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Article

Overlapping geographic clusters of food security and health: Where do social determinants and health outcomes converge in the U.S?

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ABSTRACT

We identified overlapping geographic clusters of food insecurity and health across U.S. counties to identify potential shared mechanisms for geographic disparities in health and food insecurity. By analyzing health variables compiled as part of the 2014 Robert Wood Johnson Foundation County Health Rankings, we constructed four health indices and compared their spatial patterns to spatial patterns found in food insecurity data obtained from 2014 Feeding America's County Map the Meal Gap data. Clusters of low and high food security that overlapped with clusters of good or poor health were identified using Local Moran's I statistics. Next, multinomial logistic regressions were estimated to identify sociodemographic, urban/rural, and economic correlates of counties lying within overlapping clusters. In general, poor health and high food insecurity clusters, "unfavorable cluster overlaps", were present in the Mississippi Delta, Black Belt, Appalachia, and Alaska. Overlapping good health and low food insecurity clusters, "favorable cluster overlaps", were less common and located in the Corn Belt and New England. Counties with higher black populations and higher poverty were associated with an increased likelihood of lying within overlapping clusters of poor health and high food insecurity. Generally consistent patterns in spatial overlaps between food security and health indicate potential for shared causal mechanisms. Identified regions and county-level characteristics associated with being located inside of overlapping clusters may be used in future place-based intervention and policy.

1. Introduction

Food insecurity–defined as inconsistent access to adequate food due to lack of financial and other resources–is a persistent problem in the US, particularly among low-income populations (Alisha Coleman-Jensen, Gregory, & Singh, 2014). Likewise, these same low-income populations are often more likely to have higher rates of poor health outcomes. However, little work has been done to understand the degree to which these two population health issues overlap. We fill this gap by examining the degree of spatial overlap of food insecurity and poor health in US counties.

1.1. Food Insecurity

Between 2007 and 2009, during the financial recession, the US food insecurity rate rose from 11% to 14% (Rabbitt, Coleman-Jensen, & Gregory, 2017). Since that time, overall economic conditions in the US have improved, but food insecurity rates have not returned to pre-recession levels. Roughly a quarter of the US population participates in some form of public nutrition assistance program aimed at alleviating food insecurity. These programs include the Supplemental Nutrition Assistance Program (SNAP), Women Infants and Children (WIC), or school meal programs. While food insecurity is associated with worse economic well-being, not all low-income populations and places face the same degree of food insecurity (Alaimo, 2005; Coleman-Jensen, Rabbitt, Gregory, & Singh, 2017; Rose, 1999). For example, 33% of households earning incomes below the federal poverty threshold reported no food insecurity (Wight, Kaushal, Waldfogel, & Garfinkel, 2015). Further, among SNAP participants, those living in areas with higher food prices were 5% more likely to report food insecurity than those living in average-priced food areas (Gregory & Coleman-Jensen, 2013). Food insecurity rates are similar when comparing urban and rural areas, despite the fact that poverty conditions are often worse in rural areas (Brown & Hirschl, 1995; Gundersen, Dewey, Hake, Engelhard, & Crumbaugh, 2017). One hypothesis about why food insecurity and poverty do not correlate geographically is that the spatial

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distribution of charitable food services (i.e. food banks, federal program participation, etc.) is uneven, thus resources to combat food security are more abundant in some high poverty areas than others (Gundersen et al., 2017). Thus, while higher food insecurity rates are expected in counties with higher poverty rates, the spatial pattern of food insecurity is not necessarily the same as the spatial pattern of poverty.

1.1.1. Relationship between food insecurity & health

A growing literature has established robust relationships between food insecurity and worse health. Food insecure households have difficulty meeting basic needs such as refilling medical prescriptions (Afulani, Herman, Coleman-Jensen, & Harrison, 2015) and providing adequate nutrition (Duffy, Zizza, Jacoby, & Tayie, 2009). Food insecurity is associated with poorer self-rated mental and physical health among adults (Alaimo, 2005; Stuff, Casey et al., 2004; Stuff, Horton et al., 2004) and food insecure households with children have higher risk of iron deficiency and poorer dental outcomes (Chi, Masterson, Carle, Mancl, & Coldwell, 2014; Skalicky et al., 2006).

Policy solutions for improving food insecurity and health are geographic in nature. A sophisticated network of regional food banks and component pantries associated with Feeding America exists throughout the United States. These organizations work to match available food resources (e.g. surplus retail supplies, USDA funded food items) with households in need (Prendergast, 2017), and each of these food banks has a geographically-bounded distribution region. Federal food assistance programs (i.e. SNAP and WIC) also vary by state. For example, SNAP may be administered at the county or state level, may be jointly administered with other federal programs such as Medicaid or Temporary Assistance for Needy Families (TANF), require various types of household reporting standards, and vary in eligibility standards (United States Department of Agriculture, 2018). Additionally, healthcare systems and health services providers generally serve distinct geographic regions; and healthcare policies such as those impacting Medicaid and Medicare eligibility vary at the state level.

Our work fills an immediate gap in our understanding of the relationship between food insecurity and poor health by focusing on the geographic patterns of these two inter-related aspects of well-being. We use novel spatial statistical methods to identify overlapping geographic clusters—i.e., regions with significant burdens of both poor health and high food insecurity—and assess correlates of these spatial patterns. Our results lay the foundation for future population health research efforts to understand the shared mechanisms and pathways driving observed relationships between food insecurity and poor health. Our results also have implications for intervention. For example, they may be used to prioritize place-based multi-sector collaborations between food assistance and healthcare safety-net systems in contexts in which dual burdens of poor health and food insecurity are likely to be high.

2. Materials and methods

We examined county-level health and food insecurity measures for every US County with available data (n = 3142). Data analysis took place between Jan 15 and December 29, 2017.

2.1. Variables

The percent of the population that is food insecure was obtained from Feeding America's Map the Meal Gap (MMG) 2014 data; the methodology is described in detail elsewhere (Gundersen, Engelhard, Satoh, & Waxman, 2016). These data use Current Population Survey (CPS) food security measures, which are based on the Core Food Security Module established in 1996 by the USDA as a means of measuring food insecurity status of households (Gundersen et al., 2017; Gundersen & Ziliak, 2015; Herman, Afulani, Coleman-Jensen, & Harrison, 2015). Reliability of the estimated food insecurity measures has been established in the literature (Gundersen, Engelhard, & Waxman, 2014).

Health variables were obtained from the Robert Wood Johnson Foundation County Health Rankings (CHRs) data (Roberty Wood Johnson Foundation, 2017). We identified variables reflecting the percent of each county's population –or the population of the county's Medicare enrollees-experiencing a health condition or behavior and did not include ranked data. Unless otherwise noted, variables procured from the CHRs data were provided by the Behavioral Risk Factor Surveillance System (BRFSS) (Center for Disease Control and Prevention, 2015). Variables were grouped into 4 constructs. *Food-related Population Health Indicators* include percentage of obese adults (body mass index > 30), and percent of Medicare enrollees living with diabetes as reported by the Dartmouth Institute (DI). *Preventive Health Behaviors* include the percent reporting insufficient sleep, percent of Medicare enrollees current with mammography screening reported by DI, percent of adults who smoke, and the percent of adults reporting no leisure-time physical activity. *Indicators of Poor Physical Health* include average number of reported physically unhealthy days in the past month, percent reporting fair/poor health, years of potential life lost rate per 100,000 reported by the National Center for Health Statistics (NCHS), and percent reporting frequent physical distress. Finally, *Indicators of Poor Mental Health* include the average number of reported mentally unhealthy days per month and percent reporting frequent mental distress.

County-level socio-demographic data were obtained from the US Census American Community Survey (ACS) 2011–2015 5-year estimates. Variables ascertained include race/ethnicity (percent of population that is non-Hispanic (NH) black, percent Hispanic, percent NH white, and percent Native American), percent of households below poverty, percent of adults unemployed, indicator for female headed households, percent foreign born, and population density. In addition, 2013 Rural-Urban Continuum Codes (also known as Beale Codes) were obtained from the USDA Economic Research Service (USDA, 2017).

3. Calculation

We assessed internal consistency reliability of each construct using Cronbach's alpha. To facilitate comparative analysis across US counties, each variable was standardized and reverse coded as needed so that higher values indicate more unfavorable outcomes. The standardized variables for each construct were then averaged. The construct average for each county was assigned a decile ranking with higher deciles representing more unfavorable outcomes.

To assess the relationship between food insecurity and each health construct, we created scatter plots. The plots quantify the population burden and regional distribution of residents living in counties experiencing high food insecurity and poor health and the relationship between food insecurity and poor health. The plots demonstrate how many counties are in the worst 2 deciles of both well-being indicators and show the distribution of by population size and U.S. region (Midwest, Northeast, South, West).

In order to assess the spatial distribution of clusters of counties with similar measures, we conducted univariate cluster analysis for each health construct and for food insecurity as separate variables. Univariate cluster analysis was implemented by calculating local Moran's I statistics to identify geospatial clusters of both high and low food insecurity and health. To account for multiple hypothesis testing, we implemented the Benjamini-Hochberg method for adjusting p-values. Clusters with adjusted p-values < 0.10 were selected as statistically significant.

Next we conducted bivariate analysis. We identified counties located in *overlapping clusters* of both high food insecurity and poor health constructs as having *unfavorable outcomes*, and counties located in overlapping clusters of both low food insecurity and good health as having *favorable outcomes*.

For each health construct, we created categorical variables to indicate whether counties were in overlapping favorable, unfavorable or