

Returning to our roots: The use of geospatial data for nurse-led community research

Kelli N. DePriest PhD, RN¹ | Timothy M. Shields MA² | Frank C. Curriero PhD²

¹School of Nursing, Johns Hopkins University, Baltimore, Maryland

²Department of Epidemiology, Spatial Science for Public Health Center, Johns Hopkins Bloomberg School of Public Health, Baltimore, Maryland

Correspondence

Kelli N. DePriest, Johns Hopkins University School of Nursing, 525 N Wolfe Street, Baltimore, MD 21205.
Email: KDePriest@jhu.edu

Funding information

National Institute of Nursing Research, Grant/Award Number: F31NR017319

Abstract

In the early 20th century, public health nurse, Lillian Wald, addressed the social determinants of health (SDOH) through her work in New York City and her advocacy to improve policy in workplace conditions, education, recreation, and housing. In the early 21st century, addressing the SDOH is a renewed priority and provides nurse researchers with an opportunity to return to our roots. The purpose of this methods paper is to examine how the incorporation of geospatial data and spatial methodologies in community research can enhance the analyses of the complex relationships between social determinants and health. Geospatial technologies, software for mapping and working with geospatial data, statistical methods, and unique considerations are discussed. An exemplar for using geospatial data is presented regarding associations between neighborhood greenspace, neighborhood violence, and children's asthma control. This innovative use of geospatial data illustrates a new frontier in investigating nontraditional connections between the environment and SDOH outcomes.

KEYWORDS

community, design development, environment, geographic information system, public health, social and economic aspects of illness

1 | INTRODUCTION

Lillian Wald, a pioneer of public health nursing, believed the nursing discipline should focus on holistic care to improve well-being and prevent disease. Wald wrote, "the call to the nurse is not only for the bedside care of the sick, but to help in seeking out the deep-lying basic causes of illness and misery, that in the future there may be less sickness to nurse and to cure" (Wald, 1915, p. 65). Wald founded the Henry Street Settlement, which sent public health nurses to care for the sick in their homes. The Henry Street Settlement also mobilized community resources including tangible items like medicine, food, and bedding; arranging for loans and housing subsidies; organizing community clean-ups; and providing job training and community education (Pittman, 2019). Not only was the Henry Street Settlement addressing individual social needs, they were also advocating for policy reform in the areas of workplace safety, education, recreation, and housing, to make the systematic changes necessary to address the root causes of poor health (Castrucci & Auerbach, 2019).

Nearly 100 years after Wald's efforts in New York City, there is a renewed investment in addressing social determinants of health (SDOH), defined as the conditions in which people are "born, live, learn, work, play, worship, and age" that affect their health and well-being (U.S. Department of Health and Human Services, 2015). In 2005, the World Health Organization established the Commission on Social Determinants of Health to compile evidence on how to promote health equity (Commission on Social Determinants of Health, 2008). According to the Robert Wood Johnson Foundation, "health equity means that everyone has a fair and just opportunity to be healthier. This requires removing obstacles to health such as poverty, discrimination, and their consequences, including powerlessness and lack of access to good jobs with fair pay, quality education, and housing, safe environments, and health care (Braveman, Arkin, Orleans, Proctor, & Plough, 2017, p. 2)." In other words, addressing the SDOH promotes health equity where everyone has a fair opportunity to achieve their optimal health and well-being. In the United States, there has been a push to address the SDOH by several entities including the US Government (U.S. Department of

Health and Human Services, 2015), the American Academy of Nursing (American Academy of Nursing, 2019), the National Academy of Medicine (Adler et al., 2016), and the Robert Wood Johnson Foundation (RWJF, 2018). Place plays an important part in addressing the SDOH; although SDOH originates at several levels, they are often collated at the neighborhood level.

One way to address the SDOH and to work towards achieving health equity is to utilize geospatial data, that is, information tied to a geographic location with characteristics of a natural or constructed feature (FAA reauthorization act of 2018: Geospatial data act of 2018, 2018). These data and associated technologies can be used along the research spectrum (a) in designing studies, (b) in current research, and (c) in carrying out interventions and policy efforts based on evidence derived from the research. The use of geospatial data in health research and practice has evolved dramatically over the past two decades to include advancements in technologies for obtaining geospatial data, software for mapping and working with these data, and spatial statistical methods for analyzing these data. The purpose of this paper is to examine the uses of geospatial data in current research to analyze innovative connections between social determinants and health. We will explore relationships between geospatial data and SDOH, discuss considerations for working with these data, present an exemplar of nursing research using geospatial data, and discuss implications for nurses working with geospatial data in research and practice.

2 | GEOSPATIAL DATA AND THE SDOH

Depending on the study's purpose and research questions, the SDOH can be characterized by analyzing geospatial data at several levels of exposure (e.g., home address, zip code, or county). With an individual's address, a researcher could determine their exposure to crime and violence; toxic substances; or nearby parks or green space (i.e., land with grass, trees, or other vegetation [U.S. Environmental Protection Agency, 2016]), all of which have been found to influence health (U.S. Department of Health and Human Services, 2015). Commonly, geospatial data characterize the physical environment such as parks, grocery store density, and number of vacant buildings. Less commonly and perhaps indirectly, geospatial data characterize the social environment such as neighborhood social cohesion, safety (measured using crime statistics), or neighborhood disorder. This can be done by aggregating survey data to a geographic area. For example, social cohesion, defined as the willingness of individuals to cooperate with each other, is measured by asking individuals about relationships with neighbors including mutual trust, value sharing, willingness to help each other, and whether or not they get along (Gebreab et al., 2017). Neighborhood disorder could be measured by someone physically walking around and performing a visual evaluation or surveying residents regarding indicators of disorder such as litter, graffiti, boarded up/vacant homes, or broken windows. For example, raters in Baltimore City walked city blocks while filling out the Neighborhood Inventory for

Environmental Typology assessment instrument for indicators that have been theoretically associated with increases in violence, alcohol, and other drug exposures for neighborhood residents (Furr-Holden et al., 2008). The assessment covers several domains including physical features, adult and youth activity, and signs of disorder. Measuring the percent of vacant or abandoned homes in an area can be used as a proxy for measuring disorder; this information is found in easily accessible administrative datasets. Both social and physical environments interact to influence an individual's experience of a particular place.

The theoretical approach to geospatial data may be informed by Bronfenbrenner's Social-Ecological Model (Bronfenbrenner, 1979), wherein the individual is situated within the context of several nested social and physical environments. The interaction between the individual and these layers influences their development (Bronfenbrenner, 1979). In a more recent schematic, Diez Roux and Mair (2010) summarize the complex interactions between the physical and social neighborhood environments that contribute to health and health inequities. With location information, we place a dot on the map and begin asking what is going on around or in the neighborhood of that location. The answers to these questions provide clues to other affecting health outcomes and geospatial data to consider in our analysis.

The SDOH are complex, overlapping processes that influence health. Geospatial data enable researchers to discover and map specific phenomena, then overlay them with other variables, to get a better idea of how they may interact to influence health. For example, consider the concept of a "healthy food priority area" (previously known as a food desert). Four criteria have been proposed to define a healthy food priority area: Median household income is at or below 185 percent of the Federal Poverty Level, over 30 percent of households have no vehicle available, the distance to a supermarket is more than one-quarter of a mile, and the average Healthy Food Availability Index score for food stores is low (Misiaszek, Buzogany, & Freishtat, 2018). Each of these criteria has its own implications for health. When all four are present, they represent a larger phenomenon affecting health. Similarly, when individual SDOH are mapped and overlaid, new patterns begin to emerge. An added benefit of using geospatial data is that the maps produced are powerful visual tools to present relationships among variables. A geospatial approach can be used to test interventions to influence the social determinants as well as to provide evidence to support policy improvements.

3 | TECHNOLOGY ADVANCES FOR OBTAINING GEOSPATIAL DATA

Technology advances have resulted in new forms of output produced by "placing a dot on the map." Traditionally, geospatial data used reported location such as a home address, to link information to a geographic location. Using smartphones and wearable technology, researchers are now able to capture a participant's location and

activity for investigating connections between physical activity and the built environment (human-made structures such as buildings and parks; Chambers et al., 2017). Wearable technology also supports measuring environmental exposures based on individual locations (Dieffenderfer et al., 2016). Sadler, Clark, Wilk, O'Connor, and Gilliland (2016) used activity trackers to connect adolescents' food environment exposures with their junk food purchasing habits. Researchers are also beginning to use georeferenced social media data, including text and photos, to assess subjective experiences of particular places (Mennis & Yoo, 2018; Nguyen et al., 2016).

4 | SOFTWARE FOR MAPPING AND WORKING WITH GEOSPATIAL DATA

The availability and accessibility of geospatial data have increased dramatically over recent years. The Centers for Disease Control and Prevention categorizes public health geospatial resources into the following four, nonexclusive groups and provides links for data access: Public health data at local, state, and national levels; geographic information systems (GIS) data; SDOH data; and environmental health data (National Center for Chronic Disease Prevention and Health Promotion & Division for Heart Disease and Stroke Prevention, 2018). Public health data resources include publicly available health-related datasets. One example, County Health Rankings, is a website listing demographic and health information that can be used for comparison among counties in the United States (University of Wisconsin Population Health Institute, 2019). The GIS data page provides links to population data and boundary files, which outline measurement areas (e.g., census tracts and zip codes) that are used in population-level data. The SDOH data provide links to data, maps, statistics, and information related to the SDOH. The environmental health data resources provide links to data on Superfund sites (areas that have been contaminated by hazardous waste and are identified by the Environmental Protection Agency as areas to be cleaned due to their risk to human health [U.S. Environmental Protection Agency, 2019]), air quality, water quality, and access to parks.

Geospatial data come in various formats (i.e., vector and raster). Vector data are in three types: Points representing discrete data points such as home addresses, lines representing linear features such as roads or streams, and polygons representing boundary areas such as census tracts or zip codes. Data with a geographic link are associated with these map features. Raster data use pixels to represent surfaces measuring variables such as population density or geographic elevation. Each type of data is represented as a map layer.

GIS is a software system designed to store, manipulate, and display geospatial data. In addition, GIS integrates and links multiple layers of geospatial data. Although commonly associated with the presentation of data through maps, GIS also enables visual exploration of data across space and time along with supporting statistical analysis to quantify relationships between geospatial data and health outcomes. Due to its powerful utility, over the last 25 years, GIS has

evolved to become an integral tool in public health research (Fletcher-Lartey & Caprarelli, 2016). Recent advances in GIS increase the capability to share data. The software program, ArcGIS Pro (ESRI, 2010), has restructured GIS with a new emphasis on sharing data, map layers, and whole projects with other users.

5 | SPATIAL STATISTICAL METHODS FOR ANALYZING GEOSPATIAL DATA

The statistics subfield of spatial statistics uses original methods to handle various types of geospatial data and analysis objectives including assessing patterns such as clustering, cluster detection, and spatial variation in risk (Cressie & Wile, 2015; Elliott, Briggs, Best, & Wakefield, 2001; Getis, 1999). The types of geospatial data ranging from spatial point locations, commonly seen with monitored environmental exposures, to spatially aggregated data, such as disease rates summarized at census tracts or zip codes. Spatial statistical methods often focus on the concept of spatial variation (i.e., spatial dependence), in that observations close together are more similar than observations farther apart. Spatial variation is often visualized on the map as spatial clustering. Analyses often proceed in an inferential approach, adjusting regression analyses to account for spatial variation. Predictive models can be used to spatially estimate observations (e.g., environmental exposure or health outcome risk) at unsampled locations. There are also methods for cluster detection, known as "hot spot" detection, where statistical algorithms search for and identify areas where mapped geospatial data are anomalous (e.g., rates significantly higher or lower) as compared to other map areas (Anselin, 1995; Kulldorff, 1997). Hot spot detection is frequently used in crime mapping and research (Wortley & Townsley, 2017).

6 | UNIQUE CONSIDERATIONS FOR A GEOSPATIAL APPROACH

Several important considerations are involved with using geospatial data for community research. One, in particular, is determining the scale of analysis. Scale of analysis refers to the geographic unit of analysis, which can range from a dot on the map, such as with a geocoded address, to numerous summaries of data aggregated to various area level units, such as a number of crimes per census tract. Data are often aggregated, which changes their scale, for privacy issues or to incorporate other data such as census variables that are only available at an area level such as the census tract. A common pitfall is to use data that are available and accessible rather than data on the scale that is determined a priori by the research question (Preston, Yuen, & Westaway, 2011). Exposure to a violent crime, for example, might affect an individual if it happens within a few blocks of their home, but a researcher's access may be limited to violent crime records aggregated to the census tract level. Changes in scale are also due to the geographic extent of variables. Although

computation capability has improved exponentially there are still limitations, and key variables, such as ozone level or particulate matter, may only be available at a coarse resolution, that is, 1 km. Using this level of data at a local level may not provide adequate spatial variation to discern relationships. Researchers investigating social factors in neighborhoods might measure variables on a different spatial scale than investigations involving food environments, crime environments, or the built environment.

Data may also be aggregated by the researcher to draw comparisons between variables, which may lead to error and bias, especially when including both biophysical and socioeconomic information (Preston et al., 2011). One potential bias, ecological bias, occurs when interpretations of aggregated data are extended to smaller units, such as the individual. Although it may be necessary to aggregate data, researchers should disclose this potential introduction of bias and exercise caution when interpreting results in units at other levels. Often it may be difficult to determine the best method to employ to measure individual exposures to environmental characteristics; this is known as the uncertain geographic context problem (Kwan, 2012). The researcher often does not know the exact delineation of a geographic area that is causally relevant to an outcome. The concept of one's neighborhood can be measured in several ways depending on the research question being asked. Individuals may consider their neighborhood to be the block where they live, the several blocks surrounding their residence, or an area as large as their city. For example, violence exposure has been associated with more severe asthma in children, but it is unclear at what level the exposure has the greatest effect (Beck et al., 2016; Eldeirawi et al., 2016; Kopel et al., 2015). Does crime in a smaller area, such as zip code, have a greater effect on the child than crime measured at the census tract or county level? To address the uncertain geographic context problem sensitivity analyses can be run to determine how different delineations of geographic units affect study results and contextual variables (Kwan, 2012).

With multiple measurement choices, such as the scale of analysis, comparing results across studies can be difficult. Future researchers should replicate analyses in different samples while using the same measurement techniques. This consistent measurement will help develop an evidence base to draw conclusions (Diez Roux & Mair, 2010). As for any sound scientific endeavor that includes modeling of data, the model should be empirical while also having a strong substantive connection to the theoretical processes under investigation. The use of a strong theoretical model assists the researcher in developing testable hypotheses regarding the relationships between specific social determinants and health outcomes (Diez Roux & Mair, 2010). Emphasis should be placed on strategizing the appropriate representation of space and time for data collection and analysis, as these elements will affect the interpretation of findings (Mennis & Yoo, 2018).

As with all data containing personal identifiers, confidentiality is an important consideration for geospatial data. Many publicly available datasets have already aggregated individual addresses to a census tract. When hospitals collaborate with researchers they are

required to aggregate data to a geographic level that protects patient confidentiality (Comer, Grannis, Dixon, Bodenhamer, & Wiehe, 2011; Poulis, Loukides, Skiadopoulou, & Gkoulalas-Divanis, 2017). When primary geospatial data are collected, several steps can be taken to ensure confidentiality for participants. Kounadi and Resch (2018) propose preserving privacy before beginning research, during data collection, and during disclosure of datasets and presentation of results. The study should be designed using a privacy-preserving research plan that ensures all participants are made aware of location privacy disclosure risks when signing informed consent. Researchers must also be sure they have a secure computer system to store their data. For example, once data from sensor devices are stored in a secure system, the data must be deleted from the sensor devices. One concern when presenting results with maps is that they may breach confidentiality because addresses can be discovered through reverse geocoding (Zandbergen, 2014). This breach can be avoided using a process called geographic masking, where the researcher systematically applies a random amount of perturbation to individual addresses to reduce the risk of reidentification (Zandbergen, 2014). One such technique, "spatial k-anonymity," displaces point locations within larger areas, defined by the population density, so that no one location be distinguished from the other locations. Kounadi and Resch (2018) describe additional geomasking techniques including spatial blurring, where displacement is based on a normal distribution, and a spatial aggregation approach. They also present the benefits and limitations of several additional approaches. Langarizadeh, Orooji, and Sheikhtaheri (2018) claim from their systematic review that anonymization methods alone cannot completely eliminate reidentification risk. Best practice takes patient confidentiality into account during the entire process from designing the study through the presentation of the results.

7 | APPLICATIONS OF GEOSPATIAL DATA TO ANSWER RESEARCH QUESTIONS

A variety of research questions can be answered using geospatial data. For studies in neighborhoods, geospatial data on physical and social environments can be explored. Examples of physical data include measuring access to parks and fast-food restaurants as they relate to insulin resistance or measuring walking path quality's influence on urban elementary school children's active transport to school (Curriero et al., 2013; Hsieh et al., 2014). Several studies of physical environments analyzed relationships between the food environment and dietary behavior (Sadler et al., 2016), and among the built environment (e.g., sidewalks and parks) and physical activity (Chambers et al., 2017; Curriero et al., 2013), obesity (Christian, Giles-Corti, Knuijman, Timperio, & Foster, 2011), and diabetes (Hsieh et al., 2014). Studies of the neighborhood social environments are less frequent and tend to focus on social stressors such as safety and violence, or social strengths such as social cohesion and social capital. These studies link social environments to physical health and mental health outcomes, such as depression and substance use. Researchers

have linked community violence to elementary school achievement and psychological distress (Bergen-Cico et al., 2018; Goldman-Mellor, Margerison-Zilko, Allen, & Cerda, 2016). Christian et al. (2011) analyzed relationships among measures of body mass index and neighborhood social cohesion (measured using the Neighborhood Cohesion Scale), social capital (using a survey measuring neighborliness), neighborhood walkability, greenness, and the presence or absence of healthy food outlets. One innovative method utilizes social media to integrate geographic data with qualitative data measuring the influences of place on perceptions of and interactions between individuals (Nguyen et al., 2016; Stephens & Poorthuis, 2015).

The policy is often driven by large-scale studies using national or regional geospatial data (Zook, Wollersheim, Erbas, & Jacobsen, 2018). One research team investigated relationships between “greening” vacant lots (i.e., adding plants and vegetation) and outcomes such as neighborhood crime and mental health (Kondo, Hohl, Han, & Branas, 2016; South, Hohl, Kondo, MacDonald, & Branas, 2018). The results of these studies, utilizing geospatial data to test interventions, demonstrated the positive health benefits of neighborhood greenspace in urban cities. They provide evidence in support of policies such as the *Outdoors for All Act*, introduced by Senator Kamala Harris in September 2018, to establish a dedicated source of funding to create and improve state and locally owned parks and recreation areas (S. 1458, 2019). In a descriptive use of geospatial data, Hudson et al. (2017) used a national dataset to identify geographic locations of veterans in rural areas and variations in their health and health care use to inform policies and programs to provide them with care. Jennings et al. (2014) correlated neighborhood alcohol outlets with violent crime, providing evidence for recommendations to improve zoning policies. Whereas these and other published reports speak to a direct influence of geospatial data-based research on policy implications, the map can serve as a powerful visual aid to translate important relationships and enhance understanding for policymakers and other stakeholders.

8 | EXEMPLAR OF NURSE-LED COMMUNITY RESEARCH USING GEOSPATIAL DATA

One example of examining nontraditional connections between SDOH and specific health outcomes is from a nurse-led study in Baltimore, MD, investigating associations among neighborhood greenspace, violence, and children's asthma control by adding geospatial data into an existing dataset. The study protocol (DePriest, 2019; DePriest, Butz, & Gross, 2018) was based on the theoretical framework that greenspace decreases air pollution and heat and is associated with decreased stress and increased physical activity (Markevych et al., 2017); these latter variables are linked theoretically to improved asthma control. The researchers hypothesized that children who lived in areas with more greenspace would have better asthma control compared with children living in areas with less greenspace. The researchers also examined neighborhood violence,

hypothesizing that through increased psychosocial stress and keeping children indoors, children who lived in areas with higher violence would have poorer asthma control than those living in areas with lower violence (Wright & Subramanian, 2007).

The outcome of asthma control was calculated based on the report of asthma symptoms, activity limitations, and rescue inhaler uses when children were enrolled in the study. The geospatial data used in this study, greenspace and violence exposure, were calculated using the children's reported home address in Baltimore, MD.

Greenspace was measured using the Normalized Difference Vegetation Index (NDVI), calculated by measuring near-infrared and infrared light. Near-infrared light is reflected by vegetation and infrared is absorbed by vegetation through the process of photosynthesis (Weier & Herring, 2000). Light reflectance is captured using satellite sensors. The NDVI ranges from -1 to 1 with higher values indicated areas with more dense vegetation (Jackson & Huete, 1991). To put things in perspective, an NDVI of 1 would be a tropical rainforest, an NDVI of 0 would be desert or tundra, and an NDVI approaching -1 would be a body of water (Weier & Herring, 2000).

For this study, NDVI was calculated using LANDSAT 8 satellite data. These freely available data were accessed using the United States Geological Survey website, <https://earthexplorer.usgs.gov/>. The satellite images were reviewed for the study time period and the clearest image with minimal cloud cover was selected. Once selected, this image was downloaded and imported into the GIS software, ArcGIS v10.5 (ESRI, 2010). Once in ArcGIS, the Image Analysis processing tools were used to convert the data into composite bands of infrared and near-infrared reflectance. The NDVI was calculated using the NDVI command under image analysis in ArcGIS. NDVI was calculated in 30 m by 30 m resolution. A 100 m radius was generated around each home address and the average NDVI within that buffer was calculated and assigned to each child. This average NDVI measures the child's neighborhood greenspace exposure. Figure 1 presents the NDVI map of Baltimore.

Violence exposure was measured using the violent crime victimization rate in the census tract within which the child lived. Victim-based crime data were downloaded from the Baltimore Police Department for the year of the study. Data included all violent crimes defined by the Federal Bureau of Investigation's Uniform Crime Reporting Program: Homicide/manslaughter, rape, aggravated assault, and robbery (U.S. Department of Justice, 2016). Using latitude and longitude coordinates, the victimizations were mapped to create a point layer and then aggregated to the census tract. The total number of victimizations was divided by the census tract population to calculate the violent crime victimization rate. Figure 2 presents the map of violent crime victimization rates by census tract in Baltimore.

The NDVI and violence exposure variables created using GIS were added to the pool of existing variables from the study on social risk, the season of enrollment, asthma medication use, outdoor allergen sensitization, and secondhand smoke exposure to test for associations with children's asthma control. The children's asthma

Normalized Difference Vegetation Index Baltimore, MD 2013

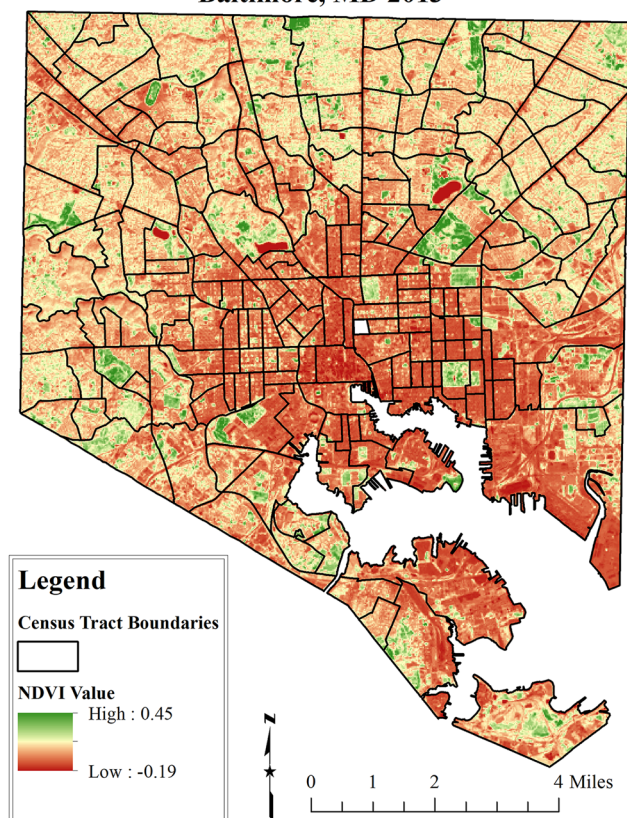


FIGURE 1 Normalized Difference Vegetation Index (NDVI) in Baltimore, MD. Map of the normalized difference vegetation index measured in 2013 for Baltimore, MD. The census tract boundaries are outlined in black [Color figure can be viewed at [wileyonlinelibrary.com](#)]

control outcome was categorized as binary and hence logistic regression was used to model the odds of very poorly controlled to not well-controlled asthma as a function of changes in these variables.

An assumption in the standard use of regression analysis (e.g., linear, logistic or Poisson regression) is that of independence of observations. As discussed earlier, however, spatial data often exhibit dependence (observations closer together are more similar than observations farther apart) which would need to be accounted or adjusted for in the regression analysis so as to allow for proper statistical inference (i.e., to obtain proper estimates of the regression β coefficients and their standard errors). One approach for assessing such a situation is to estimate the level of spatial dependence in the regression residuals from a model with no variables (a null regression model) compared to that from the final model with included variables and possible interaction effects (Curriero et al., 2013; Hsieh et al., 2014). This provides a means and interpretation to assess how much/if any did the included regression variables account for spatial dependence in the regression outcome. A semivariogram is a tool from the field of spatial statistics that can be used to estimate spatial dependence for this type of data (Cressie, 1992). The semivariogram requires the distance between all sample points to be known, which

Violent Crime Victimization Rate Baltimore, MD 2013

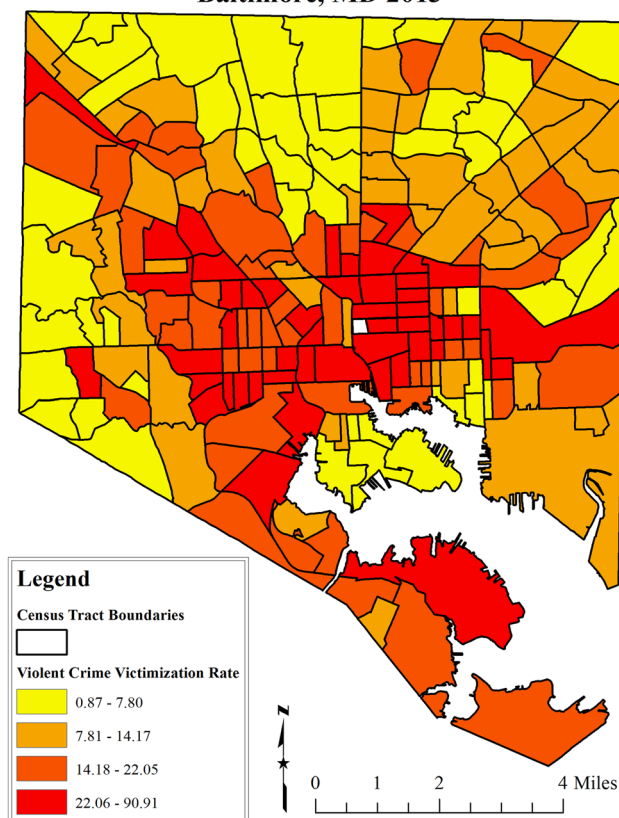


FIGURE 2 Violent crime victimization rate in Baltimore, MD. Map of the violent crime victimization rate per 1,000 people in 2013 for Baltimore, MD. Rate calculated and presented for each census tract [Color figure can be viewed at [wileyonlinelibrary.com](#)]

were obtained via the coordinate locations of each child's home. Results from the semivariogram analysis, which have not yet been published, showed the spatial dependence in the regression outcome (asthma control) was fully accounted for by the variables in the final regression model, thus satisfying the needed assumption of regression independence (DePriest, 2019).

8.1 | Lessons learned

The researchers originally chose community areas each comprising a few census tracts as the geographic unit to measure neighborhood exposures. Unfortunately, there was not enough variability in greenspace or violence across the sample, so the geographic unit was adjusted to measure greenspace as a 100 m buffer around each child's home and violence exposure was measured at the census tract level. The researchers subsequently adjusted the analysis from a multilevel model to analyzing relationships at the individual level, thereby weakening the analysis and limiting the application of the findings. Determining the level of exposure is an essential process when working with geospatial data. While best practice is to determine the exposure level a priori, changes to the protocol may be necessary.

The researchers chose to use NDVI because it is an objective and valid measure of neighborhood greenspace, but there are limitations to its use. This measure of greenspace accurately captures the quantity of greenspace, but it does not measure the quality of greenspace. There are qualitative differences between a vacant lot full of weeds and a well-manicured city park in that the park is more likely to encourage physical activity and promote psychological restoration. The inability to distinguish between the quality of different greenspace exposures likely affected study results. In the future, researchers should consider different geospatial measures, such as tree canopy or percentage of land covered in public parks, to estimate greenspace exposure.

9 | THE FUTURE OF GEOSPATIAL MEASUREMENT IN NURSING RESEARCH AND PRACTICE

Relative to other disciplines, nurse researchers have not realized the benefit of incorporating geospatial data in community research. With the assistance of the university informationist, a search in PubMed for publications using spatial data (including related MeSH and text words) returned 19,871 results. When this search was narrowed to include publications from the community or public health nurses, the search returned 21 results including studies on the built environment, access to care, and health outcomes. There were also several articles advocating nurses to use GIS in their research, the most recent of which was published in 2007 (Baker, 2007). As some of the first practitioners of public health, it is surprising that nurses are not utilizing geospatial data to conduct community research. Why might this be? Formal education in spatial analysis is not offered at most nursing schools. Having elective courses in spatial analysis or collaborating with nearby schools of public health or with other universities where these courses are offered are options for nursing students interested in pursuing research using geospatial data. Nursing students and faculty might also be exposed to spatial analysis through guest lectures and seminars from nurses or public health researchers with experience in spatial analysis. Exposing and training nurse researchers is a preliminary step in expanding the use of geospatial data amongst nurses. The accessibility and availability of geospatial data have increased dramatically, along with the rapid advancement of spatial data technologies, providing unique opportunities for nurse researchers. Through their uniquely holistic view of health, nurses are perfectly situated for this study.

Whereas this paper focused on the use of geospatial data in research, geospatial data can and should also be utilized by practicing nurses to test interventions and influence policy efforts based on research results. As was presented by Choi, Afzal, and Sattler (2006), practicing public health nurses might also use GIS combined with patient-reported environmental health information to map environmental exposures. Nurse leaders could use GIS to map service locations against health needs and to analyze health utilization behaviors (Baker, 2007). State health departments are a great

resource for the use of GIS and of databases to gather geospatial data (Baker, 2007). Nurses interested in learning about GIS can utilize books on the topic (Cromley & McLafferty, 2011; Kurland & Gorr, 2014) or online resources (found here: <https://www.gislounge.com/learn-gis-for-free/>) such as massive open online courses in GIS; free courses from GIS software developers; open courses offered by universities; or online, fee-based programs for certificates or degrees.

Addressing the SDOH is a renewed priority and presents nurse researchers with an opportunity to return to our roots. A hundred years ago, Lillian Wald led the nursing field to physically go into the community to assess health determinants. This paper describes geospatial data and considerations for working with these data as an innovative method for nurse researchers to visit communities across the country in a virtual sense, to investigate and intervene in relationships between social determinants and health in a robust, low cost, reproducible manner.

ACKNOWLEDGMENTS

The first author is funded by the National Institute of Nursing Research of the National Institutes of Health (NIH) under Award Number F31NR017319. The content is solely the responsibility of the authors and does not necessarily represent the official views of the NIH.

CONFLICT OF INTERESTS

The authors declare that there are no conflict of interests.

ORCID

Kelli N. DePriest  <http://orcid.org/0000-0002-2876-5297>

REFERENCES

- American Academy of Nursing (2019). *The American Academy of Nursing, Policy priorities 2019–2020*. Washington, DC: American Academy of Nursing. Retrieved from https://higherlogicdownload.s3.amazonaws.com/AANET/c8a8da9e-918c-4dae-b0c6-6d630c46007f/UploadedImages/Academy_Federal_Policy_Priorities_Final.pdf
- Adler, N. E., Cutler, D. M., Fielding, J. E., Galea, S., Glymour, M. M., Koh, H. K., & Satcher, D. (2016). Addressing social determinants of health and health disparities: A vital direction for health and health care. *NAM Perspectives*, 6(9), <https://doi.org/10.31478/201609t>
- Anselin, L. (1995). Local indicators of spatial association-LISA. *Geographical Analysis*, 27(2), 93–115. <https://doi.org/10.1111/j.1538-4632.1995.tb00338.x>
- Baker, V. L. (2007). Health services research methods: Tools for nurse leaders. *Nursing Administration Quarterly*, 31(4), 304–311. <https://doi.org/10.1097/01.NAQ.0000290428.49313.b2>
- Beck, A. F., Huang, B., Ryan, P. H., Sandel, M. T., Chen, C., & Kahn, R. S. (2016). Areas with high rates of police-reported violent crime have higher rates of childhood asthma morbidity. *The Journal of Pediatrics*, 173, 175–182.e1. <https://doi.org/10.1016/j.jpeds.2016.02.018>
- Bergen-Cico, D., Lane, S. D., Keefe, R. H., Larsen, D. A., Panasci, A., Salaam, N., & Jennings-Bey, T. (2018). Community gun violence as a social determinant of elementary school achievement. *Social Work in Public*

- Health, 33(7-8), 439–448. <https://doi.org/10.1080/19371918.2018.1543627>
- Braveman, P., Arkin, E., Orleans, T., Proctor, D., & Plough, A. (2017). What is health equity? And what difference does a definition make? Princeton, NJ: Robert Wood Johnson Foundation.
- Bronfenbrenner, U. (1979). The ecology of human development. Cambridge, MA: Harvard Univ. Press.
- Castrucci, B., & Auerbach, J. (2019, January 16). Meeting individual social needs falls short of addressing social determinants of health [Health Affairs]. Retrieved from <https://www.healthaffairs.org/doi/10.1377/hblog20190115.234942/full/>
- Chambers, T., Pearson, A. L., Kawachi, I., Rzotkiewicz, Z., Stanley, J., Smith, M., & Barr, M. (2017). Kids in space: Measuring children's residential neighborhoods and other destinations using activity space GPS and wearable camera data. *Social Science & Medicine*, 193, 41–50. <https://doi.org/10.1016/j.socscimed.2017.09.046>
- Choi, M., Afzal, B., & Sattler, B. (2006). Geographic information systems: A new tool for environmental health assessments. *Public Health Nursing*, 23(5), 381–391. <https://doi.org/10.1111/j.1525-1446.2006.00577.x>
- Christian, H., Giles-Corti, B., Knuiman, M., Timperio, A., & Foster, S. (2011). The influence of the built environment, social environment and health behaviors on body mass index. Results from RESIDE. *Preventive Medicine*, 53(1), 57–60. <https://doi.org/10.1016/j.ypmed.2011.05.004>
- Comer, K. F., Grannis, S., Dixon, B. E., Bodenhamer, D. J., & Wiehe, S. E. (2011). Incorporating geospatial capacity within clinical data systems to address social determinants of health. *Public Health Reports*, 126(Suppl 3), 54–61.
- Commission on Social Determinants of Health (2008). *Closing the gap in a generation: Health equity through action on the social determinants of health. Final report on the commission on social determinants of health*. Geneva: World Health Organization.
- Cressie, N. (1992). *Statistics for spatial data*. London, UK: John Wiley & Sons.
- Cressie, N., & Wike, C. (2015). *Statistics for spatio-temporal data*. Hoboken, NJ: John Wiley & Sons.
- Cromley, E. K., & McLafferty, S. L. (2011). *GIS and public health*. New York, NY: The Guilford Press.
- Curriero, F. C., James, N. T., Shields, T. M., Gouvis Roman, C., Furr-Holden, C. D., Cooley-Strickland, M., & Pollack, K. M. (2013). Exploring walking path quality as a factor for urban elementary school children's active transport to school. *Journal of Physical Activity & Health*, 10(3), 323–334. <https://doi.org/10.1123/jpah.10.3.323>
- DePriest, K. (2019). *Investigating the relationships among neighborhood factors and asthma control in African American children* (Unpublished doctoral dissertation) Johns Hopkins University, Baltimore, MD.
- DePriest, K., Butz, A., & Gross, D. (2018). Investigating the relationships among neighborhood factors and asthma control in African American children: A study protocol. *Research in Nursing & Health*, 41(5), 428–439. <https://doi.org/10.1002/nur.21901>
- Dieffenderfer, J., Goodell, H., Mills, S., McKnight, M., Yao, S., Lin, F., & Beppler, E. (2016). Low-power wearable systems for continuous monitoring of environment and health for chronic respiratory disease. *IEEE Journal of Biomedical and Health Informatics*, 20(5), 1251–1264. <https://doi.org/10.1109/JBHI.2016.2573286>
- Diez Roux, A. V., & Mair, C. (2010). Neighborhoods and health. *Annals of the New York Academy of Sciences*, 1186(1), 125–145. <https://doi.org/10.1111/j.1749-6632.2009.05333.x>
- Eldeirawi, K., Kunzweiler, C., Rosenberg, N., Riley, B., Gao, Y., Hebert-Beirne, J., & Persky, V. (2016). Association of neighborhood crime with asthma and asthma morbidity among Mexican American children in Chicago, Illinois. *Annals of Allergy, Asthma & Immunology*, 117(5), 507.e1. <https://doi.org/10.1016/j.anai.2016.09.429>
- Best, N. G., & Wakefield, J. C. (2001). In Elliott, P., Wakefield, J. C., Best, N. G., & Briggs, D. J. (Eds.), *Spatial epidemiology: Methods and applications*. Oxford: Oxford University Press. <https://doi.org/10.1017/9780198515326.003.0001>
- ESRI. (2010). ArcGIS desktop: Release 10 [computer software], Redlands, CA: Environmental Systems Research Institute.
- FAA reauthorization act of 2018: Geospatial data act of 2018, 751–759, (2018). Retrieved from <https://www.fgdc.gov/gda/geospatial-data-act-of-2018.pdf>
- Fletcher-Lartey, S. M., & Caprarelli, G. (2016). Application of GIS technology in public health: Successes and challenges. *Parasitology*, 143(4), 401–415. <https://doi.org/10.1017/S0031182015001869>
- Furr-Holden, C. D. M., Smart, M. J., Pokorni, J. L., Jalongo, N. S., Leaf, P. J., Holder, H. D., & Anthony, J. C. (2008). The NifETy method for environmental assessment of neighborhood-level indicators of violence, alcohol, and other drug exposure. *Prevention Science*, 9(4), 245–255. <https://doi.org/10.1007/s11212-008-0107-8>
- Gebreab, S. Y., Hickson, D. A., Sims, M., Wyatt, S. B., Davis, S. K., Correa, A., & Diez-Roux, A. V. (2017). Neighborhood social and physical environments and type 2 diabetes mellitus in African Americans: The Jackson heart study. *Health & Place*, 43, 128–137. <https://doi.org/10.1016/j.healthplace.2016.12.001>
- Getis, A. (1999). Spatial statistics. *Geographic Information Systems*, 1, 239–251.
- Goldman-Mellor, S., Margerison-Zilko, C., Allen, K., & Cerda, M. (2016). Perceived and objectively-measured neighborhood violence and adolescent psychological distress. *Journal of Urban Health*, 93(5), 758–769. <https://doi.org/10.1007/s11524-016-0079-0>
- Hsieh, S., Klassen, A. C., Curriero, F. C., Caulfield, L. E., Cheskin, L. J., Davis, J. N., & Goran, M. I. (2014). Fast-food restaurants, park access, and insulin resistance among Hispanic youth. *American Journal of Preventive Medicine*, 46(4), 378–387. <https://doi.org/10.1016/j.amepre.2013.12.007>
- Hudson, T., Littman, A., Bollinger, M., Wong, E., Drummond, K., Finley, E., & Abraham, T. (2017). Harnessing multiple data sources to good program planning for rural U.S. veterans. *International Journal of Population Data Science*, 1(1), <https://doi.org/10.23889/ijpds.v1i1.394>
- Jackson, R. D., & Huete, A. R. (1991). Interpreting vegetation indices. *Preventive Veterinary Medicine*, 11(3), 185–200. [https://doi.org/10.1016/S0167-5877\(05\)80004-2](https://doi.org/10.1016/S0167-5877(05)80004-2)
- Jennings, J. M., Milam, A. J., Greiner, A., Furr-Holden, C. D. M., Curriero, F. C., & Thornton, R. J. (2014). Neighborhood alcohol outlets and the association with violent crime in one mid-Atlantic city: The implications for zoning policy. *Journal of Urban Health*, 91(1), 62–71. <https://doi.org/10.1007/s11524-013-9821-z>
- Kondo, M., Hohl, B., Han, S., & Branas, C. (2016). Effects of greening and community reuse of vacant lots on crime. *Urban Studies*, 53(15), 3279–3295. <https://doi.org/10.1177/0042098015608058>
- Kopel, L. S., Gaffin, J. M., Ozonoff, A., Rao, D. R., Sheehan, W. J., Friedlander, J. L., & Permaul, P. (2015). Perceived neighborhood safety and asthma morbidity in the school inner-city asthma study. *Pediatric Pulmonology*, 50(1), 17–24. <https://doi.org/10.1002/ppul.22986>
- Kounadi, O., & Resch, B. (2018). A geoprivacy by design guidelines for research campaigns that use participatory sensing data. *Journal of Empirical Research on Human Research Ethics*, 13(3), 203–222. <https://doi.org/10.1177/1556264618759877>
- Kulldorff, M. (1997). A spatial scan statistic. *Communications in Statistics—Theory and Methods*, 26(6), 1481–1496. <https://doi.org/10.1080/03610929708831995>
- Kurland, K. S., & Gorr, W. L. (2014). *GIS tutorial for health*. Redlands, CA: Esri Press.
- Kwan, M. P. (2012). The uncertain geographic context problem. *Annals of the Association of American Geographers*, 102(5), 958–968. <https://doi.org/10.1080/00045608.2012.687349>
- Langarizadeh, M., Orooji, A., & Sheikhtaheri, A. (2018). Effectiveness of anonymization methods in preserving patients' privacy: A systematic literature review. *Studies in Health Technology and Informatics*, 248, 80. <https://www.ncbi.nlm.nih.gov/pubmed/29726422>

- Markevych, I., Schoierer, J., Hartig, T., Chudnovsky, A., Hystad, P., Dzhambov, A. M., & de Vries, S. (2017). Exploring pathways linking greenspace to health. *Environmental Research*, 158, 301–317. <https://doi.org/10.1016/j.envres.2017.06.028>
- Mennis, J., & Yoo, E. H. E. (2018). Geographic information science and the analysis of place and health. *Transactions in GIS*, 22(3), 842–854. <https://doi.org/10.1111/tgis.12337>
- Misiaszek, C., Buzogany, S., & Freishtat, H. (2018). *Baltimore city's food environment: 2018 report*. Baltimore, MD: Johns Hopkins Center for a Livable Future. Retrieved from <http://clf.jhsph.edu/sites/default/files/2019-01/baltimore-city-food-environment-2018-report.pdf>
- National Center for Chronic Disease Prevention and Health Promotion, & Division for Heart Disease and Stroke Prevention. (2018). Geo-spatial data resources.
- Nguyen, Q. C., Li, D., Meng, H. W., Kath, S., Nsoesie, E., Li, F., & Wen, M. (2016). Building a national neighborhood dataset from geotagged twitter data for indicators of happiness, diet, and physical activity. *JMIR Public Health and Surveillance*, 2(2), e158. <https://doi.org/10.2196/publichealth.5869>
- Outdoors for All Act, S. 1458., 116th Cong. (2019).
- Pittman, P. (2019). *Activating nursing to address unmet needs in the 21st century*. Princeton, NJ: Robert Wood Johnson Foundation.
- Poulis, G., Loukides, G., Skiadopoulos, S., & Gkoulalas-Divanis, A. (2017). Anonymizing datasets with demographics and diagnosis codes in the presence of utility constraints. *Journal of Biomedical Informatics*, 65, 76–96. <https://doi.org/10.1016/j.jbi.2016.11.001>
- Preston, B. L., Yuen, E. J., & Westaway, R. M. (2011). Putting vulnerability to climate change on the map: A review of approaches, benefits, and risks. *Sustainability Science*, 6(2), 177–202. <https://doi.org/10.1007/s11625-011-0129-1>
- RWJF. (2018). *Moving forward together: An update and building and measuring a culture of health*. Princeton, NJ: Robert Wood Johnson Foundation. <https://www.rwjf.org/content/dam/COH/PDFs/MovingForwardTogetherFullReportFinal.pdf>
- Sadler, R. C., Clark, A. F., Wilk, P., O'Connor, C., & Gilliland, J. A. (2016). Using GPS and activity tracking to reveal the influence of adolescents' food environment exposure on junk food purchasing. *Canadian Journal of Public Health*, 107(S1), eS14–eS20. <https://doi.org/10.17269/CJPH.107.5346>
- South, E. C., Hohl, B. C., Kondo, M. C., MacDonald, J. M., & Branas, C. C. (2018). Effect of greening vacant land on the mental health of community-dwelling adults: A cluster randomized trial. *JAMA Network Open*, 1(3), e180298. <https://doi.org/10.1001/jamanetworkopen.2018.0298>
- Stephens, M., & Poorthuis, A. (2015). Follow thy neighbor: Connecting the social and spatial networks on twitter. *Computers, Environment and Urban Systems*, 53, 87–95. <https://doi.org/10.1016/j.compenvurbsys.2014.07.002>
- University of Wisconsin Population Health Institute. (2019). County health rankings & roadmap. Retrieved from <https://www.countyhealthrankings.org/>
- U.S. Department of Health and Human Services. (2015). *Social determinants of health: Healthy people 2020*. Retrieved from <https://www.healthypeople.gov/2020/topics-objectives/topic/social-determinants-of-health>
- U.S. Department of Justice. (2016). Federal bureau of investigation: Uniform crime reporting statistics: UCR offense definitions.
- U.S. Environmental Protection Agency. (2016). What is open space/green space. Retrieved from <https://www3.epa.gov/region1/eco/uep/openspace.html>
- U.S. Environmental Protection Agency. (2019). What is Superfund? Retrieved from <https://www.epa.gov/superfund/what-superfund>
- Wald, L. D. (1915). *The house on Henry Street*. New York: Holt.
- Weier, J., & Herring, J. (2000). Measuring vegetation (NDVI and EVI). *NASA Earth Observatory*, 20.
- Wortley, R., & Townsley, M. (2017). *Environmental criminology and crime analysis* (2nd ed.). New York, NY: Routledge. <https://doi.org/10.4324/9781315709826>
- Wright, R. J., & Subramanian, S. V. (2007). Advancing a multilevel framework for epidemiologic research on asthma disparities. *Chest*, 132(5 Suppl), 757S–769S. <https://doi.org/10.1378/chest.07-1904>
- Zandbergen, P. A. (2014). Ensuring confidentiality of geocoded health data: Assessing geographic masking strategies for individual-level data. *Advances in Medicine*, 2014, 1–14. <https://doi.org/10.1155/2014/567049>
- Zook, M., Wollersheim, D., Erbas, B., & Jacobsen, K. H. (2018). Integrating spatial analysis into policy formulation: A case study examining traffic exposure and asthma. *World Medical & Health Policy*, 10(1), 99–110. <https://doi.org/10.1002/wmh3.258>

How to cite this article: DePriest KN, Shields TM, Curriero FC. Returning to our roots: The use of geospatial data for nurse-led community research. *Res Nurs Health*. 2019;42:467–475. <https://doi.org/10.1002/nur.21984>