

The Spatial Context of Health Disparities: A Literature Review

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I. Introduction

An emerging focus in the literature defining health disparities has been the “spatial context” of the problem. In other words, what role does one’s *living environment* play in explaining poorer health outcomes among certain population subgroups? Research has examined whether health disparities can be linked to “contextual variables,” that is the characteristics of a residential neighborhood or context (e.g., the degree of racial segregation, income inequality, immigrant status, poverty/education levels, or environmental factors for specific spatial areas such as neighborhoods or towns) as well as population “composition variables,” that is, characteristics of the population living in a specific area (e.g., income, race, or educational level for a specific population). In doing so, analyses have not only identified characteristics of specific populations at risk, but they have also outlined the geographic areas where disparities occur. This research has generally concluded that certain sub-populations as well as geographic clusters or “hot spots” require special attention from the research community.

In looking at the research on the spatial context of health disparities as a distinct body of literature, several themes become apparent. First, there is a realm of research that has linked health disparities to contextual variables by constructing and comparing unique area-based socioeconomic measures (ABSMs). A variety of these analyses have identified health disparities by using specific ABSMs at unique spatial levels ranging from the micro-geographic scales (such as census block groups or census tracts) to the larger geographic scales (such as zip-code areas or counties). Second, a related body of research has investigated the relationship between health disparities and residential segregation. Studies in this vein have also focused on a variety of geographic scales, while using segregation indices to define potential areas of segregation.

Third, there is a realm of literature that has examined and linked disparities to both compositional and contextual factors³ using multi-level modeling techniques (MLM). Research in this area has focused on the idea that there are distinct scales at which specific health-related processes operate. MLM provides the statistical means by which these processes, and their relevant scales, can be identified. Within this milieu have emerged several public health disparities projects that are geared toward eliminating disparities at either the national, state, or local levels.

II. ABSMs and Health Disparities

ABSMs are indices that can be conceptualized as useful indicators of socioeconomic context. In other words, ABSMs can be used as proxy variables to estimate differences between the areas in which individuals reside (e.g., differences in the context of areas). ABSMs have been particularly useful in health disparities research where contextual data are oftentimes absent from individual-level health records. While it is beyond the scope of this review to outline all examinations relating ABSMs to health disparities, two sub-themes deserve recognition. First, health disparities-oriented research has tested the appropriateness of specific ABSMs. Second, research has examined the differences between the scales of ABSMs in their power to explain health disparities.

³ Compositional factors refer to individual or group level socio-economic and/or demographic characteristics for a given population(s) residing within specific geographic areas. Contextual factors refer to the collective attributes of a place such as the level of poverty, residential discrimination, or the physical environment for those specific geographic areas (Vias and Osleeb 2007).

Research has tested the appropriateness of specific ABSMs. Within the literature that has tested the appropriateness of specific ABSMs, some research has questioned the legitimacy of such measures. Geronimus et al. (1996) investigated the validity of ABSMs as proxies for individual-level data in a regression analysis that examined the influence of (or factors related to) income and education on specific health outcomes. The study determined the level of bias associated with using the aggregate measures of income and education within the regression analysis. This was summarized as an “errors-in-variables bias, [which] arises because the aggregate variable is only imperfectly correlated with the micro variable that it is representing” and “an aggregation bias, [which] arises from the fact that the aggregate variable may itself be correlated with the residual in the micro level equation” (531). The results indicated a tendency for the aggregate measures to exaggerate the influence of the individual-level measures. The authors concluded that “it would be problematic to interpret the estimate as a contextual effect, because, in the absence of a micro level measure, the aggregate measure picks up individual as well as contextual effects” (536). With this in mind, Geronimus (2006) suggested that “when using ABSMs, investigators should exercise caution in interpreting study results, be transparent about the limitations, and inform assessment of these limitations with thoughtful consideration of theory and substantive knowledge that are relevant to the specific application” (839).

Several researchers have compared the results of analyses based on individually assigned measures with results generated using ABSMs. In a study of cardiovascular disease risk and mortality in Scotland, Smith et al. (1998) regressed the trends in several factors, including various individual and aggregate socioeconomic measures, with mortality rates. The results

suggested that both individual-level measures and ABSMs make unique contributions to the understanding of health effects and disparities.

Dominguez-Berjon et al. (2006) agreed with this opinion in their work on measuring the usefulness of employment, education, and class-oriented ABSMs in monitoring health disparities in Spain. In their examination of the association between health outcomes and social class, the authors used logistic regression to generate odds ratios using individual-level variables and ABSMs. Comparison of the odds ratios demonstrated that for many of the health disparities observed, the ABSM-based odds ratios were similar to those generated using individual-level variables. The authors concluded that in absence of individual level data, ABSMs can be used to accurately measure disparities.

Spencer et al. (1999) examined the differences in the predictive power of the Townsend Deprivation Index (an ABSM) and the Registrar General's social class index (an individual-level measure)⁴ for monitoring birth weight disparities in the United Kingdom. The Townsend Deprivation Index is a composite measure comprised of four variables related to employment, car ownership, home ownership, and overcrowding. The variables produce an overall score that allows for specific geographic areas under consideration to be ranked (Townsend et al. 1988). The Registrar General's social class index divides individuals into seven classes based on their occupational or industrial characteristics. Using both measures, the study estimated the proportion of newborns with low birth weights that was attributable to social disparities. The relative risk of birth for each birth weight group between the lowest versus the highest socioeconomic groups was also calculated. The authors concluded that the area-based Townsend

⁴ T.H.C. Stevenson, a statistician in the General Registrar Office of the United Kingdom, originally developed this measure.

Deprivation Index was a “better discriminator in the study of pregnancy outcomes in this population than classification by occupational social class” (495).

Complementing the research on the comparison of individual-level measures with ABSMs has been an important stratum of literature that has compared two or more ABSMs. The most notable advances in this field have come from the Public Health Disparities Geocoding Project. Krieger and colleagues (2002) investigated eleven single variable measures and eight composite variable measures related to income, poverty, occupation, education, and wealth. Single variable measures included unemployment, median household income, and percentage of persons below the U.S. poverty line. The composite measures included the aforementioned Townsend Deprivation Index as well as indices based on various combinations of the single variable measures. In the study, age-standardized mortality and cancer rates were stratified by the socio-economic levels generated in each ABSM. This allowed for calculation of the mortality and incidence rate ratios, thus providing the means to determine the rate gradients between those individuals with the most resources and those with the least resources (i.e., economic deprivation). The study also determined the relative index of inequality (RII), a measure that takes into account the size of the population in each ABSM stratum (245-6). The authors found that measures related to economic deprivation (e.g., income and poverty) detected gradients that were not established by the education or wealth measures.

Expanding on this work, Krieger and colleagues used a similar methodology to examine low birthweight and childhood lead poisoning (2003a). The investigators found that measures related to poverty detected stronger gradients than measures of education, wealth, and occupation. Furthermore, in their assessment of “whether ABSMs can be meaningfully used for

diverse race/ethnicity-gender groups” (1656), Krieger et al. (2003b) demonstrated that compared to other measures, those related to economic deprivation detected unique gradients. Subsequent research by the Public Health Disparities Geocoding Project has compared and validated the use of certain ABSMs for specific instances (see Krieger et al. 2003c, Krieger et al. 2005, Rehkopf et al. 2006, Subramanian et al. 2006).

Research has tested the differences between the scales of ABSMs when examining disparities.

Geographic studies have long concluded that the spatial level of analysis has an influence on the relationship(s) that exists between specific variables (Gelhke and Biehl 1934, Openshaw 1977, Openshaw 1984, Messner 1999, Vias 2001, Manley 2006). In general, this research asserts that the correlation between variables can change as data are aggregated into different scales. With this in mind, numerous studies have tested and compared ABSMs at unique geographic scales in order to determine which levels of ABSMs are best to monitor specific disparities. For example, Krieger et al. (2002) applied 11 single variable and eight composite variable measures at three different geographic scales: the census block group level, the census tract level, and the zip-code area level. The study found that at the finer geographic scales, census block group and census tract, gradients were detected that were not evident at the more aggregated level of zip code.

This finding was further substantiated in later studies by Krieger and colleagues (2003a; 2003b; 2003c). Testing for disparities across a variety of health outcomes – including tuberculosis, low birth weight, childhood lead poisoning, sexually transmitted infections, and violence – revealed that census tract-level ABSMs or census block group level ABSMs provide the most meaningful indicators. In subsequent reports, the Public Health Disparities Geocoding

Project has focused solely on census tract-level ABSMs due to the consistent results they found at that level, and because census tracts relate well to other geographic entities such as urban empowerment zones.

Reijneveld et al. (2000) correlated ABSMs to disparities in self-rated health, mental health, physical health, and long term functional limitations at three levels of geography in the Netherlands: neighborhood, postcode sector, and borough (in order from the finest geographic scale to the most aggregated geographic scale). Using three different ABSMs (average income, the proportion of earners dependent on benefits, and the proportion of earners with a low income), the study found that “the choice of the geographical classification affects the degree of clustering of poor health by area but it has hardly any impact on the size of health differences by area deprivation [ABSM]” (306).

Thomas et al. (2006) compared zip-code area level ABSMs with census tract-level ABSMs as predictors of mortality. Using two different ABSMs, income and the proportion of individuals below the poverty level, the authors compared the results for all-cause and cause-specific hazard ratios⁵ by each level of geography. The study indicated that while both geographic levels at which the ABSMs were applied offered significant independent predictors, in a combined model, the “tract-based income was a slightly stronger mortality predictor” (586).

III. Segregation and Health Disparities

Given research on the appropriateness of specific ABSMs and the differences between the geographic scales of ABSMs, several projects have tested for disparities among specific

⁵ A hazard ratio is the effect of an explanatory variable, in this case an ABSM, on the hazard or risk of an event (Harper and Lynch 2007).

populations or within certain geographic areas. Most of these projects have concluded that disparities exist. However, disparities have been linked to other variables aside from those commonly associated with ABSMs. Examples of this come from a body of research that has examined how variables related to residential segregation affect health disparities.

Residential segregation “refers to segregation in regard to the composition and spatial distribution of the population of an entire metropolitan area across its neighborhoods” (Acevedo-Garcia 2003: 215). These neighborhood areas are typically “characterized by poverty, disempowerment, economic disinvestment, and limited availability of health care and other resources” (Jackson 2000: 615). Williams and Collins (2001) have argued that residential segregation is the “cornerstone” by which health disparities exist and grow. Given this assertion, research has focused on linking the aggregate characteristics of segregated areas to health disparities that may be occurring among individuals who reside there. In this regard, many research approaches have created segregation indices that are inherently similar to those used in ABSM formulations.

One of the earliest and most basic indices of segregation used to quantify health disparities across segregated areas was identified by Yankauer (1950). The author classified 318 New York City neighborhoods (used as the units of observation) into six categories based on the percent of live births classified as non-White. The author derived the relationship between each of the six classes and infant mortality. The study found a significant positive correlation between residential segregation and infant mortality. Jackson et al. (2000) used a similar classification to investigate health disparities at the census tract level. The authors created four categories of residential segregation based on the percent of African Americans residing within the census

tracts. The study then determined the age-adjusted mortality rates within the segregation categories for each age, race, and sex group. Using a Cox proportional hazard model, the authors found that the “age-adjusted relationships between all-cause mortality, family income, and residential segregation” (616). The model yielded risk ratios that reflected the contribution of segregation to mortality. The study concluded that in areas with high levels of African American segregation, mortality risk increased for both African American and White residents.

Despite the significant relationship(s) found by Yankauer and Jackson et al., the indices these researchers used are relatively simplistic in that they only enumerated the percentage of a specific group within spatial units. More complex indices have been used to estimate residential segregation. For example, Duncan and Duncan (1955) first articulated the index of dissimilarity, which measures the unevenness of the residential distribution of a specific minority group across all spatial units within a study area. It has a theoretical range from 0 to 100, with 100 representing a perfectly concentrated (or uneven distribution of a) group or population. Polednak (1991; 1993; 1996a; 1996b) used the index of dissimilarity as a measure of residential segregation among African Americans at varying levels of geography, ranging from the census block group level to the metropolitan statistical area level. In each of the investigations, Polednak found significant correlations between segregated areas and disparities in all-cause and infant mortality. Similarly, Hart et al. (1998) used the index of dissimilarity at the metropolitan statistical area level. The authors found significant correlations between residentially segregated areas and all-cause mortality among African Americans. Morello-Frosch and Jesdale (2006) used the index of dissimilarity at the census tract level in associating exposures to ambient air toxins in U.S. metropolitan areas with residential segregation. The authors found that Hispanics

were the most segregated group of all races or ethnicities examined, and that for all groups, “increasing segregation amplified the cancer risks associated with ambient air toxics for all racial groups combined” (386).

Acevedo-Garcia (2001) tested three different segregation indices at the census block group level: the isolation index, the index of contact with immigrants, and the partial density measure. The isolation index measures the extent and probability that a member of a particular racial or ethnic group is likely to be in contact with other members of this same group. The index of contact with immigrants tests the probability that within a specific geographic unit (e.g., town, census tract), the average member of a particular group will have contact with immigrants in his/her local area (e.g., block group, block). The partial density measure provides a statistic on the number of persons of a particular race or ethnicity per square kilometer (or mile) that are likely to be encountered by another member of that race or ethnicity. Overall, the study indicated a significant relationship between residential segregation and tuberculosis incidence, especially among Hispanics and African Americans.

The literature that links residential segregation to health disparities has progressed in a variety of manners. This is reflected in the advancement of segregation indices from simplistic measures such as the percent of a neighborhood that is a specific group to more complicated indices such as the index of dissimilarity. Like the research on ABSMs and health disparities, most research has concluded that disparities exist and can be linked to the indices examined. However, both ABSMs and the residential segregation indices are limited in their ability to quantify the influence of both individual- and contextual-level factors.

IV. Multi-Level Modeling and Health Disparities

In recent years, studies on the spatial context of health disparities have focused more on analyzing health outcomes using MLM. The major advantage of MLM is that it quantifies the impact of both individual-level variables and contextual variables on particular health outcomes. In this regard, multi-level models can be seen as being generalizations of linear models that incorporate the effects of both individual- and area-level explanatory variables on a specific independent variable. In a review of the significant literature surrounding MLM in public health research, Diez-Roux (2000) asserted that the additional complexity that MLM offers might explain disparities in health conditions that cannot be found when modeling at a single level. This point was accentuated in a review by Macintyre et al. (2002), where the authors noted the importance that several variables can have on health outcomes. The study highlighted mainly the influence of contextual variables including the physical environment, the availability of healthy environments at home and at work, services to support people in their daily lives, socio-cultural features of a neighborhood, and the reputation of an area. The authors concluded that MLM is a “valuable” tool in helping public health researchers explain why different health outcomes vary by location, even if they have similar population characteristics.

O’Campo et al. (1997) used MLM to examine the factors leading to low birth weight in Baltimore neighborhoods. The study used individual-level variables related to maternal education, maternal age, health insurance status, and trimester of prenatal care initiation among the individuals examined. Several census tract variables on social risk (ratio of home owners to

renters, number of community groups, unemployment rate, rate of housing violations,⁶ per capita crime rate, average wealth, and per capita income) were used as the area-level data. The results showed that all of the area-level variables had associations with low birth weight, and that all of the individual-level variables had relationships with at least one area-level variable.

Accordingly, the authors concluded that certain area-level variables such as those relating to poor housing conditions and high unemployment could alter the relationship between individual risk factors and low birth weight.

Similar results were found by Yen and Kaplan (1999) in an examination of data from the 1983 wave of the Alameda County Study⁷, which demonstrated that area-level variables contributed more heavily to health risk factors than individual-level variables. The study focused on a sub-sample of the data (n = 1,129), which included several individual-level variables such as income, education, race/ethnicity, smoking status, body mass index (BMI), alcohol consumption, and perceived health status. Area-level data, defined at the census tract level, were developed as a “three-component neighborhood social environment scale: 1) commercial stores; 2) population socioeconomic status; and 3) environment/housing” (898). Using MLM techniques, the authors found that “mortality risks were significantly higher in neighborhoods with a low social environment, even after accounting for individual income level, education, race/ethnicity, perceived health status, smoking status, body mass index, and alcohol consumption” (898).

⁶ The Community Planning Division of the City of Baltimore's Department of Planning calculates statistics on the number of houses that have recorded violations of a specific planning code or ordinance.

⁷ The Alameda County Study was a longitudinal health study of 6,928 individuals in Alameda County, California. The study was administered by the Human Population Laboratory Section of the California Department of Health Services, and was guided through the use of self-administered questionnaires at ten-year increments from 1965 through 1994 (Berkman et al. 1983).

Malmstrom et al. (1999) used MLM techniques to investigate the impact of a neighborhood socioeconomic environment on self-reported health status. The study combined 9,240 random surveys of self-reported health status in Sweden with two area-level measures: the Townsend Deprivation Index and the Care Needs Index (CNI). The CNI is a social deprivation index similar to the Townsend Deprivation Index. The authors applied the two area-level measures at the small-area market statistics (SAMS) geographic level for the entire country. SAMS areas are a standardized system of geographical boundaries containing, on average, between 1,000 and 2,000 residents. The results indicated that the social deprivation of neighborhoods, as measured by both indices, was an important independent risk factor in determining the quality of health for those surveyed.

Diez-Roux et al. (1997) used MLM techniques in investigating “whether neighborhood socioeconomic characteristics are associated with coronary heart disease prevalence and risk factors” across four communities in the U.S.: Washington County, Maryland; Forsyth County, North Carolina; Minneapolis, Minnesota; and Jackson, Mississippi” (48). The study used individual-level health data (a sample of 12,601 individuals residing within the communities) and area-level data on neighborhood characteristics at the census block group level. Taken from the 1990 census, the area-level data were compiled from census variables related to education, median household income, and occupational characteristics. The results showed that across the communities examined, “living in deprived neighborhoods was associated with increased prevalence of coronary heart disease and increased levels of risk factors, with associations generally persisting after adjustment for individual-level variables” (48). A follow-up examination by Diez-Roux et al. (2003), using a similar method and set of variables, investigated

the influence of area-level variables (education, median household income, and occupational characteristics) on the prevalence of smoking among different races. The study concluded that living in disadvantaged areas greatly increased the likelihood of smoking among Whites. Meanwhile, neighborhood characteristics did not appear to influence the smoking prevalence among African Americans. Together, these findings show the benefits of using MLM. That is, MLM quantifies the influence of both population composition variables and contextual variables on the health of individuals.

Although most public health researchers using MLM have found it to be a very helpful tool in understanding the prevalence and causation of disease and health conditions, they acknowledge that there are several methodological issues that still need to be addressed. One of the major issues was identified by O'Campo (2003). The author noted the lack of theory on how neighborhood environments influence health risks and outcomes. In order to solve this problem, the author suggested that more qualitative research be done to fully understand the effects that neighborhood environments have on the health of the local population. Public health and epidemiological research using MLM have also primarily focused on using cross-sectional data of individuals and neighborhoods to analyze health risks and outcomes. However, since neighborhood characteristics are in a process of continual change due economic and demographic factors, more longitudinal studies must be done using MLM to see if health risks and outcomes are affected by neighborhood change over time.

Another problematic issue when using MLM is choosing how to define a neighborhood. In public health research, it is common to delineate neighborhoods as census tracts. Although census tracts are widely used because they can be monitored longitudinally and are one of the

few readily available ways to define neighborhoods, several public health researchers have discussed problems with using them in MLM. Riva et al. (2007) stated that many studies that have used census tract divisions do not take into account the spatial interaction that occurs between neighborhoods, because it is generally assumed that each neighborhood is independent. Diez-Roux (2001) argued that using census tracts for neighborhood analyses assumes that individual tracts are cohesive communities, which may not be true in reality. O'Campo (2003) noted that many MLM techniques presume that neighborhood characteristics can influence an individual's health, even though when using certain census data, it is impossible to know how long an individual has lived in a neighborhood. This is specifically an issue with individuals and families in low-income neighborhoods, because they often have a high degree of residential mobility. Despite these methodological issues associated with defining neighborhoods in MLM, studies have consistently shown that neighborhood characteristics do play a role in health outcomes.

V. Public Health Disparities Projects

Increased interest in the spatial context of health disparities has spawned public health disparities projects focused on eliminating health differences at either the national, state, or local level. While projects that publish methods for the use of ABSMs, residential segregation indices, or MLM techniques are of particular relevance to this review, few actually exist. For example, an informal 2008 Internet survey of public health departments in the United States demonstrated that fewer than 10 percent of the surveyed units contained publicly available research data or

reports on the spatial context of health disparities. Of the departments surveyed, one of most prominent examples comes from Washington State.

The Washington Department of Health has largely replicated the methodology used by the Public Health Disparities Geocoding Project to help identify health disparities within the state. In particular, the project has contrasted health disparities with the demographic and socioeconomic profiles of census tracts in Washington, while using the Public Health Disparities Geocoding Project as a template to their study. To do this, state researchers have compiled census tract level variables that they have grouped into several key perspectives including income inequality (relative deprivation), social capital, racial discrimination, medical care, factors related to lifestyle choices, variables related to the physical environment, a life-course perspective, and social support. The variables used to define these perspectives are outlined in the Washington Department of Health's Internet web-document, "The Health of Washington State," (<http://www.doh.wa.gov/HWS/doc/AppendixB.doc>). The agency has used these perspectives in their reporting of each of the major causes of death in the state. The publicly available reports include detailed statistical and spatial analyses aimed at associating the explanatory variables (related to one or more of the perspectives) with each cause of death. The Washington Department of Health has used these reports to develop a community-level intervention strategy titled, "Communities Count," to help address the well-being of specific areas in the state.

The New York State Department of Health offers a similar examination of community health to the Washington study; however, the analysis is provided at the county level rather than the census tract level. Of note, New York State Department of Health researchers have created

the New York Community Health Assessment Clearinghouse

(<http://www.health.state.ny.us/statistics/chac/>) as a, “one-stop resource for community health planners, practitioners, and policy developers” (2008). The clearinghouse offers a gateway by which each county in the state can be examined according to one of 14 health topic areas ranging from cancer and heart disease to health behaviors and socio-economic status with each topic being represented by several explanatory variables. For example, health behaviors are represented by smoking, drinking, and obesity data obtained from the Behavioral Risk Factor Surveillance System (BRFSS), while socio-economic status is represented by census derived unemployment, income, poverty, education, insurance, and Medicaid data. A full list of variables used is provided at <http://www.health.state.ny.us/statistics/chac/chai/overview.htm>. Overall, the New York State Department of Health has used the health topic surveys in applying grades to each county.

The Pennsylvania State Department of Health provides a comparable resource to the New York Community Health Assessment Clearinghouse. The Pennsylvania Community Health Assessment Resources: Links to Local Data is a website by which the public can access county level health, behavioral, and socio-economic data (<http://www.dsf.health.state.pa.us/health/cwp/view.asp?a=175&Q=241237>). Unlike New York however, the Pennsylvania Community Health Assessment Resources website also provides relevant data for over 20 major municipalities in Pennsylvania. Furthermore, the website offers links to other pertinent information such as hospital discharge, injury, youth survey, school violence, and air quality data.

Other public health disparities projects have proceeded with a less holistic approach to understanding the spatial context of differences in health. For example, the Texas Department of State Health Services has created an index to measure health disparities among different areas and populations in the state (<http://www.dshs.state.tx.us/oehd/docs/hdeartwgrpt.pdf>). Included in this health disparities index are ABSMs such as poverty rates and education levels. The Rhode Island Department of Health offers the Center for Health Data and Analysis with links to health data, fact sheets, and health risk reports (<http://www.health.ri.gov/chic/statistics/index.php>). Some of these reports have approached a methodology similar to the Public Health Disparities Geocoding Project whereby census tracts are grouped into categories based on their poverty levels. Health differences are noted between the various categories (<http://www.health.ri.gov/chic/statistics/Hbn2-4.pdf>). The Virginia Department of Health has initiated a study linking poverty levels to AIDS and sexually transmitted diseases (http://apha.confex.com/apha/135am/techprogram/paper_159177.htm). The Georgia Department of Public Health has partitioned the state into eighteen distinct demographic clusters in analyzing health outcomes among specific groups. According to their website (<http://health.state.ga.us/demographicprofiles/index.htm#x>), these clusters were created using census tract level variables related to age, income, family structure, housing value and housing type, education, and employment type. Finally, the New York City Department of Health and Mental Hygiene has published a study on health disparities in New York City that analyzed how income and ethnicity are associated with increased mortality rates from certain conditions and the prevalence of disease (<http://www.nyc.gov/html/doh/downloads/pdf/epi/disparities-2004.pdf>).

VI. Conclusion

This review has identified the major research themes related to the spatial context of health disparities. Some research has linked health disparities to contextual variables using unique ABSMs at differing spatial levels. A related body of research has investigated the relationship between health disparities and residential segregation. More advanced studies have examined and linked health disparities to both compositional and contextual factors using MLM.

Health disparity research using ABSMs has been applied in some public health departments or institutions focused on the reduction of disparities among specific populations or within certain areas. An investigation into the breadth and depth of these projects reveals the importance of health disparities to the respective organizations at a wide range of spatial scales. In the future, it is anticipated that cross-scaled approaches will add to the breadth of this body of research. Overall, these projects underscore the importance of the spatial context of health disparities.

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