconomic Data

We used 2013 five-year estimates from the American Community Survey to control for demographic differences among counties.[38] Demographic variables included population density; percentage female, Hispanic, non-Hispanic Black, non-Hispanic Asian, and American Indian/Alaska Native; percentage not proficient in English; and percentage aged <18 and ≥65. All these variables were standardized to have a mean of 0 and standard deviation of 1. We created a composite variable for economic disadvantage using the percentage of female-headed households, children living in poverty, some college (reverse coded), unemployment rate, and median household income (reverse coded). In addition, we controlled for violent crime rate per 100 000 population,[39,40] the ratio of population to number of primary care physicians,[41-45] and average daily density of fine particulate matter in micrograms per cubic meter ($PM_{2.5}$)[46,48] to account for other neighborhood characteristics that influence health.

Health Outcome Data

We obtained data on county-level health outcomes from the 2019 County Health Rankings for adults aged ≥18.[52] We examined prevalence of adult obesity, prevalence of diabetes, physical inactivity, frequent physical and mental distress, poor or fair self-rated health, and premature death (in years of potential life lost). We derived these measures from the 2014 Centers for Disease Control and Prevention (CDC) Diabetes Interactive Atlas, the 2016 Behavioral Risk Factor Surveillance System, and 2014-2016 mortality data from the CDC Wide-ranging ONline Data for Epidemiologic Research.[53-55]

Statistical Analysis

For each county, we calculated the prevalence of the built-environment indicator or the percentage of total number of images that contained a given feature of the built environment (eg, [number of images with a crosswalk/total number of images] × 100 = percentage with crosswalk). Tertiles were created based on the county-level prevalence of the built-environment indicator. The third tertile represents the tertile with the highest percentage of the built-environment indicator, and the lowest tertile represents the reference group. We modeled health outcomes as continuous variables. We fit multivariate linear regression models to estimate the effects of features of the built environment and covariates on the selected outcomes. We ran separate regressions for each health outcome, but we included the GSV-derived indicators in the same model. We hypothesized that counties with more crosswalks (an indicator of walkability) and non–single-family homes (an indicator of mixed commercial/residential use) would be associated with better health outcomes as compared with counties with fewer numbers of these built-environment features. We further hypothesized that counties with more single-lane roads (an indicator of low levels of urban development) and more visible utility wires (an indicator of high levels of physical disorder) would be associated with worse health outcomes compared with counties with fewer numbers of these features.

We used stratified models to examine whether relationships between features of the built environment and health outcomes differed by metropolitan status as defined by rural–urban continuum codes. We assessed multicollinearity between independent variables using variance inflation factors (variance inflation factor < 10) and did not find any multicollinearity in the data. We calculated Moran *I* of the residuals estimated from the linear regression models as a measure of spatial autocorrelation. We used Stata IC15 (StataCorp) for all data analyses. The University of Maryland Institutional Review Board approved this study.

Results

Samples of processed GSV images show intersections with different features of the built environment (Figure). Our image classification model, described in the Methods section, made predictions for presence or absence of neighborhood features for all the GSV images. Our investigative team assigned "true" labels (ie, labels manually assigned by the research team) to a few of these GSV images for presence or absence of neighborhood features. Across all counties in the United States, 3.0% of images contained a crosswalk, 32.1% of images contained buildings that were not single-family homes, 52.5% of images contained a single-lane road, and 58.0% of images had visible utility wires (Table 1).

A 1-SD increase in population aged <18 and ≥65 was associated with a 0.51% and 0.46% county average decrease, respectively, in crosswalks and a 2.29% and 4.00% county average increase, respectively, in buildings that were not single-family homes (Table 2). A 1-SD increase in population aged <18 was associated with a 1.44% and 2.17% county average increase in single-lane roads and visible wires, respectively. A 1-SD increase in non-Hispanic Black and non-Hispanic Asian population was associated with a 0.57% and 1.49% county average increase, respectively, in crosswalks. A 1-SD increase in Hispanic, non-Hispanic Black, and American Indian/Alaska Native population was associated with a 14.29%, 1.45%, and 4.89% county average increase, respectively, in non–single-family homes. A 1-SD increase in Hispanic population was associated with a 3.89% county average increase in visible wires, and a 1-SD increase in American Indian/Alaska Native population was associated with a 1.50% county average decrease in visible utility wires. A 1-SD increase in economic disadvantage was associated with a 0.62%, 5.46%, and 1.76% county average decrease, respectively, in crosswalks, buildings that were not single-family homes, and visible utility wires.

GSV-derived features of the built environment were associated with county-level health outcomes. Compared with counties in the lowest tertile, counties in the third (highest) tertile for the presence of crosswalks had a lower prevalence of all examined negative health outcomes, including a lower prevalence of adult obesity, physical inactivity, and fair or poor self-rated health, as well as 477 fewer years of potential life lost per 100 000 population before age 75 (Table 3). An

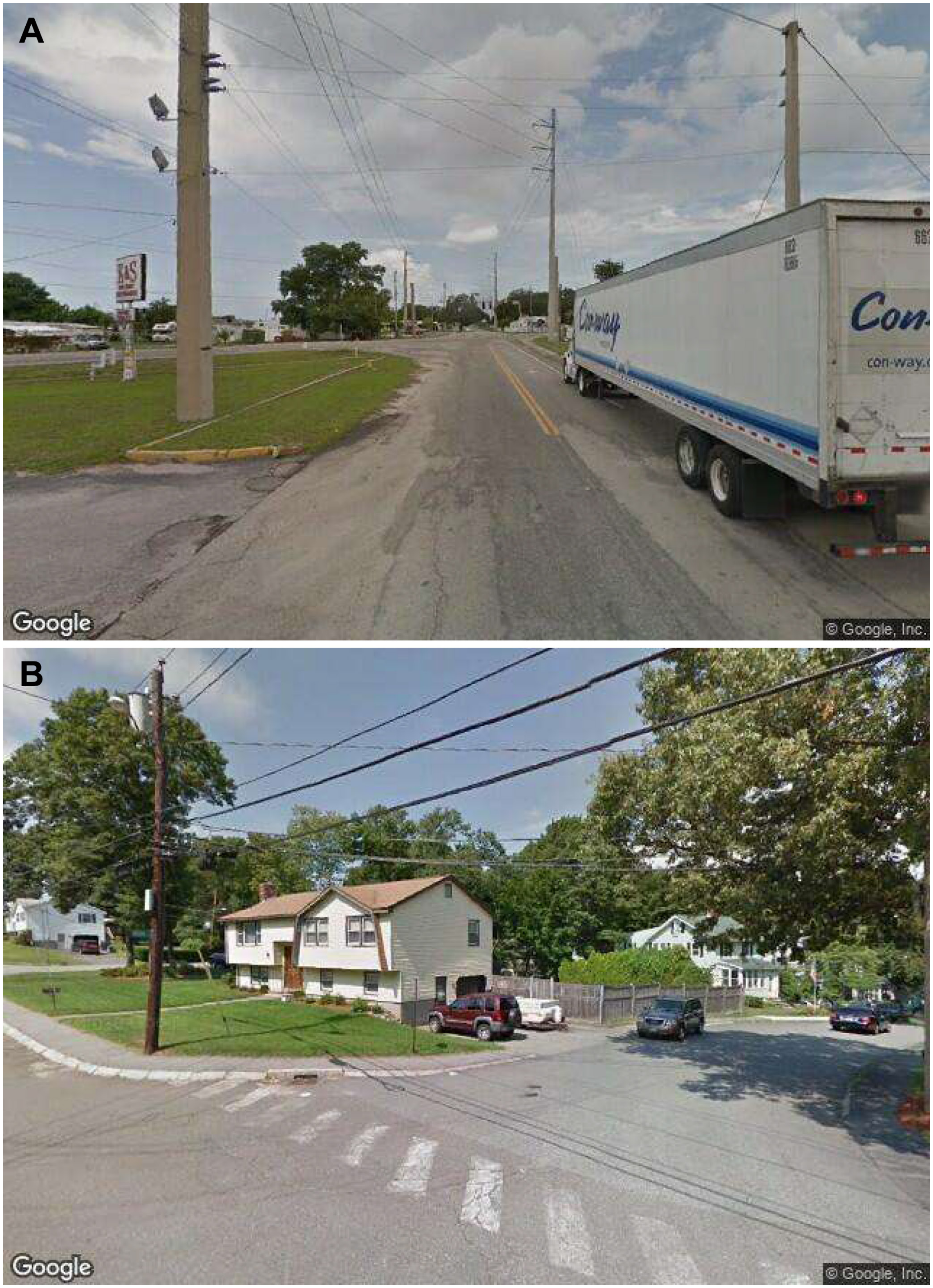

Figure. Samples of processed Google Street View images. Predictions were algorithm-derived labels for neighborhood features. (A) A commercial scene with multiple lanes of traffic, no crosswalk, and visible utility wires overhead (1 non–single-family home, 1 visible utility wire, no crosswalk, no single-lane roads); (B) a residential neighborhood with all single-family homes, a crosswalk, and visible utility wires overhead (0 non–single-family homes, 1 visible utility wire, 1 crosswalk, 1 single-lane road).

Table 1. Descriptive statistics for county-level prevalence of built-environment features derived from Google Street View images of street intersections across the United States and health outcomes at the county level, 2013-2018

Characteristic	No. of images	No. of counties	Mean (standard deviation)
Built-environment indicators[a]			
Presence of a crosswalk	31 247 167	2916	3.0 (4.6)
Presence of buildings that were not single-family homes (eg, school, store)	31 247 167	2916	32.1 (19.3)
Presence of a single-lane road	31 247 167	2916	52.5 (15.9)
Presence of visible utility wires overhead	31 247 167	2916	58.0 (15.3)
County health outcomes[b]			
Prevalence of obesity	—	3135	31.5 (4.5)
Prevalence of diabetes	—	3135	11.4 (2.5)
Prevalence of leisure-time physical inactivity	—	3135	26.3 (5.2)
Prevalence of frequent physical distress	—	3135	12.0 (2.3)
Prevalence of frequent mental distress	—	3135	12.2 (1.9)
Prevalence of fair or poor self-reported health	—	3135	17.5 (4.7)
Years of potential life lost for all residents in a county	—	3071	401.1 (109.2)

[a]Google Street View images were accessed from December 15, 2017, through July 17, 2018, to detect features of the built environment. Each image was examined for presence of a crosswalk, non–single-family home, single-lane roads, and visible utility wires. The percentage of total number of images that contained a specific built-environment indicator was calculated for each county. The values in the table represent mean percentages across 2916 counties.
[b]Data sources for health outcomes: mortality data from 2014-2016 Centers for Disease Control and Prevention (CDC) Wide-ranging ONline Data for Epidemiologic Research; 2014 CDC Diabetes Interactive Atlas for prevalence of obesity and leisure-time physical activity among adults aged ≥18; 2016 Behavioral Risk Factor Surveillance System for percentage of adults reporting poor mental health and physical health days.[53-55]

Table 2. Associations between county social and demographic characteristics and prevalence of built-environment indicators (derived from Google Street View image data for street intersections), at the county level (N = 2594 counties), United States, 2013-2017[a,b]

	Prevalence of built-environment indicator (95% CI) [*P* value[c]]			
County characteristics	Presence of a crosswalk	Presence of buildings that were not single-family homes (eg, school, store)	Presence of a single-lane road	Presence of visible utility wires overhead
Percentage aged <18	−0.51 (−0.70 to −0.31) [<.001]	2.29 (1.41 to 3.16) [<.001]	1.44 (0.57 to 2.31) [.001]	2.17 (1.36 to 2.98) [<.001]
Percentage aged ≥65	−0.46 (−0.65 to −0.28) [<.001]	4.00 (3.16 to 4.84) [<.001]	0.06 (−0.77 to 0.89) [.89]	0.14 (−0.63 to 0.92) [.72]
Percentage Hispanic	−0.08 (−0.45 to 0.30) [.68]	14.29 (12.61 to 15.97) [<.001]	−0.82 (−2.50 to 0.85) [.33]	3.89 (2.33 to 5.45) [<.001]
Percentage non-Hispanic Black	0.57 (0.37 to 0.77) [<.001]	1.45 (0.56 to 2.35) [.001]	−0.22 (−1.11 to 0.67) [.63]	0.09 (−0.74 to 0.91) [.84]
Percentage non-Hispanic Asian	1.49 (1.30 to 1.67) [<.001]	0.71 (−0.12 to 1.54) [.10]	−1.41 (−2.24 to −0.58) [<.001]	0.59 (−0.18 to 1.36) [.13]
Percentage American Indian/Alaska Native	−0.02 (−0.20 to 0.16) [.82]	4.89 (4.09 to 5.70) [<.001]	−1.75 (−2.55 to −0.94) [<.001]	−1.50 (−2.25 to −0.75) [<.001]
Economic disadvantage[d]	−0.62 (−0.78 to −0.45) [<.001]	−5.46 (−6.19 to −4.74) [<.001]	0.22 (−0.50 to 0.94) [.55]	−1.76 (−2.43 to −1.08) [<.001]
Percentage not proficient in English	0.61 (0.33 to 0.89) [<.001]	−1.47 (−2.73 to −0.21) [.02]	−1.39 (−2.64 to −0.13) [.03]	−0.44 (−1.61 to 0.73) [.46]
Violent crime rate	0.38 (0.22 to 0.54) [<.001]	0.95 (0.23 to 1.67) [.01]	0.89 (0.18 to 1.61) [.01]	1.24 (0.57 to 1.90) [<.001]
Ratio of population to number of primary care physicians	0.42 (0.20 to 0.65) [<.001]	−0.88 (−1.88 to 0.11) [.08]	−0.08 (−1.06 to 0.91) [.88]	0.20 (−0.72 to 1.12) [.67]

[a]Adjusted linear regression models were run for each outcome separately. Models controlled for county-level demographic characteristics: population density, percentage female, percentage aged <18, percentage aged ≥65, percentage Hispanic, percentage non-Hispanic Black, percentage non-Hispanic Asian, percentage American Indian/Alaska Native, economic disadvantage, percentage not proficient in English, violent crime rate, primary care physicians, and average daily $PM_{2.5}$.
[b]The county-level prevalence of built-environment indicators was obtained by calculating the percentage of images that contained a specific built-environment indicator for all the counties.
[c]Using the 2-tailed *t* test, with $P < .05$ considered significant.
[d]Economic disadvantage factor score derived from the following county characteristics: percentage female-headed households, percentage children living in poverty, unemployment rate, percentage attended some college (reverse coded), and median household income (reverse coded).

Table 3. Associations between county health outcomes and county-level prevalence of built-environment features derived from Google Street View images (N = 2594 counties), United States, 2014-2016[a,b]

County characteristics	County health outcomes, prevalence difference (95% CI) [*P* value[c]]						
	Prevalence of obesity (%)	**Prevalence of diabetes (%)**	**Prevalence of physical inactivity (%)**	**Prevalence of frequent physical distress (%)**	**Prevalence of frequent mental distress (%)**	**Prevalence of fair or poor self-rated health (%)**	**Premature death (years of potential life lost) (%)**
Presence of a crosswalk							
Third tertile (highest)	−1.31 (−1.68 to −0.94) [<.001]	−0.85 (−1.02 to −0.67) [<.001]	−2.68 (−3.09 to −2.27) [<.001]	−0.48 (−0.60 to −0.35) [<.001]	−0.36 (−0.47 to −0.26) [<.001]	−1.25 (−1.47 to −1.03) [<.001]	−476.90 (−637.53 to −316.27) [<.001]
Second tertile	−0.24 (−0.57 to 0.09) [.15]	−0.12 (−0.27 to 0.04) [.14]	−0.28 (−0.64 to 0.09) [.14]	−0.24 (−0.35 to −0.13) [<.001]	−0.19 (−0.28 to −0.09) [<.001]	−0.36 (−0.56 to −0.16) [<.001]	112.53 (−31.32 to 256.38) [.13]
Presence of buildings that were not single-family homes (eg, school, store)							
Third tertile (highest)	−1.13 (−1.55 to −0.71) [<.001]	−1.25 (−1.44 to −1.05) [<.001]	−0.97 (−1.43 to −0.50) [<.001]	0.45 (−0.59 to −0.31) [<.001]	−0.50 (−0.62 to −0.39) [<.001]	−0.73 (−0.98 to −0.48) [<.001]	66.44 (−115.84 to 248.72) [.48]
Second tertile	0.05 (−0.28 to 0.39) [.76]	−0.40 (−0.56 to −0.24) [<.001]	−0.14 (−0.52 to 0.24) [.47]	−0.11 (−0.22 to 0.00) [.05]	−0.15 (−0.24 to −0.05) [.003]	−0.11 (−0.31 to 0.09) [.29]	−5.87 (−152.74 to 141.00) [.94]
Presence of a single-lane road							
Third tertile (highest)	0.20 (−0.14 to 0.55) [.25]	−0.03 (−0.20 to 0.13) [.68]	0.90 (0.51 to 1.28) [<.001]	0.20 (0.09 to 0.32) [<.001]	0.07 (−0.03 to 0.17) [.18]	0.41 (0.20 to 0.61) [<.001]	375.08 (224.11 to 526.05) [<.001]
Second tertile	0.01 (−0.32 to 0.34) [.95]	−0.02 (−0.18 to 0.13) [.77]	0.41 (0.04 to 0.77) [.03]	0.10 (0.00 to 0.21) [.06]	0.02 (−0.08 to 0.11) [.74]	0.18 (−0.01 to 0.38) [.07]	168.76 (25.88 to 311.64) [.02]
Presence of visible utility wires overhead							
Third tertile (highest)	1.64 (1.29 to 1.99) [<.001]	0.47 (0.31 to 0.64) [<.001]	1.93 (1.54 to 2.32) [<.001]	0.22 (0.10 to 0.34) [<.001]	0.23 (0.13 to 0.33) [<.001]	0.42 (0.21 to 0.63) [<.001]	138.54 (−14.11 to 291.20) [.08]
Second tertile	0.84 (0.51 to 1.17) [<.001]	0.18 (0.02 to 0.34) [.02]	1.07 (0.70 to 1.44) [<.001]	0.18 (0.07 to 0.29) [.001]	0.10 (0.01 to 0.20) [.03]	0.24 (0.04 to 0.44) [.02]	−48.05 (−192.53 to 96.44) [.51]
Covariates							
Percentage aged <18	1.37 (1.15 to 1.58) [<.001]	0.44 (0.34 to 0.54) [<.001]	1.52 (1.28 to 1.76) [<.001]	−0.17 (−0.24 to −0.10) [<.001]	−0.25 (−0.31 to −0.18) [<.001]	0.00 (−0.13 to 0.13) [.97]	364.92 (271.32 to 458.52) [<.001]
Percentage aged ≥65	−0.24 (−0.44 to −.03) [0.025]	0.53 (0.44 to 0.63) [<.001]	0.71 (0.48 to 0.94) [<.001]	−0.42 (−0.49 to −0.35) [<.001]	−0.39 (−0.45 to −0.34) [<.001]	−0.87 (−0.99 to −0.74) [<.001]	161.48 (70.93 to 252.03) [<.001]
Percentage Hispanic	−2.78 (−3.18 to −2.39) [<.001]	−0.74 (−0.93 to −0.55) [<.001]	−1.96 (−2.40 to −1.52) [<.001]	0.26 (0.13 to 0.39) [<.001]	−0.22 (−0.33 to −0.10) [<.001]	1.42 (1.18 to 1.66) [<.001]	196.85 (23.42 to 370.29) [.03]
Percentage non-Hispanic Black	0.27 (0.07 to 0.47) [.01]	0.08 (−0.01 to 0.18) [.09]	0.23 (0.01 to 0.45) [.04]	−0.19 (−0.25 to −0.12) [<.001]	−0.16 (−0.21 to −0.10) [<.001]	−0.14 (−0.26 to −0.02) [.02]	−4.65 (−90.62 to 81.32) [.92]
Percentage non-Hispanic Asian	−0.76 (−0.98 to −0.55) [<.001]	−0.01 (−0.11 to 0.09) [.82]	−0.51 (−0.75 to −0.27) [<.001]	−0.14 (−0.21 to −0.07) [<.001]	−0.17 (−0.23 to −0.11) [<.001]	−0.11 (−0.24 to 0.02) [.10]	−64.38 (−157.77 to 29.01) [.18]
Percentage American Indian/Alaska Native	−0.13 (−0.31 to 0.06) [.17]	0.02 (−0.07 to 0.11) [.67]	−0.53 (−0.73 to −0.32) [<.001]	0.39 (0.33 to 0.45) [<.001]	0.44 (0.38 to 0.49) [<.001]	0.22 (0.11 to 0.33) [<.001]	558.88 (478.45 to 639.30) [<.001]
Economic disadvantage[d]	1.57 (1.39 to 1.74) [<.001]	1.29 (1.21 to 1.37) [<.001]	2.20 (2.01 to 2.39) [<.001]	1.82 (1.76 to 1.88) [<.001]	1.40 (1.36 to 1.45) [<.001]	3.65 (3.55 to 3.76) [<.001]	1472.13 (1397.47 to 1546.78) [<.001]
Percentage not proficient in English	0.32 (0.04 to 0.59) [.03]	−0.09 (−0.22 to 0.04) [.18]	0.03 (−0.28 to 0.34) [.86]	−0.01 (−0.11 to 0.08) [.76]	0.04 (−0.04 to 0.11) [.37]	0.05 (−0.11 to 0.22) [.53]	−720.51 (−842.44 to −598.58) [<.001]
Violent crime rate	0.14 (−0.02 to 0.30) [.10]	0.15 (0.08 to 0.23) [<.001]	0.07 (−0.11 to 0.25) [.42]	0.03 (−0.03 to 0.08) [.32]	0.04 (−0.01 to 0.08) [.09]	0.07 (−0.03 to 0.17) [.16]	251.50 (181.64 to 321.35) [<.001]
Ratio of population to number of primary care physicians	−0.57 (−0.79 to −0.35) [<.001]	−0.10 (−0.21 to 0.00) [.05]	−0.44 (−0.69 to −0.20) [<.001]	0.06 (−0.01 to 0.13) [.09]	0.08 (0.01 to 0.14) [.02]	−0.15 (−0.29 to −0.02) [.02]	−32.34 (−126.53 to 61.84) [.50]
Population density	−0.16 (−0.30 to −0.03) [.02]	−0.02 (−0.09 to 0.04) [.47]	0.18 (0.03 to 0.33) [.02]	−0.03 (−0.07 to 0.02) [.27]	−0.03 (−0.06 to 0.01) [.19]	−0.04 (−0.12 to 0.04) [.36]	−9.04 (−67.67 to 49.59) [.76]
Average daily $PM_{2.5}$	−0.04 (−0.19 to 0.11) [.61]	0.23 (0.16 to 0.30) [<.001]	0.27 (0.10 to 0.44) [.002]	0.18 (0.13 to 0.23) [<.001]	0.10 (0.05 to 0.14) [<.001]	0.28 (0.18 to 0.37) [<.001]	154.01 (87.09 to 220.94) [<.001]
Percentage female	−0.22 (−0.39 to −0.06) [.01]	0.13 (0.05 to 0.21) [.001]	−0.23 (−0.41 to −0.04) [.02]	0.13 (0.07 to 0.18) [<.001]	0.28 (0.23 to 0.33) [<.001]	0.13 (0.03 to 0.23) [.01]	58.78 (−13.51 to 131.07) [.11]
Adjusted R^2	0.45	0.59	0.48	0.76	0.74	0.81	0.63

[a]Adjusted linear regression models were run for each outcome separately. Models controlled for county-level demographic characteristics: population density, percentage female, percentage aged ≤18, percentage aged ≥65, percentage Hispanic, percentage non-Hispanic Black, percentage non-Hispanic Asian, percentage American Indian/Alaska Native, economic disadvantage, percentage not proficient in English, violent crime rate, primary care physicians, and average daily $PM_{2.5}$.

[b]Prevalence or percentage of total number of images that contained a specific built-environment indicator were calculated for each county. Tertiles were created based on the county-level prevalence of built-environment indicator. The third tertile represents the tertile with the highest percentage of the built-environment indicator and the lowest tertile represents the reference group.

[c]Using the 2-tailed *t* test, with $P < .05$ considered significant.

[d]Economic disadvantage factor score derived from the following county characteristics: percentage female-headed households, percentage children living in poverty, unemployment rate, percentage attended some college (reverse coded), and median household income (reverse coded).

increase in the number of non–single-family homes was associated with a decrease in the prevalence of all negative health outcomes except premature death. Counties in the third (highest) tertile for single-lane roads had a 0.90% increase in physical inactivity, a 0.20% increase in frequent physical distress, and a 0.41% increase in fair or poor self-rated health compared with counties in the lowest tertile. Counties in the second and third tertiles for single-lane roads had 169 and 375 more years of potential life lost per 100 000 population, respectively, compared with the lowest tertile. Visible utility wires were associated with a higher prevalence of obesity, diabetes, physical inactivity, physical and mental distress, and fair or poor self-rated health in both the second and third tertiles compared with the lowest tertile.

We also examined patterns stratified by metropolitan status. Metropolitan counties had a higher prevalence of crosswalks and visible utility wires and a lower prevalence of negative health outcomes, such as obesity and premature death, than nonmetropolitan counties (data available from authors upon request). Associations between GSV-derived variables and health outcomes were qualitatively similar in metropolitan and nonmetropolitan counties (data available from authors upon request), with the exception of associations involving visible utility wires and non–single-family homes for obesity prevalence and physical inactivity; those associations were stronger in metropolitan counties than in nonmetropolitan counties. The Moran *I*s were small but significant, indicating some residual spatial autocorrelation (data available from authors upon request).

Discussion

Consistent with the body of literature on neighborhood effects[56] and our previous analyses using similar methods,[19,30,31] features of the built environment we examined were significantly associated with health behaviors and outcomes. This analysis contributes to the literature by including both urban and rural areas, as nearly all counties in the United States are represented. Significant associations between population demographic characteristics and features of the built environment suggest group differences in access or preferences for varying neighborhood conditions. Increasing access to high-quality neighborhoods is a potential lever for addressing health disparities and improving population health.

The presence of crosswalks was associated with a lower prevalence of all negative health outcomes. Crosswalks may encourage residents to walk to commercial or leisure destinations or to access public transit, leading to higher levels of physical activity and, thus, decreasing prevalence of obesity and associated comorbidities. Crosswalks also increase perceived safety,[20] which could explain the association with decreased mental distress. Similarly, a higher frequency of buildings that were not single-family homes (indicating mixed land use) was associated with decreases in all negative outcomes except premature death. This association may be driven by the health-related advantages of urban development, which provides improved proximity to amenities. Studies have found a positive association between single-lane roads, an indicator of less urban development, and adverse health outcomes.[47,50]

Previous research has connected physical disorder with an array of detrimental health outcomes, including poor mental health, higher substance use, poor physical functioning, and chronic conditions.[20] In our study, the presence of visible utility wires, an indicator of physical disorder, was associated with an increased prevalence of all negative health outcomes except for years of potential life lost. Visible utility wires hanging overhead are visually striking and may affect residents' aesthetic sense of their environment, alter perceptions of safety or pleasure, and influence both mental health (by affecting stress levels) and physical health (by disincentivizing walking).

Strengths and Limitations

This study had several strengths. First, the use of GSV images as a source of data on the built environment brings a novel approach to neighborhood effects research. Second, the availability of a large volume of images of the built environment, in conjunction with machine learning techniques to identify features of interest with high accuracy, is a more efficient and convenient way to analyze relationships between health behaviors and outcomes than in-person audits of the neighborhood environment. In the past, data on physical features of the environment have been cumbersome to obtain on a large scale. Use of GSV data for virtual audit is particularly meaningful in rural areas, where populations are spread out over large geographic areas and public health agencies have few resources.

This study also had several limitations. First, because all GSV-derived indicators, County Health Rankings outcomes, and covariates were aggregated at the county level, the analysis was ecological; therefore, the findings should not be extrapolated to individual outcomes. Second, because all data in the models were aggregated at the county level, some residual confounding may be present. Associations found at the county level do not necessarily apply to other levels. Third, we used adjusted linear regression models, but this model assumed statistical independence of observations and spatial stationarity of the relationship between health outcomes and predictor variables. Future research will account for spatial autocorrelation with spatial regression models.

Fourth, each GSV image depicts a unique location only once, so we could not account for changes in the built environment over time. We sampled images from street intersections, which do not capture all important environmental features. A denser sampling of points from street segments would have enabled the inclusion of even more counties in the analyses (>93%). Further research is needed to validate GSV measures with other neighborhood data; for example, investigating whether GSV-derived features such as crosswalks and sidewalks add to current measures of walkability in predicting health behaviors and health outcomes. Certain features of the built environment are difficult to capture with computer vision, particularly features that are small in scale (litter or leaves), vary widely in appearance (dilapidated buildings), or require subjective assessments (perceived safety). We used one type of technique for image classification, but other methods are available and our group published a study comparing several approaches.[37] Finally, the data sources had different time frames, so the temporal alignment is not exact. For example, the 31 million GSV images were taken from cars during a period of several years; data on county health rankings are determined using CDC data ranging from 2014 to 2016; and American Community Survey data on covariates were taken from 5-year estimates to ensure that as many counties as possible had data available.

Conclusions

The built environment is associated with various health behaviors and outcomes. GSV images provide a large, publicly available source of data on the physical environment that can be assessed and categorized using machine learning techniques. This data source affords researchers the opportunity to assess associations between the prevalence of features of interest and population health outcomes. Our analysis contributes to the literature by measuring these associations on the county level consistently across geographies and includes both rural and urban areas. Additional research can use this data source to further explore how the built environment affects the health of communities across the United States.

Acknowledgments

The authors thank Ross Whitaker, PhD, for his input on the project.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This research was funded by the National Library of Medicine of the National Institutes of Health under award number R01LM012849 (principal investigator, Q Nguyen).

ORCID iD

Quynh C. Nguyen, PhD https://orcid.org/0000-0003-4745-6681

References

1. Roof K, Oleru N. Public health: Seattle and King County's push for the built environment. *J Environ Health*. 2008;71(1):24-27.
2. National Center for Environmental Health, Centers for Disease Control and Prevention. *Impact of the Built Environment on Health*. Centers for Disease Control and Prevention; 2011.
3. Browning M, Lee K, Wolf K. Tree cover shows an inverse relationship with depressive symptoms in elderly residents living in U.S. nursing homes. *Urban Forestry Urban Greening*. 2019;41:23-32. doi:10.1016/j.ufug.2019.03.002
4. Sallis JF, Saelens BE, Frank LD, et al. Neighborhood built environment and income: examining multiple health outcomes. *Soc Sci Med*. 2009;68(7):1285-1293. doi:10.1016/j.socscimed.2009.01.017
5. Burls A. People and green spaces: promoting public health and mental well-being through ecotherapy. *J Public Mental Health*. 2007;6(3):24-39. doi:10.1108/17465729200700018
6. Nutsford D, Pearson AL, Kingham S. An ecological study investigating the association between access to urban green space and mental health. *Public Health*. 2013;127(11):1005-1011. doi:10.1016/j.puhe.2013.08.016
7. Fein AJ, Plotnikoff RC, Wild TC, Spence JC. Perceived environment and physical activity in youth. *Int J Behav Med*. 2004;11(3):135-142. doi:10.1207/s15327558ijbm1103_2
8. Giles-Corti B, Donovan RJ. The relative influence of individual, social and physical environment determinants of physical activity. *Soc Sci Med*. 2002;54(12):1793-1812. doi:10.1016/S0277-9536(01)00150-2
9. Morland K, Wing S, Diez Roux A. The contextual effect of the local food environment on residents' diets: the Atherosclerosis Risk in Communities Study. *Am J Public Health*. 2002;92(11):1761-1767. doi:10.2105/AJPH.92.11.1761
10. Laraia BA, Siega-Riz AM, Kaufman JS, Jones SJ. Proximity of supermarkets is positively associated with diet quality index for pregnancy. *Prev Med*. 2004;39(5):869-875. doi:10.1016/j.ypmed.2004.03.018
11. Chaiyachati KH, Hom JK, Hubbard RA, Wong C, Grande D. Evaluating the association between the built environment and primary care access for new Medicaid enrollees in an urban environment using Walk and Transit Scores. *Prev Med Rep*. 2017;9:24-28. doi:10.1016/j.pmedr.2017.12.001
12. Penedo FJ, Dahn JR. Exercise and well-being: a review of mental and physical health benefits associated with physical activity. *Curr Opin Psychiatry*. 2005;18(2):189-193. doi:10.1097/00001504-200503000-00013
13. McIntosh WA, Sobal J. Rural eating, diet, nutrition, and body weight. In: Glasgow N, Morton LW, Johnson NE, eds. *Critical Issues in Rural Health*. Blackwell Publishing; 2004:113-126.
14. Eberhardt MS, Pamuk ER. The importance of place of residence: examining health in rural and nonrural areas. *Am J Public Health*. 2004;94(10):1682-1686. doi:10.2105/AJPH.94.10.1682
15. Befort CA, Nazir N, Perri MG. Prevalence of obesity among adults from rural and urban areas of the United States: findings from NHANES (2005-2008). *J Rural Health*. 2012;28(4):392-397. doi:10.1111/j.1748-0361.2012.00411.x
16. Cossman JS, James WL, Cosby AG, Cossman RE. Underlying causes of the emerging nonmetropolitan mortality penalty. *Am J Public Health*. 2010;100(8):1417-1419. doi:10.2105/AJPH.2009.174185

17. Monnat SM, Beeler Pickett C. Rural/urban differences in self-rated health: examining the roles of county size and metropolitan adjacency. *Health Place*. 2011;17(1):311-319. doi:10.1016/j.healthplace.2010.11.008
18. Smith KB, Humphreys JS, Wilson MGA. Addressing the health disadvantage of rural populations: how does epidemiological evidence inform rural health policies and research? *Aust J Rural Health*. 2008;16(2):56-66. doi:10.1111/j.1440-1584.2008.00953.x
19. Keralis JM, Javanmardi M, Khanna S, et al. Health and the built environment in United States cities: measuring associations using Google Street View–derived indicators of the built environment. *BMC Public Health*. 2020;20(1):215. doi:10.1186/s12889-020-8300-1
20. Ross CE, Mirowsky J. Neighborhood disadvantage, disorder, and health. *J Health Soc Behav*. 2001;42(3):258-276. doi:10.2307/3090214
21. Sampson RJ, Raudenbush SW. Systematic social observation of public spaces: a new look at disorder in urban neighborhoods. *Am J Sociol*. 1999;105(3):603-651. doi:10.1086/210356
22. Ross CE, Mirowsky J. Disorder and decay: the concept and measurement of perceived neighborhood disorder. *Urban Aff Rev*. 1999;34(3):412-432.
23. The White House. State & local government. Accessed December 3, 2019. https://obamawhitehouse.archives.gov/1600/state-and-local-government
24. Day K, Boarnet M, Alfonzo M, Forsyth A. The Irvine–Minnesota inventory to measure built environments: development. *Am J Prev Med*. 2006;30(2):144-152. doi:10.1016/j.amepre.2005.09.017
25. Bader MDM, Mooney SJ, Lee YJ, et al. Development and deployment of the Computer Assisted Neighborhood Visual Assessment System (CANVAS) to measure health-related neighborhood conditions. *Health Place*. 2015;31:163-172. doi:10.1016/j.healthplace.2014.10.012
26. Rundle AG, Bader MDM, Richards CA, Neckerman KM, Teitler JO. Using Google Street View to audit neighborhood environments. *Am J Prev Med*. 2011;40(1):94-100. doi:10.1016/j.amepre.2010.09.034
27. Mooney SJ, DiMaggio CJ, Lovasi GS, et al. Use of Google Street View to assess environmental contributions to pedestrian injury. *Am J Public Health*. 2016;106(3):462-469. doi:10.2105/AJPH.2015.302978
28. Dendup T, Astell-Burt T, Feng X. Residential self-selection, perceived built environment and type 2 diabetes incidence: a longitudinal analysis of 36,224 middle to older age adults. *Health Place*. 2019;58:102154. doi:10.1016/j.healthplace.2019.102154
29. Weiss CC, Purciel M, Bader M, et al. Reconsidering access: park facilities and neighborhood disamenities in New York City. *J Urban Health*. 2011;88(2):297-310. doi:10.1007/s11524-011-9551-z
30. Nguyen QC, Sajjadi M, McCullough M, et al. Neighbourhood looking glass: 360º automated characterisation of the built environment for neighbourhood effects research. *J Epidemiol Community Health*. 2018;72(3):260-266. doi:10.1136/jech-2017-209456
31. Nguyen QC, Khanna S, Dwivedi P, et al. Using Google Street View to examine associations between built environment characteristics and U.S. health outcomes. *Prev Med Rep*. 2019;14:100859. doi:10.1016/j.pmedr.2019.100859
32. Li X, Zhang C, Li W, Ricard R, Meng Q, Zhang W. Assessing street-level urban greenery using Google Street View and a modified green view index. *Urban Forestry Urban Greening*. 2015;14(3):675-685. doi:10.1016/j.ufug.2015.06.006
33. Yin L, Wang Z. Measuring visual enclosure for street walkability: using machine learning algorithms and Google Street View imagery. *Appl Geogr*. 2016;76:147-153. doi:10.1016/j.apgeog.2016.09.024
34. Google. Google Maps Street View. Accessed December 2, 2019. https://www.google.com/streetview/explore
35. US Census Bureau. TIGER/Line Shapefiles. 2019. Accessed December 3, 2019. https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html
36. PostGIS: spatial and geographic objects for PostgreSQL. Accessed November 1, 2019. https://postgis.net
37. Javanmardi M, Huang D, Dwivedi P, et al. Analyzing associations between chronic disease prevalence and neighborhood quality through Google Street View images. *IEEE Access*. 2019;99:1.
38. US Census Bureau. American Community Survey 2013-2017 5-year data release. Accessed December 2, 2019. https://www.census.gov/newsroom/press-kits/2018/acs-5year.html
39. McEwen BS. Stress, adaptation, and disease. Allostasis and allostatic load. *Ann N Y Acad Sci*. 1998;840:33-44. doi:10.1111/j.1749-6632.1998.tb09546.x
40. Seeman TE, Singer BH, Rowe JW, Horwitz RI, McEwen BS. Price of adaptation—allostatic load and its health consequences. MacArthur studies of successful aging. *Arch Intern Med*. 1997;157(19):2259-2268.
41. Gorin AA, Wiley J, Ohannessian CM, Hernandez D, Grant A, Cloutier MM. Steps to Growing Up Healthy: a pediatric primary care based obesity prevention program for young children. *BMC Public Health*. 2014;14:72. doi:10.1186/1471-2458-14-72
42. Logue J, Allardice G, Gillies M, Forde L, Morrison DS. Outcomes of a specialist weight management programme in the UK National Health Service: prospective study of 1838 patients. *BMJ Open*. 2014;4(1):e003747. doi:10.1136/bmjopen-2013-003747
43. Athas WF, Adams-Cameron M, Hunt WC, Amir-Fazli A, Key CR. Travel distance to radiation therapy and receipt of radiotherapy following breast-conserving surgery. *J Natl Cancer Inst*. 2000;92(3):269-271. doi:10.1093/jnci/92.3.269
44. Fortney JC, Booth BM, Blow FC, Bunn JY, Loveland Cook CA. The effects of travel barriers and age on the utilization of alcoholism treatment aftercare. *Am J Drug Alcohol Abuse*. 1995;21(3):391-406. doi:10.3109/00952999509002705
45. Fortney J, Rost K, Zhang M, Warren J. The impact of geographic accessibility on the intensity and quality of

depression treatment. *Med Care*. 1999;37(9):884-893. doi:10.1097/00005650-199909000-00005
46. Seaton A, MacNee W, Donaldson K, Godden D. Particulate air pollution and acute health effects. *Lancet*. 1995;345(8943):176-178. doi:10.1016/S0140-6736(95)90173-6
47. University of California Division of Agriculture and Natural Resources. Rural roads webinar series. Accessed May 10, 2020. https://ucanr.edu/sites/forestry/Webinars/Rural_Roads_Webinar_Series/
48. To T, Zhu J, Villeneuve PJ, et al. Chronic disease prevalence in women and air pollution—a 30-year longitudinal cohort study. *Environ Int*. 2015;80:26-32. doi:10.1016/j.envint.2015.03.017
49. Atkinson JE, Chandler BE, Betkey V, et al. *Manual for Selecting Safety Improvements on High Risk Rural Roads*. Federal Highway Administration, US Department of Transportation; 2014.
50. Berkes H. The deadliest roads are rural. *National Public Radio.* November 29, 2009. Accessed November 20, 2019. https://www.npr.org/2009/11/29/120716625/the-deadliest-roads-are-rural
51. Remigio RV, Zulaika G, Rabello RS, et al. A local view of informal urban environments: a mobile phone–based neighborhood audit of street-level factors in a Brazilian informal community. *J Urban Health*. 2019;96(4):537-548. doi:10.1007/s11524-019-00351-7
52. County Health Rankings & Roadmaps. 2019 measures. Accessed December 12 2019. https://www.countyhealthrankings.org/explore-health-rankings/measures-data-sources/2019-measures
53. Centers for Disease Control and Prevention. Centers for Disease Control and Prevention diabetes interactive atlas. 2014. Accessed October 22, 2020. https://www.cdc.gov/diabetes/atlas/
54. Centers for Disease Control and Prevention. Behavioral Risk Factor Surveillance System (BRFSS). 2016. Accessed October 22, 2020. https://www.cdc.gov/brfss/
55. Centers for Disease Control and Prevention, National Center for Health Statistics. Compressed Mortality File 2014-2016. Accessed October 22, 2020. https://wonder.cdc.gov/mortSQL.html
56. Chandrabose M, Rachele JN, Gunn L, et al. Built environment and cardio-metabolic health: systematic review and meta-analysis of longitudinal studies. *Obes Rev*. 2019;20(1):41-54. doi:10.1111/obr.12759