GeoJournal
DOI 10.1007/s10708-011-9445-3

An application of Bayesian spatial statistical methods to the study of racial and poverty segregation and infant mortality rates in the US

P. Johnelle Sparks · Corey S. Sparks · Joseph J. A. Campbell

Abstract The infant mortality rate is a fundamental measure of population health used internationally. In the United States, the infant mortality rate is higher than what would be expected for a country of its affluence. We present an analysis of US county infant mortality rates using modern Bayesian spatial statistical methodologies. Our key predictors in our statistical analysis are residential racial and poverty segregation, measured by the dissimilarity, interaction and spatial proximity indexes. We use both Exploratory Spatial Data Analysis methods and Hierarchical Bayesian spatial regression models to examine the influences of these segregation measures on the infant mortality rate for each county, net of income inequality, degree of rurality and relative socioeconomic deprivation. The spatial measures of racial segregation suggest that when blacks live in close proximity to each other, this tends to increase the infant mortality rate. The results for poverty segregation suggest the same pattern, when poor populations live in close proximity to one another this is generally detrimental to the county infant mortality rate. However, interaction between blacks and whites and poor and non-poor residents of an area is protective for infant mortality.

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Keywords Infant mortality · Residential segregation · Spatial statistics · Bayesian modeling

Introduction

Most studies examining disparities in infant mortality and other infant health outcomes tend to focus on individual level risk factors, including sociodemographic characteristics (Goza et al. 2007; Singh and Kogan 2007a, b), low birthweight (Basso and Wilcox 2009; Collins and David 2009; Morales et al. 2005), prematurity status and small for gestational age infants (Kramer et al. 2000; MacDorman et al. 2007; Shapiro-Mendoza et al. 2006, 2008; VanderWeele et al. 2009), and sleep positions and location within the household (Fu et al. 2008; Lahr et al. 2007; Ostfeld et al. 2006). Other research makes use of multilevel methods to assess the impact of environmental and contextual characteristics on individual risk of infant mortality, preterm birth, or low birthweight (Bell et al. 2006; Cerda et al. 2008; Collins and David 2009; Collins and Schulte 2003; Finch et al. 2007; Hearst et al. 2008; Kramer and Hogue 2008; Masi et al. 2007; Mason et al. 2009; Pearl et al. 2001; Pickett et al. 2009). A number of multilevel studies focusing on infant health outcomes have addressed the important association between residential segregation and differential infant health risks (Acevedo-Garcia 2000; Acevedo-Garcia and Lochner 2003;

Published online: 11 January 2012

Acevedo-Garcia and Osypuk 2008; Bell et al. 2006; Grady 2006; Hearst et al. 2008; Polednak 1991, 1996). However, it is less common in the infant mortality literature for authors to address the role of the spatial context (Yang et al. 2009). Through the use of the Bayesian Hierarchical Model (Shoultz et al. 2007a; Yang et al. 2009) commonly used in epidemiology (Waller and Gotway 2004; Lawson 2009), the spatial context of residential segregation and infant mortality may be incorporated at an aggregate level.

In most commonly applied regression models, local area attributes are considered without spatial reference to neighboring values or attributes. By taking a spatially explicit approach to modeling, the spatial configuration of the data may contribute information about the outcome not captured by other area attributes. The contribution of the current study to the literature on infant mortality is twofold. First we compare the effects of both racial and poverty segregation on infant mortality risk in United States counties. We explore this association using three different dimensions of each form of residential segregation, which has not been considered in the literature before. The three dimensions of segregation used in the current study are: dissimilarity, interaction/isolation, and spatial proximity. Secondly, we employ modern Bayesian Hierarchical regression models to directly incorporate the effects of space and spatial inequality on infant mortality risk in our statistical modes. This allows us to examine the contextual effects of these different measures of residential segregation and county level socioeconomic conditions on county infant mortality rates.

Residential segregation and infant mortality

Hearst et al. (2008) argue that segregation negatively impacts infant health outcomes of non-Hispanic blacks compared to non-Hispanic whites, because patterns of racial and socioeconomic residential segregation generally expose minority groups to negative structural, social, economic, material, and individual-level resources. More specifically, poor housing quality, environmental contaminants, lower educational and employment opportunities, access restrictions to social services, limited access to healthy and fresh food options, high crime rates, low investment in infrastructure, and poor access to medical services based on different residential segregation patterns are offered as potential mechanisms linking segregation to higher infant mortality rates (Buka et al. 2003; Collins and Williams 1999; Collins and Schulte 2003; Hummer 1993; LaVeist 1993). Further some authors argue that segregation based on race leads to economic inequality among racial/ethnic groups, because minorities are isolated from employment opportunities and social services available in more white areas (Kain 1968; Mason et al. 2009; Massey and Eggers 1990; Schulz et al. 2002; Yang et al. 2009).

Less work has examined the impact of explicit poverty segregation measures on infant health outcomes. Most research studying residential segregation, poverty, and infant mortality simply controls for a measure of the percentage of the population in a given area that have incomes below the poverty threshold (Kramer and Hogue 2008; Masi et al. 2007; Schempf et al. 2009; Sims et al. 2007). Acevedo-Garcia and Osypuk (2008) highlight the methodological difficulty in studying the impact of residential segregation and health outcomes due to the high correlation between minority segregation concentration and poverty rates. However it may be the relative differences in economic resources for minority residents that impact infant mortality chances; persons living in areas with higher than expected economic circumstances, also noted as positive income incongruity, may benefit from certain forms of residential segregation (Pickett et al. 2005; Pickett et al. 2009; Vinikoor et al. 2008; Wilkinson 1996).

Research on residential segregation, whether based on race or income, and infant health outcomes must also address the multidimensional nature of segregation and its inherently spatial nature. Researchers have commented and noted that different dimensions of residential segregation exist, and several indices appropriate to the study of residential segregation have been discussed elsewhere (Massey and Denton 1988; Reardon 2006; Collins and Schulte 2003). Empirical work using different dimensions of residential segregation find mixed associations with different operationalizations of these dimensions and infant health outcomes (Bell et al. 2006; Grady 2006; Grady and Ramirez 2008; LaVeist 1989; Pickett et al. 2005; Polednak 1991; Roberts 1997). Therefore it is not clear how certain dimensions of residential segregation are protective or harmful against infant mortality risks, particularly when measuring both racial and poverty residential segregation in a spatial context.

Bell et al. (2006) found that racial residential isolation, or no interaction between individuals of different races/ethnicities, led to poorer infant health outcomes in 225 US Metropolitan Statistical Areas (MSAs), while racial clustering led to better infant health outcomes. It terms of poverty segregation, it would follow that more interaction between poor and non-poor residents of an area would lead to lower infant mortality rates, because more interaction between poor and non-poor residents would lead to diverse investments and access to local area resources and more understanding between different types of people as detailed above and therefore would decrease infant mortality in those areas (Guest et al. 1998; Polednak 1991, 1996). However, this particular measure of residential segregation is rarely explored as it relates to infant health outcomes.

From a spatial perspective, state and local policies may influence the level of social and health services available in a give location, therefore the actual location of residents within counties may contribute to the association between residential segregation measured spatially and infant mortality rates. Reardon and O'Sullivan (Reardon and O'Sullivan 2004) propose the use of the spatial proximity index, a measure of evenness akin to the dissimilarity index, as one spatially explicit measure of segregation. No current research exists, to our knowledge, that examines this measure of segregation and mortality outcomes. The effect of this dimension of segregation is assumed to influence mortality by limiting contact between neighbors with different characteristics, be it race/ethnicity or poverty status. This index is differentiated from the interaction index in that the locations themselves of residents within a county are considered in the calculations. It is suggested that such geographic proximity will contribute more information than the isolation index described previously. Furthermore, counties with lower levels of inter-resident contact may have higher infant mortality rates, and these associations will likely vary across space due to variation in segregation patterns across the US (Iceland et al. 2005)

To our knowledge, no research has used spatial statistical methods to explore the potential variation in associations over space between measures of racial and poverty segregation, measured by three different dimensions of segregation, and aggregate infant health outcomes. This type of methodology can be particularly informative to the study of county infant mortality rates since we allow the spatial nature of the data to be modeled explicitly. Spatial variation is particularly important when examining poverty segregation and infant mortality rates, because spatial variation has been observed in poverty (Voss et al. 2006) and adult mortality (McLaughlin et al. 2007; Sparks and Sparks 2010) rates. Therefore the purpose of this paper is to identify possible explanations for the variation in county infant mortality rates controlling for appropriate composition and poverty segregation patterns in US counties using spatial Bayesian hierarchical statistical models. We think this spatial statistical approach can guide policy discussions about the way poverty segregation in the US may influence county infant mortality rates differently by allowing researchers and policymakers alike to understand how different dimensions of segregation operate to influence infant health outcomes.

Data and methods

Data for this analysis were taken from two sources: the 2008 Area Resource File from the US Department of Health and Human Services and the 2000 US Census of Population and Housing, Summary File 3. These two data sources were selected because all variables could be measured at the county level for all contiguous states in the US, including county measures of infant mortality, racial and poverty segregation, and county economic and compositional characteristics. A total of 3,069 counties were used and make up the sample size for this analysis. Three year total count of infant deaths from 1999 to 2001 for each county in the 48 contiguous US states serve as the basis for our outcome variable, and the 3-year total number of births serve to define the population at risk. A total of 24,487 infant deaths were recorded in the data for these years out of 4,041,042 live births, or a rate of 60.6 deaths per 10,000 live births.

Independent variables

Independent variables for this analysis were taken from the Census and serve as county-level economic and social indicators that would likely impact patterns of segregation and infant mortality risk. Three control variables were considered that have been shown to have an association with infant mortality: the percentage of the county population that was rural (Sparks et al. 2009), the Gini coefficient for income inequality within a county (Huynh et al. 2005; McLaughlin et al. 2007), and an index of relative deprivation (Singh and Kogan 2007a, b). The percent rural variable was defined as the proportion of the county population not classified as urban by the Census Bureau. The Gini coefficient was included as a measure of relative inequality in household incomes within a county, with a value of 1 indicating complete inequality and a value of 0 indicating complete income equality. The index of relative deprivation consisted of a linear combination of eight measures of county socioeconomic conditions. These included: the poverty rate, the unemployment rate, the proportion of households with female heads with children, the proportion of households receiving public assistance income, the proportion of the population age 25 with a college education, the median household income, and the proportion of the workforce in technical or professional occupations for each county. These variables are each standardized (z-scored) and averaged to produce the index following the technique of other authors (Kawachi et al. 1999; Matthews et al. 2010; Yang et al. 2009, 2011).

The substantive predictors in our model measure three different elements of residential segregation. Massey and Denton (1988) outline evenness, exposure, concentration, centralization, and clustering as five dimensions of residential segregation. We measure residential segregation using three indexes including: the dissimilarity index (D) to measure evenness, the interaction index (${}_xP_y^*$) to measure exposure, and the spatial proximity index to measure clustering (Massey and Denton 1988; Reardon 2006). These measures were selected since they compare two subgroups to each other when calculating the segregation measure instead of considering one group by itself. The three measures used here capture both racial (black–white) and poverty segregation, where poverty is defined as the number of persons living below the federally designated poverty threshold in each block group. Measures for three of these dimensions (evenness, exposure, and clustering) were utilized to examine if racial and poverty segregation affects infant mortality in different ways, and likewise to examine which dimension of segregation is most influential on the infant mortality rate. The index of dissimilarity and the interaction index are not in and of themselves explicitly spatial measures of segregation; however the spatial proximity index incorporates the spatial distribution of population subgroups within each county directly into the calculations. We measure each index of segregation by aggregating up from the block-group level to the county level. Census block-groups are the level of census geography that form tracts, and are the lowest level of Census geography for which the Summary File 3 sample data are available.

The index of dissimilarity, the most widely used measure of residential evenness, measures the invariability of the distribution between two groups across a county. The dissimilarity index can be interpreted as the proportion of residents with a particular characteristic (white race, poor) that would have to move to a different block group in the county in order to produce an even distribution with those residents dissimilar to them (black race, non-poor). One formula for the index of dissimilarity that can measure poverty segregation is:

$$D = \frac{1}{2}\sum_{i=1}^{n}\left|\frac{x_i}{X} - \frac{y_i}{Y}\right|$$

where x_i is the number of residents in the ith block group in a county living below the poverty threshold, X is the total number of county residents living below the poverty threshold, y_i is the number of residents in the ith block group living above the poverty threshold, and Y is the total number of county residents living above the poverty threshold. This index varies between 0.0 and 1.0, with 0.0 corresponding to an even distribution amongst persons of the two races or persons living below the poverty threshold and persons living above the poverty threshold in a county and 1.0 corresponding to perfect segregation.

Residential exposure refers to the possibility of interaction between residents of different races or those living below the poverty threshold and residents living above the poverty threshold within a county. Indexes of exposure measure the extent to which residents come into contact with one another simply by sharing a common residential area. The interaction index, a basic measure of residential exposure, measures the extent to which residents different racial groups (white–black) or residents living below the poverty threshold are exposed to residents living above the poverty threshold. It has been denoted as ${}_xP_y^*$ by Lieberson (1982):

$$ {}_xP_y^* = \sum_{i=1}^{n} \left| \frac{x_i}{X} * \frac{y_i}{t_i} \right| $$

where x_i, y_i, and t_i are the number of residents who are black or are living below the poverty threshold, the number of residents who are white or living above the poverty threshold, and the total population of block group i within a county, respectively. X represents the total number of black residents or residents living below the poverty threshold in the county. The index varies between 0.0 and 1.0 and can be interpreted as the probability a black resident shares an area with a white resident or a resident living below the poverty threshold shares an area with a resident living above the poverty threshold.

Spatial clustering refers to the extent to which population subgroups live next to other groups or cluster in space. The index of spatial proximity is adapted from white (1986) to measure the clustering of racial and economic subgroups in space. To adequately calculate the spatial proximity index, the average proximity between members of the same group must first be calculated. The average proximity between members of an arbitrary group Z can by approximated by:

$$ P_{xx} = \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{z_i z_j c_{ij}}{Z^2} $$

where c_{ij} is a dichotomous variable with a value of one indicating block group i is continuous to block group j and zero otherwise, z_i is the subgroup population of the ith block group in a county, z_j is the subgroup population of the jth block group in a county, and Z is the total subgroup population of the county. The index of spatial proximity is simply the average of the intra-group proximities weighted by the fraction of each group in the population:

$$ SP = \frac{XP_{xx} - YP_{yy}}{TP_{tt}} $$

where P_{xx}, P_{yy} and P_{tt} are the average proximity between residents that are either black or living below the poverty threshold, the average proximity between residents that are either white or living above the poverty threshold, and the average proximity between residents for the total population, respectively. X is the total number of residents that are either black or living below the poverty threshold in the county, Y is the total number of residents that are either white or living above the poverty threshold in the county, and T is the total population of the county. If there is no differential clustering between residents, the spatial proximity index has a value equal to 1.0; it is greater than 1.0 when members of each group live nearer to one another than to members of the other group. The ratio would be less than 1.0 in the event that residents that are either black or living below the poverty threshold and residents that are either white or living above the poverty threshold populations reside closer to each other than to members of their own group.

Statistical methods

Two methods of spatial statistical analysis were used for this paper. First basic Exploratory Spatial Data Analysis was conducted by mapping the geographic distribution of the variables and calculating the values of the global Moran's I statistic (Moran 1950; Schabenberger and Gotway 2005). The value of Moran's I can be interpreted similarly to a normal correlation coefficient, except positive values of I suggest an association between an individual county and the average of the county's neighbors.

The main statistical model uses a spatial Bayesian Hierarchical regression model (Banerjee et al. 2004). For this model, it is assumed that the outcome, the number of infant deaths, d_i, is distributed as a Poisson random variable, and we can specify a log-linear model for the infant deaths as:

$$ d_i \sim Poisson(E_i \theta) $$
$$ \ln \theta = X' \beta $$

where the number of infant deaths in each of the i counties is a function of the expected number of deaths, E_i, and a county specific risk, θ, which is equivalent in this setting to the standardized mortality ratio (SMR). The expected number of deaths, E_i, is calculated by internal standardization assuming each county has the infant mortality rate for the whole nation, or:

$$ E_i = n_i * \left(\sum y_i / \sum n_i \right) $$

where n_i is the number of births in each county, and y_i is the number of infant deaths in each county. We use a

Bayesian estimation method by specifying prior information about each of the parameters in these models to be estimated. This information, in combination with the traditional information contained in the data allows us to come up with a posterior distribution for each of the parameters in the model. This is the advantage of the Bayesian framework for such complicated models. The Bayesian framework uses the concept of posterior inference to arrive at estimates of the model parameters. The posterior distribution of the parameters is defined as:

$$p(\theta|y) \propto p(y|\theta)p(\theta)$$

where $p(\theta|y)$ is the posterior distribution of the model parameter of interest, $p(y|\theta)$ is the model likelihood function, here defined as a Poisson likelihood, and $p(\theta)$ is the prior distribution for the parameter of interest. Inference for all parameters is done via their posterior distribution, which can be used to derive mean values, quantiles or any other descriptive statistic. One useful method for summarizing these distributions is the Bayesian Credible Interval (BCI), not unlike frequentist confidence interval, which gives the values of the density that contain $100 * (1 - \alpha)\%$ of the posterior density. Inference on these BCI regions usually consists of examining if the null hypothesis value of the parameter is contained in the interval. For example, the BCI for a regression parameter could be examined to see if it contains 0, which would be consistent with the traditional frequentist hypothesis test that $\beta = 0$.

If each county is allowed to have its own inherent risk parameter, θ_i, then the model specification is called the Bayesian Hierarchical convolution model (Besag et al. 1991; Lawson 2009), and the county specific risk estimate is based on a linear function of the total intercept, α_0, the "fixed" effects of the predictors, $X'\beta$, which allows an estimate of the effects of the predictors and a combination of random county-specific random components, one of which is random, and another spatially structured. This is a commonly used approach in the spatial analysis of health outcomes (Lawson et al. 2000; Waller and Gotway 2004; Banerjee et al. 2004; Arato et al. 2006; Kato et al. 2009; Ocana-Riola and Mayoral-Cortes 2010; Sartorius et al. 2010) based on the earlier work of Besag (1974); Besag et al. (1991). This method has also been used as a basis for local demographic estimation (Assuncao et al. 2005) and other applications in demography (Schmertmann et al. 2008), criminology (Matthews et al. 2010) and human population health research (Shoultz et al. 2007b).

The SMR is often seen as a highly unstable outcome (Elliott and Wartenberg 2004; Chen et al. 2008), because the variance in the SMR is highly sensitive to and highly unstable because of the number of events and the size of the population at risk. Since this model is specified in terms of the SMR, this instability needs to be accounted for in the model. By using methods of hierarchical Bayesian smoothing, this can be addressed directly.

When the model is specified as:

$$Y_i \sim Poisson(E_i\theta_i)$$
$$\ln\theta_i = \alpha_0 + X'\beta + v_i + u_i$$

which considers both a county specific unstructured random effect (u_i) and a county specific spatially structured random effect (v_i), the SMR in each county is effectively smoothed. This happens a result of the v_i term. This model term is a conditionally autoregressive term, which says that each county's SMR is a function of its neighboring counties. This, in effect, draws strength from the values of the neighbors SMR to smooth the SMRs in counties with more unstable values. Spatial neighbors are identified using a first order Queen contiguity rule. Alternative neighbor specifications were tried (Rook and $k = 3$ nearest neighbor) and did not substantially impact the model results. Prior distributions were specified using standard protocols for spatial Bayesian models (Lawson 2009). A flat, uninformative prior was used for α_0, a non-informative Normally distributed prior for the regression effects (β's) and the unstructured heterogeneity effects (u_i). The v_i effects are given a Conditionally Autoregressive Normal prior distribution, with mean equal to the average risk of the neighboring counties of county i, and with precision parameter τ_v. Both precision parameters for the structured and unstructured random effects are given a uniform (0.5) distribution for the square root of their respective precision parameters (Gelman 2006). R software (R Development Core Team 2010) for data preparation and OpenBUGS 3.2.1 (Lunn et al. 2000, 2009) were used to sample from the posterior distribution of the parameter estimates via multiple chain Markov-Chain Monte Carlo simulation from the posterior distribution. A total of 150,000 Monte Carlo samples were sampled and the first 100,000 samples were thrown out as a burn-in period, and the results were derived from another 50,000 samples from this distribution, which was thinned so that only every 50th sample was used to minimize autocorrelation. Two Markov chains were started at divergent ends of the parameter space and convergence was monitored using trace plots and standard diagnostics. 2,000 estimates of each model parameter were consider for inference. Convergence of the Markov Chains was monitored by the Gelman-Rubin statistic (Gelman and Rubin 1992), which indicated convergence by the 100,000th iteration. Model fit and model improvement were monitored with the Deviance Information Criterion (DIC) (Spiegelhalter et al. 2002).

Twelve separate models were fit, each specified with a different dimension of residential segregation. The first six models consider only the effect of the specific segregation index, without any of the control variables. The next six models include the segregation indices and all controls. This is done to examine possible mediating effects of the control variables on the outcome. Models were compared using the relative values of their DIC.

Results

Descriptive results

Table 1 shows the descriptive statistics for the dependent variable and the predictor variables in the analysis.

The mean number of infant deaths was 8.9 and the mean SMR was 1.00. The range in infant deaths was between 0 and 776, with 18% of counties having 0 infant deaths in the 3 year period. The infant mortality rate and the SMR show significant levels of global spatial autocorrelation, as shown by the Moran's I value of 0.28 for the infant deaths and less so for the SMR with $I = 0.10$, although this is significant using a randomization hypothesis test. Figure 1 shows the spatial distribution of the SMR.

The SMR shows disadvantaged areas ($SMR > 1$) in the southeastern US, and with less concentration throughout the central area of the country. Likewise, low SMRs ($SMR < 1$) occur throughout the Northeast, central and Western portions of the US. Notable is how much variation, or noise there is to the SMR (see discussion above), with little real spatial clustering evident, as suggested by the low value of Moran's I. This is indicative of the high variability in the population at risk (number of births), and the ensuing instability of the traditional SMR.

Table 1 Descriptive statistics for all variables in the statistical models

	Mean	Std.	Moran's I*
Variable			
Infant deaths	8.97	30.39	0.28
Standardized mortality ratio (SMR)	1.00	0.74	0.10
Predictors			
% Rural	60.4	30.47	0.31
Gini coefficient	0.43	0.04	0.39
Relative deprivation index	0.00	3.48	0.54
Segregation measures			
Black–white dissimilarity	0.59	0.17	0.41
Black–white interaction	0.71	0.26	0.35
Black–white spatial proximity	0.91	0.23	0.29
Poor/non-poor dissimilarity	0.24	0.09	0.32
Poor/non-poor interaction	0.81	0.08	0.45
Poor/non-poor spatial proximity	1.00	0.09	0.20

* All results significant at $p = 0.001$, Significance based on 999 Monte Carlo re-samples

Many counties in the US are highly rural, and this variable also shows significant spatial autocorrelation ($I = 0.31$). The Gini coefficient has a mean of 0.43, and a significant Moran's I value of 0.39. The index of relative deprivation has a mean of 0, and a Moran's I value of 0.54. This variable is mapped in Fig. 2. Negative values of the index represent counties with poorer relative socioeconomic status compared to higher values of the index, which indicate lower levels of deprivation.

Finally, maps of the spatial distributions of the six measures of racial and poverty segregation used in the present study are presented in Fig. 3.

The three poverty segregation indices show differing levels of spatial structure, as alluded to by the values of Moran's I in Table 1. The dissimilarity and spatial proximity indices appear to be less clustered compared to the isolation index, which shows clustering in areas traditionally associated with high poverty: Appalachia, the deep-South and the areas along the border with Mexico (Slack et al. 2009). The three racial segregation measures all show strong

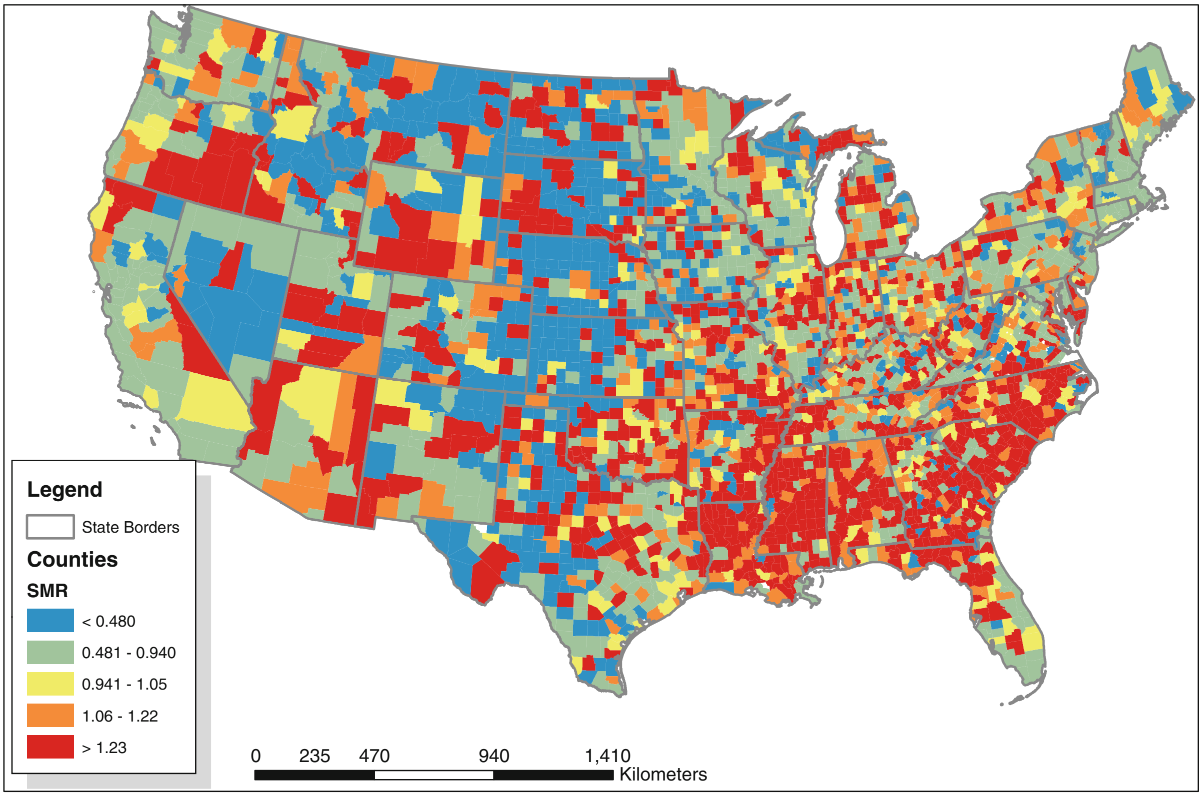

Fig. 1 Spatial distribution of infant mortality standardized mortality ratio

clustering in the Southern US, with the spatial proximity index showing high values in many areas in the Eastern US.

Bayesian model results

As described in the methodology section, twelve separate models were considered, with the first six only containing one of the segregation indices. The second six models were fit with each model containing the same set of control variables, but with a different segregation measure. The index of relative deprivation and the Gini index showed significant correlation prior to entering the regression models, but were not found to seriously confound one another in the regression models as they showed a variance inflation factor of 1.21. The results from the first six models are presented in Table 2 and the next set of models in Table 3. The posterior mean of the parameter is presented, as is the 95% BCI. The Bayesian credible interval gives the actual values of the posterior density of the parameter that contain 100 * $(1 - \alpha)$% of the density, in this case, 95% of the density was chosen, making these values similar to those of a 95% confidence interval for the regression parameter in traditional statistical models.

The first model contains the black-white dissimilarity index only, and shows a positive association with infant mortality risk, suggesting in counties with higher black–white unevenness, infant mortality risk is higher. The second model contains the black–white interaction index, and shows a negative association with infant mortality risk. This is expected to be the opposite of the dissimilarity index, since the two indices measure opposite dimensions of racial segregation. This suggests that in areas where blacks and white are more integrated, and come into contact more often, the infant mortality risk is lower. The final racial segregation model contains the spatial proximity index. Again a positive association with infant mortality risk is observed, suggesting that in areas where blacks and whites live apart from one another spatially, the risk is higher. Stated differently, when blacks or whites live more closely to other blacks and

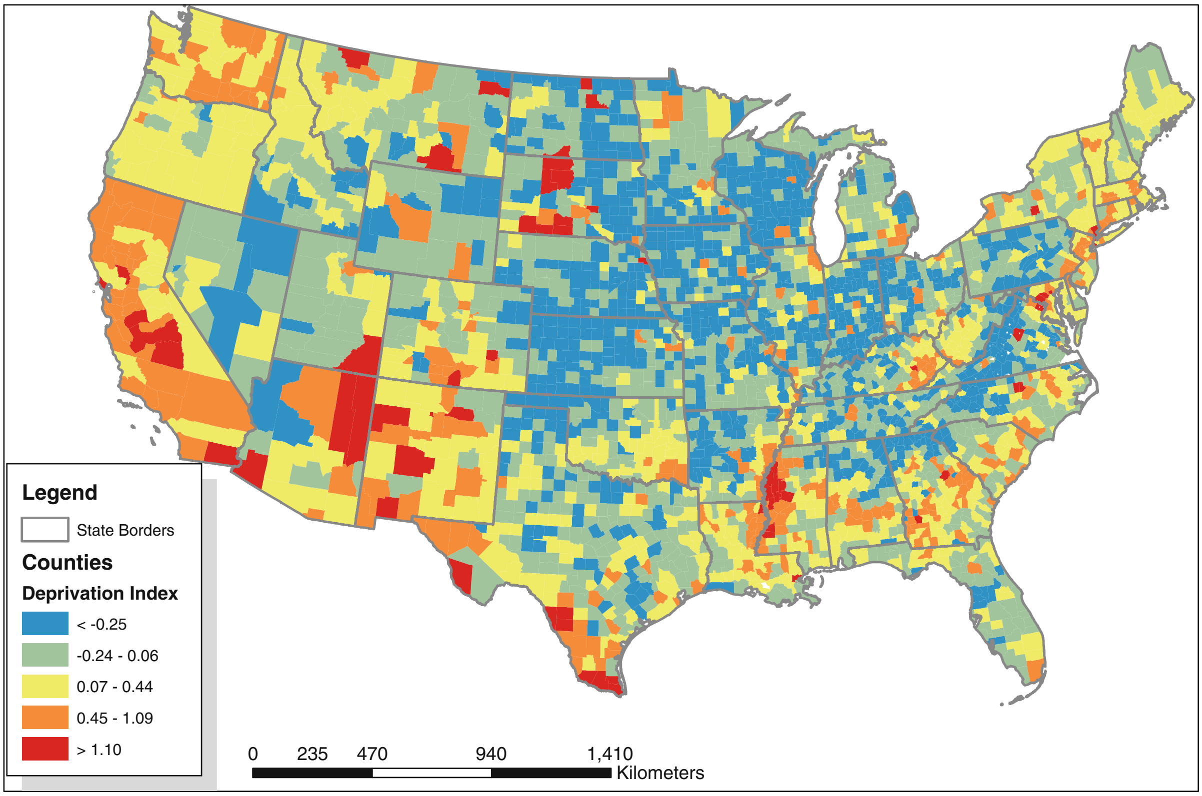

Fig. 2 Spatial distribution of relative deprivation index

whites, respectively, the infant mortality risk is higher. When there is more spatial intergration between blacks and whites, the effects of segregation based on this dimension are less deleterious.

The next three models include the poverty segregation indices. The first model (Model 4) again shows a positive association with infant mortality and the poverty dissimilarity index, suggesting that in areas where poor and non-poor residents are highly segregated, the infant mortality risk is higher. Model 5 contains the poverty interaction index, and suggests that in areas where poor and non-poor residents are more integrated, and come into contact more often, the infant mortality risk is lower. Finally, Model 6 includes the poverty spatial proximity index. Again a positive association with infant mortality risk is observed, suggesting that in areas where poor residents live closely spatially, the risk is higher.

The next six models include the segregation index, but also include three control variables. The first three models again measure racial segregation and the next three models measure poverty segregation. In the first model an infant mortality disadvantage is observed for counties with higher Gini coefficients and higher levels of relative deprivation. The dissimilarity index shows a positive coefficient suggesting higher racial segregation is associated with higher infant mortality. Model 2 shows a rural infant mortality disadvantage, but otherwise very similar results for the control variables, but the interaction index is negative, as would be expected. Model 3 shows again, the rural disadvantage and the influence of income inequality and the effect of relative deprivation. The black-white spatial proximity index suggests that as counties become more spatially segregated, the infant mortality rate increases. Of these three models with race-based segregation measures, Model 2, the interaction index fits the data better than Models 1 or 3, as seen by the much lower DIC value for Model 2.

Models 4 through 6 contain segregation indices that measure how people above and below the poverty line live with respect to one another. Model 4 has two "significant" effects, neither of them being segregation. The Gini coefficient and the relative deprivation

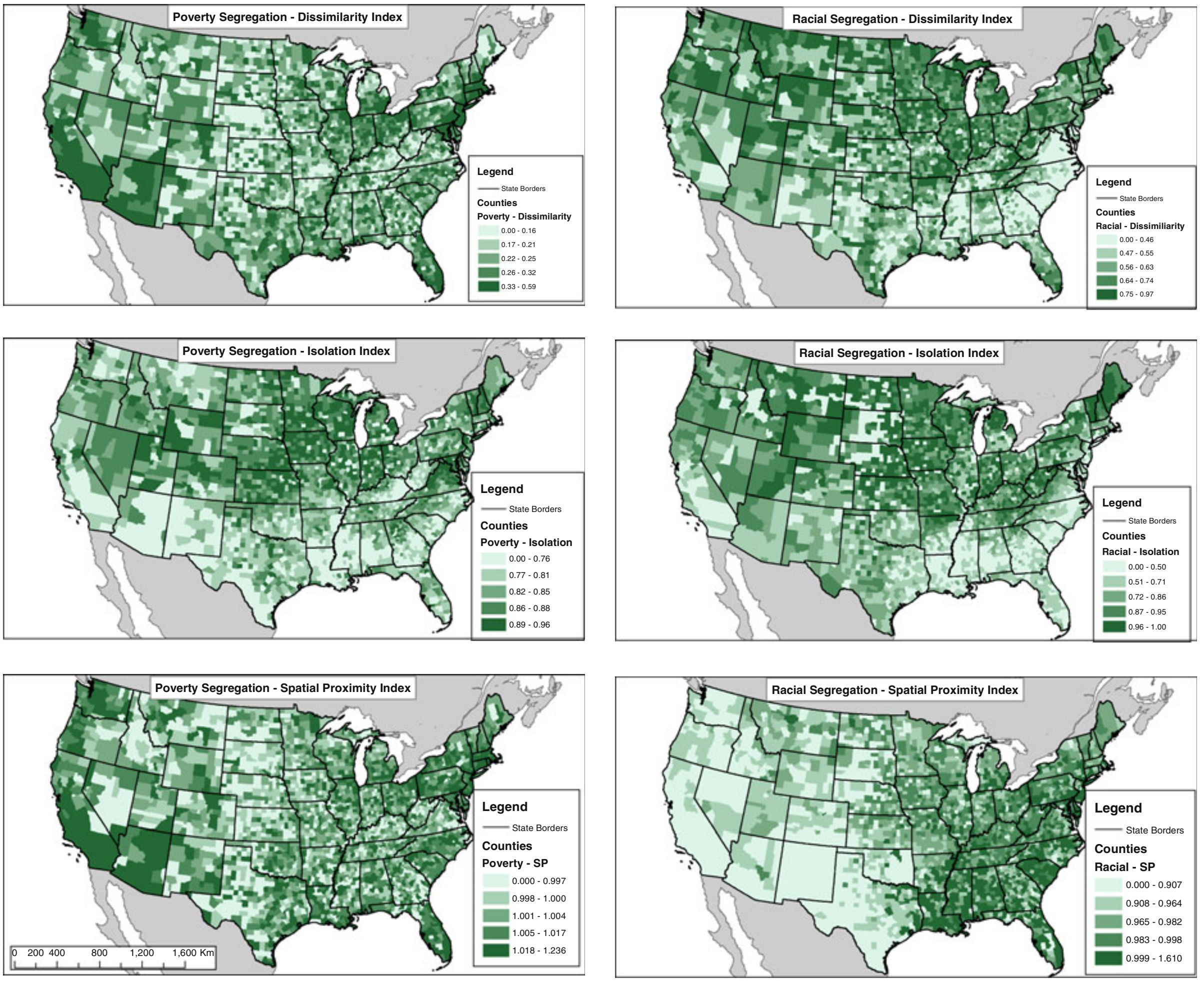

Fig. 3 Spatial distributions of the six segregation indices used in the analysis

index both show positive associations with infant mortality. Model 5 contains the poverty interaction index. The only control variable that is significant is the relative deprivation index, and the interaction index in this case suggests that as people above and below the poverty line interact more within a county, the infant mortality rate decreases. This is expected based on the previous model's result of the positive association of the dissimilarity index, as these two can often be thought of as measuring opposite dimensions of segregation. The final model, Model 6, again shows significant and expected effects of the control variables with county infant mortality rates. The spatial proximity index shows a significant positive association, suggesting that as poor residents of a county live in closer proximity to one another, the infant mortality rate increases. Of these three models, Model 5 fits the data best, as evidenced by the DIC, but when all models are compared, Model 2, the racial interaction model, fit the data best of all models considered.

Spatial variation in risk

To illustrate the spatial variation in risk and the smoothing effect of the Bayesian Hierarchical model on infant mortality in our Bayesian models, the posterior mean of the relative risk parameter (θ_i) from Model 4 (Table 3) is mapped. This models was selected because it was the best fitting model of those considered (Fig. 4).

When compared to the unsmoothed SMR map (Fig. 1), it is evident the effects of using the Bayesian hierarchical modeling approach with the spatially correlated random effect. The initial pattern from

Table 2 Results of Bayesian hierarchical regression models for county infant mortality outcome: segregation only models

Parameter	Model 1 Black–white dissimilarity Posterior mean (95% BCI)	Model 2 Black–white interaction Posterior mean (95% BCI)	Model 3 Black–white spatial proximity Posterior mean (95% BCI)	Model 4 Poor–non poor dissimilarity Posterior mean (95% BCI)	Model 5 Poor–non poor interaction Posterior mean (95% BCI)	Model 6 Poor–nonpoor spatial proximity Posterior mean (95% BCI)
Segregation index	0.364 (0.254–0.467)	−0.563 (−0.640 to −0.483)	0.655 (0.548–0.768)	0.291 (0.101–0.482)	−1.745 (−1.910 to −1.479)	1.923 (1.404–2.478)
σ_u	0.063	0.020	0.025	0.051	0.019	0.022
σ_v	0.238	0.213	0.220	0.253	0.195	0.245
DIC	10,443.6	*10,301.1*	10,378.3	10,449.7	*10,278.5*	10,404.1

Italicized DIC being the lowest (best fitting model) for that particular segregation type (racial or poverty)

Fig. 1 of the higher relative risk in the Southern US is highlighted when the SMR is effectively smoothed. Also areas of Appalachia and the Midwest emerge as areas of higher relative risk, while areas of the northern plains and the western US emerge has having much lower relative risk, when in Fig. 1 there was much more noise in these areas with little evident spatial trend or pattern. The increase in infant mortality risk corresponds well to the historical-cultural area referred to as the black-belt crescent, the area of the country that has traditionally been characterized by high racial and poverty discrimination and low social investment.

Discussion

Research has found mixed associations between residential segregation and health outcomes based on the dimension of segregation being measured. Certain dimensions of residential segregation are protective or less harmful against poor infant health outcomes (Bell et al. 2006; LaVeist 1993; Pickett et al. 2005; Roberts 1997), while other dimensions of segregation are harmful for these same or similar outcomes (Ellen 2000; Ellen et al. 2001; Guest et al. 1998; LaVeist 1989; Polednak 1991, 1996). However, it is not clear from existing research how spatial statistical methods or an explicit spatial measure of segregation can help in our understanding of the different associations noted between different dimensions of racial and poverty segregation and aggregate infant mortality rates. This paper begins to address this gap by using Bayesian Hierarchical regression models to examine the variation in associations between racial and poverty residential segregation, measured by three different indices or dimensions of segregation, and county infant mortality risk, while controlling for appropriate compositional characteristics of counties in the United States. Several findings from these analyses deserve more discussion.

First, the two forms of residential segregation resulted in opposite effects on the infant mortality rate. For racial segregation, as counties became more uneven in their distribution of white and black residents, this increased the infant mortality risk. Likewise, counties that showed higher degrees of spatial concentration of blacks also showed higher relative risk. The results for the poverty segregation

Table 3 Results of Bayesian Hierarchical Regression Models for County Infant Mortality Outcome: Segregation and control variable models

Parameter	Model 1 Black–white dissimilarity Posterior mean (95% BCI)	Model 2 Black–white interaction Posterior mean (95% BCI)	Model 3 Black–white spatial proximity Posterior mean (95% BCI)	Model 4 Poor–non poor dissimilarity Posterior mean (95% BCI)	Model 5 Poor–non poor interaction Posterior mean (95% BCI)	Model 6 Poor–non poor spatial proximity Posterior mean (95% BCI)
% Rural	0.000*	0.002	0.001	0.000*	0.000*	0.001
	(−0.001 to 0.001)	(0.001–0.003)	(0.001–0.002)	(−0.001 to 0.001)	(−0.001 to 0.001)	(0.000–0.002)
Gini coefficient	1.499	0.863	1.073	1.681	0.376*	1.347
	(1.021–1.993)	(0.432–1.288)	(0.643–1.567)	(1.255–2.175)	(−0.051 to 0.800)	(0.867–1.843)
Relative deprivation	0.062	−0.052	0.060	0.056	−0.109	0.029*
	(0.006–0.119)	(−0.105 to −0.002)	(0.008–0.106)	(0.006–0.107)	(−0.159 to −0.060)	(−0.024 to 0.082)
Segregation index	0.217	−0.663	0.615	−0.015*	−1.931	1.566
	(0.079–0.347)	(−0.761 to −0.567)	(0.486–0.774)	(−0.280 to 0.298)	(−2.161 to −1.660)	(1.017–2.082)
σ_u	0.027	0.028	0.038	0.043	0.022	0.042
σ_v	0.241	0.189	0.200	0.237	0.190	0.226
DIC	10382.5	*10275.5*	10344.8	10391.1	*10269.7*	10373.9

* The Bayesian Credible Interval contains zero

Italicized DIC being the lowest (best fitting model) for that particular segregation type (racial or poverty)

variables all suggested that as the poor and non-poor segments of the population of counties come into closer contact and have more interaction, the infant mortality risk for these counties increase. This association between poverty segregation and infant mortality most likely highlights the negative aspects of poverty segregation when accounting for the spatial patterning of the segregation, including limited access to employment, better school and higher education opportunities, health care access, prenatal care, social services, and exposure to crime and poor housing conditions that would result in higher infant mortality rates and more generally poorer infant health outcomes (Buka et al. 2003; Collins and Williams 1999; Collins and Schulte 2003; Hearst et al. 2008; Mason et al. 2009).

Secondly, the use of block groups as the basis of the construction of these segregation measures allowed for a more sensitive test of possible associations between racial and poverty segregation and infant mortality rates since this is a smaller unit of analysis not solely based on population density like a census tract (Laraia et al. 2006; Mason et al. 2009). More research is needed that tests the sensitivity of these segregation measures based on smaller spatial units used to construct them (blocks versus tracts) and infant health outcomes across areas of the United States to see if geographic variability is noted based on different units of analysis.

Through the use of the Bayesian regression models, extraneous variation due to differences in size of the population at risk in the infant mortality rates in the analysis was avoided. This method has found wide application in areas where random variation in disease or mortality rates caused not by the underling risk, but by differences in the underlying population at risk (population size) has inflated the variance in the rate of interest. As discussed by numerous authors (Assuncao et al. 2005; Chen et al. 2008; Elliott and Wartenberg 2004) and in detailed texts on the subject (Banerjee et al. 2004; Lawson 2009), the estimation of small scale demographic or disease rates is an ideal opportunity to use Bayesian statistical methods. We feel that by using such methods that may to some degree correct for variation external to the rate of interest, we may be able to provide a policy audience with a more accurate, locally estimated, infant mortality rates or other health outcomes which could serve a more powerful role in discussion of local health policy in the US.

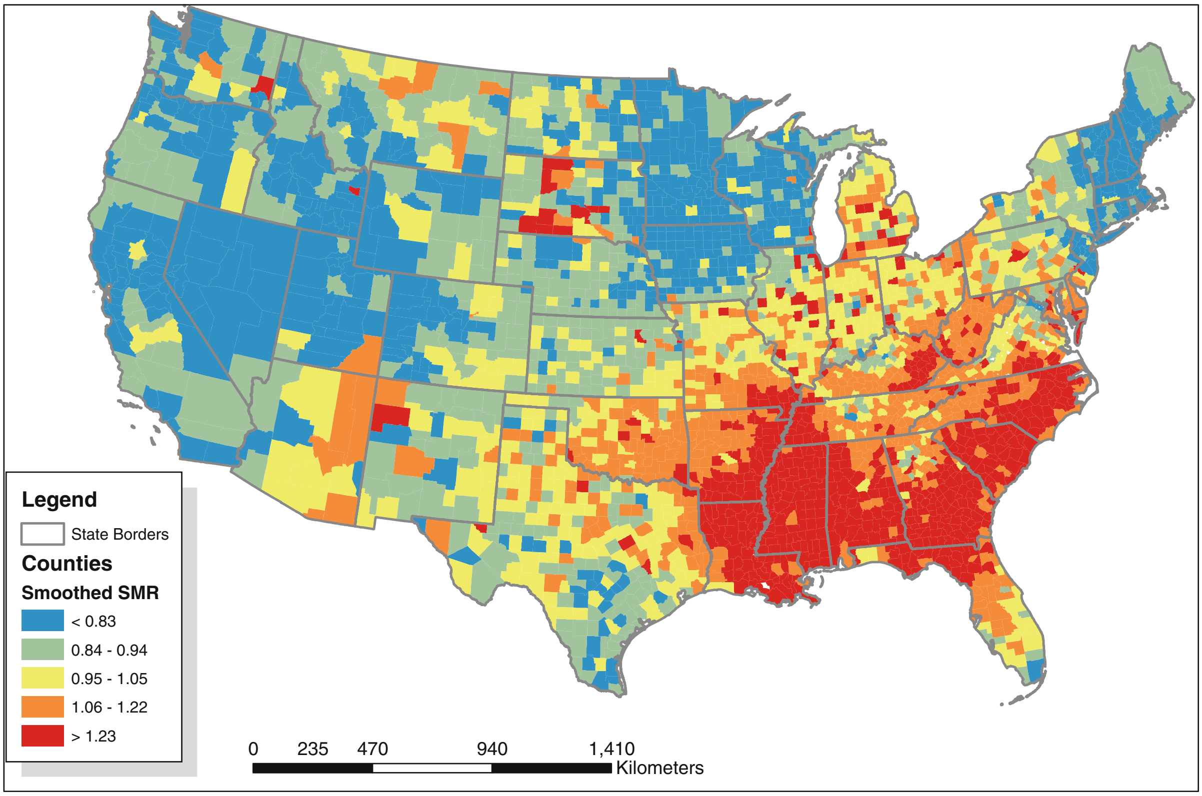

Fig. 4 Spatial distribution of the bayesian smoothed infant mortality standardized mortality ratio

Despite the smoothing effect of the hierarchical model, the dependent variable itself deserves further discussion, especially in light of the hypotheses concerning residential segregation. Messer and colleagues (Messer et al. 2010) discuss how, when events are rare, there are often no actual cases that exist in the data for highly segregated areas with other extreme conditions; such as the case when segregation is very high and deprivation or income inequality are low. Thus there is often very little data support for the effects estimated in the model for such areas. For instance, in the present analysis there are only eight counties in the US where the racial spatial proximity index is greater than one standard deviation above the mean and where the neighborhood deprivation index is below the mean. Likewise, there are problems in defining segregation indices in small population counties, because there are often very few if any blacks living in the county. For example, in the data used in this study, there were 133 counties with less than 200 black residents.

Reardon and O'Sullivan (2004) make a compelling argument that residential segregation patterns in the United States have an inherently spatial nature, and operational measures of the dimensions of residential segregation should include some type of spatially defined component. We think the use of spatially explicit segregation measures would be particularly useful in future studies of segregation and infant health outcomes. In addition with the recent release of the American Community Survey (ACS) 5 year estimates of detailed population characteristics at the census tract level, we may find more applications of the Bayesian methodology in terms of estimating such spatially constructed segregation measures, especially with such Bayesian hierarchical models that are useful when some geographies are missing information on one of the key components of the segregation measure. By using spatially grounded Bayesian methods, we can potentially provide estimates of such rates even in areas where the ACS coverage is sparse, such as discussed by Assuncao et al. (2005). The use of spatially constructed segregation indices may offer additional insight into the most effective ways to tailor public health programs to meet the needs of clearly, identifiable geographic locations. Combining spatially-based segregation measures and spatial statistical methods to study aggregate infant health outcomes presents a new approach to understanding the way these associations vary across places in the United States.

Limitations

Standard measures of residential segregation are based on the examination of residential patterns in MSA or central cities (Massey 1996; Massey and Denton 1988, 1989). In this paper, we construct segregation measures for all counties in the US. It is not clear if the interpretation and application of residential segregation indices operate in the same way between metropolitan and non-metropolitan locations in the United States. However, we feel more confident in the associations noted in the models because we explicitly control for the percentage of the county population that is rural. Future work examining residential segregation and health outcomes for the entire US population should consider the implications of using measures that were initially conceptualized as metropolitan and central city specific concepts.

Additionally this research only uses cross-sectional aggregate data. Therefore we are cautious when interpreting the association between variables in the model and county infant mortality rates. As an aggregate analysis, there was also attention given to the interpretation of these associations as to not imply that certain individuals would have increased risks of experiencing infant mortality. Multilevel methods would be helpful in future studies that assess the impacts of residential segregation on an individual women's risk of experiencing an infant death in the child's first year of life.

References

Acevedo-Garcia, D. (2000). Residential segregation and the epidemiology of infectious diseases. *Social Science and Medicine, 51*(8), 1143–1161.

Acevedo-Garcia, D., & Lochner, K. A. (2003). Residential segregation and health. In I. Kawachi & L. F. Berkman (Eds.), *Neighborhoods and health* (pp. 265–287). Oxford: Oxford University Press.

Acevedo-Garcia, D., & Osypuk, T. L. (2008). Invited commentary: Residential segregation and health-the complexity of modeling separate social contexts. *American Journal of Epidemiology, 168*(11), 1255–1258. doi:10.1093/aje/kwn290.

Arato, N. M., Dryden, I. L., & Taylor, C. C. (2006). Hierarchical Bayesian modelling of spatial age-dependent mortality. *Computational Statistics & Data Analysis, 51*(2), 1347–1363. doi:10.1016/j.csda.2006.02.007.

Assuncao, R. M., Schmertmann, C. P., Potter, J. E., & Cavenaghi, S. M. (2005). Empirical Bayes estimation of demographic schedules for small areas. *Demography, 42*(3), 537–558.

Banerjee, S., Carlin, B. P., & Gelfand, A. E. (2004). *Hierarchical modeling and analysis of spatial data*. Boca Raton, FL: Chapman & Hall/CRC.

Basso, O., & Wilcox, A. J. (2009). Intersecting birth weight-specific mortality curves: Solving the riddle. *American Journal of Epidemiology, 169*(7), 787–797. doi:10.1093/aje/kwp024.

Bell, J. F., Zimmerman, F. J., Almgren, G. R., Mayer, J. D., & Huebner, C. E. (2006). Birth outcomes among urban African-American women: A multilevel analysis of the role of racial residential segregation. *Social Science and Medicine, 63*(12), 3030–3045. doi:10.1016/j.socscimed.2006.08.011.

Besag, J. (1974). Spatial interaction and the statistical analysis of lattice systems. *Journal of the Royal Statistical Society Series B-Methodological, 36*(2), 192–236.

Besag, J., York, J. C., & Mollie, A. (1991). Bayesian image restoration with two applications in spatial statistics. *Annals of the Institute of Statistical Mathematics, 43*(1), 1–59.

Buka, S. L., Brennan, R. T., Rich-Edwards, J. W., Raudenbush, S. W., & Earls, F. (2003). Neighborhood support and the birth weight of urban infants. *American Journal of Epidemiology, 157*(1), 1–8.

Cerda, M., Buka, S. L., & Rich-Edwards, J. W. (2008). Neighborhood influences on the association between maternal age and birthweight: A multilevel investigation of age-related disparities in health. *Social Science and Medicine, 66*(9), 2048–2060. doi:10.1016/j.socscimed.2008.01.027.

Chen, J., Roth, R. E., Naito, A. T., Lengerich, E. J., & MacEachren, A. M. (2008). Geovisual analytics to enhance spatial scan statistic interpretation: an analysis of U.S. cervical cancer mortality. *International Journal of Health Geographics, 7*, 57.

Collins, J. W., & David, R. J. (2009). Racial disparity in low birth weight and infant mortality. *Clinics in Perinatology, 36*(1), 63–73. doi:10.1016/j.clp.2008.09.004.

Collins, J. W., & Schulte, N. F. (2003). Infant health: Race, risk, and residence. In I. Kawachi & L. F. Berkman (Eds.), *Neighborhoods and health* (pp. 223–232). New York: Oxford University Press.

Collins, C. A., & Williams, D. R. (1999). Segregation and mortality: The deadly effects of racism? *Sociological Forum, 14*(3), 495–523.

Ellen, I. G. (2000). Is segregation bad for your health? The case of low birth weight. In W. G. Gale & J. R. Pack (Eds.), *Brookings-Wharton papers on Urban Affairs 2000* (pp. 203–229). Washington, DC: Brookings Institution Press.

Ellen, I. G., Mijanovich, T., & Dillman, K. (2001). Neighborhood effects on health: Exploring the links and assessing the evidence. *Journal of Urban Affairs, 23*(3–4), 391–408.

Elliott, P., & Wartenberg, D. (2004). Spatial epidemiology: Current approaches and future challenges. *Environmental Health Perspectives, 112*(9), 998–1006.

Finch, B. K., Lim, N., Perez, W., & Do, D. P. (2007). Toward a population health model of segmented assimilation: The case of low birth weight in Los Angeles. *Sociological Perspectives, 50*(3), 445–468. doi:10.1525/sop.2007.50.3.445.

Fu, L. Y., Colson, E. R., Corwin, M. J., & Moon, R. Y. (2008). Infant sleep location: Associated maternal and infant characteristics with sudden infant death syndrome prevention recommendations. *Journal of Pediatrics, 153*(4), 503–508. doi:10.1016/j.jpeds.2008.05.004.

Gelman, A. E. (2006). Prior distributions for variance parameters in hierarchical models. *Bayesian Analysis, 1*(3), 515–534.

Gelman, A. E., & Rubin, D. (1992). Inference from interative simulatoin using multiple sequences (with discussion). *Statistical Science, 7*(4), 457–511.

Goza, F. W., Stockwell, E. G., & Balistreri, K. S. (2007). Racial differences in the relationship between infant mortality and socioeconomic status. *Journal of Biosocial Science, 39*(4), 517–529. doi:10.1017/s0021932006001581.

Grady, S. C. (2006). Racial disparities in low birthweight and the contribution of residential segregation: A multilevel analysis. *Social Science and Medicine, 63*(12), 3013–3029. doi:10.1016/j.socscimed.2006.08.017.

Grady, S. C., & Ramirez, I. J. (2008). Mediating medical risk factors in the residential segregation and low birthweight relationship by race in New York City. *Health & Place, 14*(4), 661–677. doi:10.1016/j.healthplace.2007.10.011.

Guest, A. M., Almgren, G., & Hussey, J. M. (1998). The ecology of race and socioeconomic distress: Infant and working age mortality in Chicago. *Demography, 35*(1), 23–34.

Hearst, M. O., Oakes, J. M., & Johnson, P. J. (2008). The effect of racial residential segregation on black infant mortality. *American Journal of Epidemiology, 168*(11), 1247–1254. doi:10.1093/aje/kwn291.

Hummer, R. A. (1993). Racial differentials in infant mortality in the U.S.: An examination of social and health determinants. *Social Forces, 72*(2), 529–554.

Huynh, M., Parker, J. D., Harper, S., Pamuk, E., & Schoendorf, K. C. (2005). Contextual effect of income inequality on birth outcomes. *International Journal of Epidemiology, 34*(4), 888–895.

Iceland, J., Sharpe, C., & Steinmetz, E. (2005). Class differences in African American residential patterns in US metropolitan areas: 1990–2000. *Social Science Research, 34*(1), 252–266. doi:10.1016/j.ssresearch.2004.02.001.

Kain, J. F. (1968). Housing segregation, Negro employment, and metropolitan decentralization. *Quarterly Journal of Economics, 82*(2), 175–197.

Kato, S. K., Vieira, D. D., & Fachel, J. M. G. (2009). Utilization of fully Bayesian modeling to detect patterns in relative risk variation for infant mortality in Rio Grande do Sul State, Brazil. *Cadernos De Saude Publica, 25*(7), 1501–1510.

Kawachi, I., Kennedy, B. P., & Wilkinson, R. G. (1999). Crime: Social disorganization and relative deprivation. *Social Science and Medicine, 48*(6), 719–731.

Kramer, M. S., Demissie, K., Yang, H., Platt, R. W., Sauve, R., Liston, R., et al. (2000). The contribution of mild and moderate preterm birth to infant mortality. *Journal of the American Medical Association, 284*(7), 843–849.

Kramer, M. R., & Hogue, C. R. (2008). Place matters: Variation in the black/white very preterm birth rate across US metropolitan areas, 2002–2004. *Public Health Reports, 123*(5), 576–585.

Lahr, M. B., Rosenberg, K. D., & Lapidus, J. A. (2007). Maternal-infant bedsharing: Risk factors for bedsharing in a population-based survey of new mothers and implications for SIDS risk reduction. *Maternal and Child Health Journal, 11*(3), 277–286. doi:10.1007/s10995-006-0166-z.

Laraia, B. A., Messer, L. C., Kaufman, J. S., Dole, N., Caughy, M., O'Campo, P., et al. (2006). Direct observation of neighborhood attributes in an urban area of the US south: characterizing the social context of pregnancy. *International Journal of Health Geographics, 5*, 1–11.

LaVeist, T. A. (1989). Linking residential segregation to the infant-mortality race disparities in U.S. cities. *Sociology and Social Research, 73*(2), 90–94.

LaVeist, T. A. (1993). Segregation, poverty, and empowerment: Health consequences for African Americans. *Milbank Quarterly, 71*(1), 41–64.

Lawson, A. B. (2009). *Bayesian disease mapping: Hierarchical modeling in spatial epidemiology*. Boca Raton: CRC Press.

Lawson, A. B., Biggeri, A. B., Boehning, D., Lesaffre, E., Viel, J. F., Clark, A., et al. (2000). Disease mapping models: An empirical evaluation. *Statistics in Medicine, 19*(17–18), 2217–2241.

Lieberson, S., & Carter, D. K. (1982). A model for inferring the voluntary and involuntary causes of residential segregation. *Demography*, *19*(4), 511–526.

Lunn, D., Spiegelhalter, D., Thomas, A., & Best, N. (2009). The BUGS project: Evolution, critique and future directions (with discussion). *Statistics in Medicine, 28*(25), 3049–3082.

Lunn, D. J., Thomas, A., Best, N., & Spiegelhalter, D. (2000). WinBUGS—a Bayesian modelling framework: Concepts, structure, and extensibility. *Statistics and Computing, 10*(4), 325–337.

MacDorman, M. F., Callaghan, W. M., Mathews, T. J., Hoyert, D. L., & Kochanek, K. D. (2007). Trends in preterm-related infant mortality by race and ethnicity, United States, 1999–2004. *International Journal of Health Services, 37*(4), 635–641. doi:10.2190/HS.37.4.c.

Masi, C. M., Hawkley, L. C., Piotrowski, Z. H., & Pickett, K. E. (2007). Neighborhood economic disadvantage, violent crime, group density, and pregnancy outcomes in a diverse, urban population. *Social Science and Medicine, 65*(12), 2440–2457. doi:10.1016/j.socscimed.2007.07.014.

Mason, S. M., Messer, L. C., Laraia, B. A., & Mendola, P. (2009). Segregation and preterm birth: The effects of neighborhood racial composition in North Carolina. *Health & Place, 15*(1), 1–9. doi:10.1016/j.healthplace.2008.01.007.

Massey, D. S. (1996). The age of extremes: Concentrated affluence and poverty in the twenty-first century. *Demography, 33*(4), 395–412.

Massey, D. S., & Denton, N. A. (1988). The dimensions of residential segregation. *Social Forces, 67*(2), 281–315.

Massey, D. S., & Denton, N. A. (1989). Hypersegregation in U.S. metropolitan areas: Black and Hispanic segregation along five dimensions. *Demography, 26*(3), 373–391.

Massey, D. S., & Eggers, M. L. (1990). The ecology of inequality: Minorities and the concentration of poverty, 1970–1980. *The American Journal of Sociology, 95*(5), 1153–1188.

Matthews, S. A., Yang, T. C., Hayslett, K. L., & Ruback, R. B. (2010). Built environment and property crime in Seattle, 1998–2000: A Bayesian analysis. *Environment and Planning A, 42*(6), 1403–1420. doi:10.1068/a42393.

McLaughlin, D. K., Stokes, C. S., Smith, P. J., & Nonoyama, A. (2007). Differential mortality across the United States: The influence of place-based inequality. In L. M. Lobao, G. Hooks, & A. R. Tickamyer (Eds.), *The sociology of spatial inequality* (pp. 141–162). Albany: State University of New York Press.

Messer, L. C., Oakes, J. M., & Mason, S. (2010). Effects of socioeconomic and racial residential segregation on preterm birth: A cautionary tale of structural confounding. *American Journal of Epidemiology, 171*(6), 664–673. doi:10.1093/aje/kwp435.

Morales, L. S., Staiger, D., Horbar, J. D., Carpenter, J., Kenny, M., Geppert, J., et al. (2005). Mortality among very low-birthweight infants in hospitals serving minority populations. *American Journal of Public Health, 95*(12), 2206–2212. doi:10.2105/ajph.2004.046730.

Moran, P. A. P. (1950). Notes on continuous stochastic phenomena. *Biometrika, 37*(1/2), 17–23.

Ocana-Riola, R., & Mayoral-Cortes, J. M. (2010). Spatio-temporal trends of mortality in small areas of Southern Spain. *BMC Public Health, 10*. doi:10.1186/1471-2458-10-26.

Ostfeld, B. M., Perl, H., Esposito, L., Hempstead, K., Hinnen, R., Sandler, A., et al. (2006). Sleep environment, positional, lifestyle, and demographic characteristics associated with bed sharing in sudden infant death syndrome cases: A population-based study. *Pediatrics, 118*(5), 2051–2059. doi:10.1542/peds.2006-0176.

Pearl, M., Braveman, P., & Abrams, B. (2001). The relationship of neighborhood socioeconomic characteristics to birthweight among 5 ethnic groups in California. *American Journal of Public Health, 91*(11), 1808–1814.

Pickett, K. E., Collins, J. W., Masi, C. M., & Wilkinson, R. G. (2005). The effects of racial density and income incongruity on pregnancy outcomes. *Social Science and Medicine, 60*(10), 2229–2238. doi:10.1016/j.socscimed.2004.10.023.

Pickett, K. E., Shaw, R. J., Atkin, K., Kiernan, K. E., & Wilkinson, R. G. (2009). Ethnic density effects on maternal and infant health in the Millennium Cohort Study. *Social Science and Medicine, 69*(10), 1476–1483. doi:10.1016/j.socscimed.2009.08.031.

Polednak, A. P. (1991). Black-white differences in infant-mortality in 38 standard metropolitan statistical areas. *American Journal of Public Health, 81*(11), 1480–1482.

Polednak, A. P. (1996). Trends in US urban black infant mortality, by degree of residential segregation. *American Journal of Public Health, 86*(5), 723–726.

R Development Core Team. (2010). R: A language and environment for statistical computing. (2.11.0 ed.). Vienna, Austria: R Foundation for Statistical Computing.

Reardon, S. F. (2006). A conceptual framework for measuring segregation and its association with population outcomes. In J. M. Oakes & J. S. Kaufman (Eds.), *Methods in social epidemiology* (pp. 169–192). San Francisco: Jossey-Bass.

Reardon, S. F., & O'Sullivan, D. (2004). Measures of spatial segregation. *Sociological Methodology, 34*(1), 121–162.

Roberts, E. M. (1997). Neighborhood social environments and the distribution of low birthweight in Chicago. *American Journal of Public Health, 87*(4), 597–603.

Sartorius, B. K. D., Kahn, K., Vounatsou, P., Collinson, M. A., & Tollman, S. M. (2010). Young and vulnerable: Spatial-temporal trends and risk factors for infant mortality in rural South Africa (Agincourt), 1992–2007—art. no. 645. *BMC Public Health, 10*, 645.

Schabenberger, O., & Gotway, C. A. (2005). *Statistical methods for spatial data analysis*. Boca Raton, FL: Chapman and Hall/CRC.

Schempf, A., Strobino, D., & O'Campo, P. (2009). Neighborhood effects on birthweight: An exploration of psychosocial and behavioral pathways in Baltimore, 1995–1996. *Social Science and Medicine, 68*(1), 100–110. doi:10.1016/j.socscimed.2008.10.006.

Schmertmann, C. P., Potter, J. E., & Cavenaghi, S. M. (2008). Exploratory analysis of spatial patterns in Brazil's fertility transition. *Population Research and Policy Review, 27*(1), 1–15. doi:10.1007/S11113-007-9052-7.

Schulz, A., Williams, D. R., Isreal, B. A., & Lempert, L. B. (2002). Racial and spatial relations as fundamental determinants of health in Detroit. *Milbank Quarterly, 80*(4), 677–707.

Shapiro-Mendoza, C. K., Tomashek, K. M., Kotelchuck, M., Barfield, W., Nannini, A., Weiss, J., et al. (2008). Effect of late-preterm birth and maternal medical conditions on newborn morbidity risk. *Pediatrics, 121*(2), E223–E232. doi:10.1542/peds.2006-3629.

Shapiro-Mendoza, C. K., Tomashek, K. M., Kotelchuck, M., Barfield, W., Weiss, J., & Evans, S. (2006). Risk factors for neonatal morbidity and mortality among "Healthy," late preterm newborns. *Seminars in Perinatology, 30*(2), 54–60. doi:10.1053/j.semperi.2006.02.002.

Shoultz, G., Givens, J., & Drane, J. W. (2007a). Urban form, heart disease, and geography: A case study in composite index formation and bayesian spatial modeling. *Population Research and Policy Review, 26*(5/6), 661–685. doi:10.1007/s11113-007-9049-2.

Shoultz, G., Givens, J., & Drane, J. W. (2007b). Urban form, heart disease, and geography: A case study in composite index formation and bayesian spatial modeling. *Population Research and Policy Review, 26*(5–6), 661–685. doi:10.1007/S11113-007-9049-2.

Sims, M., Sims, T. L., & Bruce, M. A. (2007). Urban poverty and infant mortality rate disparities. *Journal of the National Medical Association, 99*(4), 349–356.

Singh, G. K., & Kogan, M. D. (2007a). Persistent socioeconomic disparities in infant, neonatal, and postneonatal mortality rates in the United States, 1969–2001. *Pediatrics, 119*(4), E928–E939. doi:10.1542/peds.2005-2181. ISSN0031-4005

Singh, G. K., & Kogan, M. D. (2007b). Widening socioeconomic disparities in US childhood mortality, 1969–2000. *American Journal of Public Health, 97*(9), 1658–1665. doi:10.2105/ajph.2006.087320.

Slack, T., Singelmann, J., Fontenot, K., Poston, D. L., Saenz, R., & Siordia, C. (2009). Poverty in the Texas borderland and lower Mississippi delta: A comparative analysis of differences by family type. *Demographic Research, 20*(Jan–June), 353–376.

Sparks, P. J., McLaughlin, D. K., & Stokes, C. S. (2009). Differential neonatal and postneonatal infant mortality rates across US counties: The role of socioeconomic conditions and rurality. *Journal of Rural Health, 25*(4), 332–341.

Sparks, P. J., & Sparks, C. S. (2010). An application of spatially autoregressive models to the study of US county mortality rates. *Population, Space and Place, 16*(6), 465–481.

Spiegelhalter, D. J., Best, N., Carlin, B. P., & van der Linde, A. (2002). Bayesian measures of model complexity and fit (with discussion). *Journal of the Royal Statistical Society Series B-Methodological, 64*(4), 583–639.

VanderWeele, T. J., Lantos, J. D., Siddique, J., & Lauderdale, D. S. (2009). A comparison of four prenatal care indices in birth outcome models: Comparable results for predicting small-for-gestational-age outcome but different results for preterm birth or infant mortality. *Journal of Clinical Epidemiology, 62*(4), 438–445. doi:10.1016/j.jclinepi.2008.08.001.

Vinikoor, L. C., Kaufman, J. S., MacLehose, R. F., & Laraia, B. A. (2008). Effects of racial density and income incongruity on pregnancy outcomes in less segregated communities. *Social Science and Medicine, 66*(2), 255–259. doi:10.1016/j.socscimed.2007.08.016.

Voss, P. R., Long, D. D., Hammer, R. B., & Friedman, S. (2006). County child poverty rates in the US: A spatial regression approach. *Population Research and Policy Review, 25*(4), 369–391. doi:10.1007/S11113-006-9007-4.

Waller, L. A., & Gotway, C. A. (2004). *Applied spatial statistics for public health data*. New York: Wiley Interscience.

Wilkinson, R. G. (1996). *Unhealthy societies: The afflictions of inequality*. London: Routledge.

Yang, T. C., Jensen, L., & Haran, M. (2011). Social capital and human mortality: Explaining the rural paradox with county-level mortality data. *Rural Sociology, 76*(3), 347–374.

Yang, T. C., Teng, H. W., & Haran, M. (2009). The impacts of social capital on infant mortality in the U.S.: A spatial investigation. *Applied Spatial Analysis and Policy, 2*(3), 211–227.