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Research Paper

Disability and health outcomes in geospatial analyses of Southeastern U.S. county health data

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ABSTRACT

Background: People with disabilities tend to be at risk for secondary conditions. There is a need for comprehensive disability and health databases, including geographic information systems to evaluate trends in health, functioning, and employment.
Objective: We evaluated county levels in morbidity and mortality across the Southeastern United States using spatial regression, examining 2015 trends in accordance with Healthy People 2020 objectives.
Methods: We merged 2015 National County Health Rankings and the 2015 Social Security Administration's Report on SSDI Beneficiaries, all for n = 1387 Southeastern U.S. county units. We used GeoDa to regress health and disability multivariable models for the dependent variable, age-adjusted Years of Potential Life Lost (YPLL) per 100,000 population.
Results: The principal Health/Demographic multivariable model of factors impacting YPLL yielded an adjusted $R^2 = 0.743$ ($F = 188.3$, $p < 0.001$) with percentage physically inactive, preventable hospital stays, percentage diabetics, and low college attendance figuring prominently. A Socioeconomic/Demographic multivariable model impacting YPLL yielded $R^2 = 0.631$ ($F = 156.0$, $p < 0.001$), with disability and percentage unemployment being major associated variables.
Conclusions: For the Southeastern U.S., counties with higher prevalence of SSDI disability workers correlated with significantly higher YPLL and poorer health outcomes. The research augments CDC Disability and Health GIS systems to measure Healthy People 2020 outcomes for persons with disabilities nationwide. Spatial regression represents a robust approach for improved analysis of geographic data for population health measures.

The objective of this study is to geospatially analyze the degree of association between county-level health and socioeconomic factors with county levels of workers with disabilities. People with disabilities tend to be at risk for secondary conditions, including significantly higher morbidity and mortality. There is a need for comprehensive disability and health databases, including geographic information systems to evaluate trends in health, functioning, and employment for people with disabilities. The CDC Disability and Health Data System (http://dhds.cdc.gov) provides state-level GIS health data to assist health policy makers and advocates to access informative data on people with disabilities and their needs. Other state health departments have developed similar systems. Mitchell, Cockcroft, and Andersson[1] demonstrated the utility of color-coded raster layers to evaluate changes in health, socioeconomic, and prevention programs, although they stressed that GIS mapping augments rather than replaces more rigorous epidemiological techniques such as randomized controlled trials. McLafferty[2] argued that GIS applications to health policy analysis require improved analysis of spatial relationships between health providers and consumers. Shaw[3] emphasized the critical need for the public health community to capitalize on GIS technology to improve health assessments and interventions.

Fotheringham and Brunsdon[4] pioneered the use of spatial regression to address spatial autocorrelation between adjacent geographic units (e.g., counties). Anselin[5] further developed spatial regression with latent models, model filtering, and data weighting to control for the ecological fallacy. Anselin[6] documented the rapid growth and statistical enhancement of geographic spatial analysis with the incorporation of spatial autocorrelation analysis and spatial regression analysis via ESRI's ArcGIS® software and his own freeware platform GeoDa®.

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Hollar[7] utilized GeoDa (www.geodacenter.asu.edu) on the 2014 County Health Rankings (University of Wisconsin Population Health Institute, www.countyhealthrankings.org) to demonstrate geospatial prediction of higher county infant and child mortality by higher county obesity, smoking, teen birth rates, severe housing problems, lack of social supports, and urbanicity. Results corroborated the Maternal and Child Health literature on group studies of factors impacting infant morbidity and mortality.[8]

Most importantly, Fox, White, Rooney, and Rowland[9] recommended that state and county governments utilize GIS mapping in emergency planning activities so that people with disabilities can be quickly located and assisted during disasters. This concept is central to much of GIS technology applications for health care.[10,11] Tilahun et al.[12] demonstrated the use of GIS community mapping to identify risks for social and health disparities. Other studies used GIS mapping to evaluate neighborhood access to health care, poverty levels, crime rates, and pollution levels that may contribute to increased developmental disabilities among children living in these communities.[13,14] With the exception of geospatial disability data reporting systems,[9] little research has employed this methodology to the improvement of health for people with disabilities.

For this study, we examined health risk and socioeconomic factor models that incorporate work-related disability to assess age-adjusted Years of Potential Life Lost (YPLL) rates per 100,000 people at the county level for the Southeastern U.S. (n = 1387 counties) in 2015. The study is designed to test improvements in Healthy People 2020 Objectives (http://www.healthypeople.gov/2020/topics-objectives) for people with disabilities. Primary research questions included:

1. What are the patterns of YPLL for 2015 across the Southeastern states?
2. Do geospatial analyses reject the lack of association between county-level 2015 disability, health, and socioeconomic risk factors and 2015 YPLL across the Southeastern states?

Major Healthy People 2020 Objectives (http://www.healthypeople.gov/2020/topics-objectives) related to this study are presented in Table 1.

Methods

Context

We used GeoDa 1.6.2 (spatial.uchicago.edu) to spatially map variable patterns and to spatially regress county-level independent variables on independent (i.e., predictor) variables. We used SPSS Version 21.0 to examine general county demographic data.

We examined associations between disability, health risk and socioeconomic factors on YPLL at the county level for the Southeastern U.S. (n = 1387 counties) in 2015. We focused only on the Southeastern U.S. counties for the following two reasons: (1) wide variation in historical GINI socioeconomic measures across this region compared to other U.S. regions; and (2) improved resolution for mapping and identification of high risk counties compared to the entire United States.

Data sources

Linked data sources included county level data from the 2010 and 2015 National County Health Rankings (University of Wisconsin Population Health Institute and Robert Wood Johnson Foundation, www.countyhealthrankings.org) and the U.S. Social Security Administration's OASDI Beneficiaries by State and County 2014 (https://www.ssa.gov/policy/docs/statcomps/oasdi_sc/). The County Health Rankings data are compiled annually from the U.S. Census Bureau, American Community Survey, CDC National Center for Health Statistics, the National Center for Chronic Disease Prevention, the National Center for HIV/AIDS, U.S. Centers for Medicaid Services, Dartmouth Atlas of Health Care, the National Center for Education Statistics, and state and county health departments.

Variables

Health-related county variables included the dependent variable Years of Potential Life Lost (YPLL). The independent variables included Percentage with Fair/Poor Health, Number of Physically Unhealthy Days, Number of Mentally Unhealthy Days, Percentage Obesity, Percentage Smoking, Percentage Excessive Drinking, Principal Care Provider/Physician Rate, Dental Care Rate, Mental Health Care Provider Rate, Preventable Hospital Stay Rate, Percentage Diabetics, Food Environment Index, Percentage Inactive, Percentage Access to Physical Activity, Infant Mortality Rate, Child Mortality Rate, Injury Death Rate, and Motor Vehicle Mortality Rate. Two Disability variables was Percentage SSDI Disability Workers (primary), calculated from the Number of SSDI Disability Workers and Population per county in the Social Security Administration's OASDI recipient data, and Payments to SSDI Disability Workers (secondary).

Socioeconomic (SES) variables included Household Income, Percentage Uninsured, GINI index (calculated), Percentage Unemployed, Percentage Single Parent Households, Percentage Severe Housing Problems, Percentage Who Could Not Access Physician Care due to Costs, Violent Crime Rate, and Teen Birth Rate. Demographic county variables included Percentage African American, Percentage Hispanic, Percentage Older than 65 years, Percentage High School Graduates, Percentage attending some College, Social Association Rate, and Percent Rural.

Analysis

Statistical analyses included:

1. Percentile geographic maps of spatially smoothed YPLL rates for 2015 (Research Question 1);
2. Multivariable spatial regression models of Years of Potential Life Lost (YPLL) on disability, health, socioeconomic, and demographic county variables for 2015.

Therefore, YPLL represented the dependent variable for multivariable regression analyses. For each of the regression models, SSDI work-related disability served as a primary independent variable. While the YPLL and SSDI disability variables were generated from separate data sources, one limitation of our approach is the potential for de facto inflated YPLL due to SSDI related to terminal illness. It is for this reason that we focused on the work-related SSDI classification. Furthermore, the data “points” in this analysis represent county units, and there is no straightforward relationship between individual workers with disabilities and estimated YPLL, regardless of the Wisconsin Population Health Institute's calculations for YPLL. The University of Wisconsin Population Health Institute computed YPLL for people dying before the age of 75, using the method of Dranger and Remington[15] to produce an age-adjusted rate per 100,000 population in relation to the year 2000 United States Census.

Of worker SSDI beneficiaries, 8.3% have cardiovascular conditions of varying severity, and 20.4% experience any of a range of conditions that include cancer, end-stage renal disease, congenital disorders, and other diseases/injuries.[16,17] It is difficult to assess the percentage of this combined 28.7% SSDI recipients who would