Published in final edited form as:

Epidemiology. 2009 March ; 20(2): 234–241. doi:10.1097/EDE.0b013e3181935aee.

Small-Area Racial Disparity in Stroke Mortality:

An Application of Bayesian Spatial Hierarchical Modeling

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Abstract

Background—In the United States, excess burden of stroke mortality has persisted among African Americans compared with whites despite declines in stroke mortality for both groups. New insights may be gleaned by examining local, small-area patterns in racial disparities in stroke.

Methods—The study population includes all non-Hispanic African Americans and non-Hispanic whites aged 35 to 64 in the southeastern United States during 1999 to 2002. We assessed county-level numbers of stroke deaths and population estimates in a Bayesian spatial hierarchical modeling framework allowing for inclusion of potential covariates (poverty and rurality), and generating county-specific model-based estimates of both absolute and relative racial disparity. The resulting estimates of race-specific stroke death rates, relative racial disparity, and absolute racial disparity were expressed in maps.

Results—After adjustment for age, poverty, and rurality, county-level estimates of relative racial disparity ranged from 2.3 to 3.3 and estimates of absolute racial disparity ranged from 19 to 45 excess deaths per 100,000. For both racial groups, stroke death rates were higher in rural areas and with increasing poverty. High relative racial disparity was concentrated primarily in the eastern portion of the region and large absolute racial disparity was concentrated primarily in the western portion.

Conclusions—The results highlight the pervasiveness and magnitude of substantial local racial disparities in stroke mortality in the southeast.

The higher burden of stroke mortality for African Americans compared with whites in the United States is documented at least as far back as 1960¹ and persists according to recently reported mortality data for 2004.² The magnitude of African American–white disparity in stroke varies by age group, stroke subtype, and sex.^{1,3,4} Despite substantial declines in stroke death rates for both African Americans and whites during the 1970s, followed by a

leveling-off of rates in both groups in the 1990s and early 2000s, African Americans continue to experience stroke deaths at a higher age-adjusted rate than whites, over 46% higher according to recent data covering all ages and the entire United States.² New approaches are needed to address African American–white disparities in stroke mortality, a goal of Healthy People 2010.⁵

These national data on racial disparities in stroke mortality mask a considerable amount of variability at the local level. Several publications have mapped local estimates of stroke mortality for African Americans and whites separately,^{6–9} noting concentrations of high stroke death rates in the southeastern United States for both African Americans and whites. One study examined African American–white disparity in stroke mortality at the state level,¹⁰ whereas another in-progress study was designed to examine geographic and racial difference in stroke.¹¹ However, none had examined the county-level geographic pattern of African American–white geographic variation in these disparities may help to identify areas with the largest African American–white disparities in stroke mortality (enabling stroke prevention policies and resources to be directed to those areas), and also provide new hypotheses regarding the determinants of the geographic patterns, which could identify new avenues for eliminating these disparities.

Fine geographic resolution and statistical precision are goals often at tension with each other. When the geographic unit of analysis is a small area such as a county, disease maps of local mortality have well-known deficiencies. Geographically large but sparsely populated counties can visually dominate the map but provide the least reliable estimates, especially for rare diseases.¹² To address this problem, researchers increasingly turn to Bayesian methods for disease mapping, methods that stabilize rate estimates while preserving geographic resolution.¹³

The objective of this study is to examine geographic variations in county-level racial disparity in stroke death rates and potential covariates. To achieve this, we extend Bayesian disease mapping techniques to provide simultaneously small-area estimates of local race-specific rates and racial disparities. Advantages of this approach include (1) model-based estimates of local, race-specific stroke death rates, and the magnitude of racial disparity in stroke death rates (on absolute and relative scales), and (2) the ability to include potential covariates (eg, poverty and rurality) of local race-specific rates, and racial disparity in the model.

Methods

Data Sources

We abstracted county-level numbers of stroke deaths in the southeastern United States for 1999 to 2002 from national vital statistics data, maintained by the US Centers for Disease Control and Prevention's National Center for Health Statistics (NCHS). We defined deaths from stroke as those for which the underlying cause of death listed on the death certificate was coded according to the International Classification of Disease–10th Revision¹⁴ as I60 to I69. These codes comprise the category “cerebrovascular diseases.” Person-years at risk for

stroke death for the years 1999 to 2002 were derived from the bridged-race population estimates obtained from NCHS.¹⁵

In some models, we include county-level variables for poverty and rurality. Poverty is measured as the percentage of residents in a county who are below the Federal poverty level. These data were obtained from the Small Area Income and Poverty Estimates of the United States Census Bureau for the year 2000. Rurality at the county level is a dichotomous variable (rural, urban) developed by the United States Department of Agriculture's Economic Research Service. Maps depicting the geographic distribution of poverty and rurality in the southeast appear in Figure 1.

Study Population

The population for this analysis was all non-Hispanic African Americans and non-Hispanic whites aged 35 to 64 years in the southeastern United States during 1999 to 2002. We used self-identified race data as reported to the US Census Bureau and subsequently bridged by NCHS to the 1977 Office of Management and Budget standards for the person-years at risk and race as reported on the death certificate for the mortality counts. We note that racial classifications reflect socially constructed categories.¹⁶ We restricted the age group to those younger than 65 to capture premature stroke mortality. We do not consider those younger than 35 as there were very few cases in that group. We defined the southeast as the 755 counties in the following 9 states: Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, Tennessee, North Carolina, and South Carolina. This definition captures a contiguous region with substantial county-level populations of both African Americans and whites, and with high stroke death rates for both African Americans and whites.⁶⁻⁹

These data included 19,758 stroke deaths during 85,028,804 person-years. There were 8339 stroke deaths and 17,554,597 person-years at risk for African Americans and 11,419 deaths and 67,474,207 person-years at risk for whites. African Americans accounted for about 42% of stroke deaths and 21% of person-years of risk. The overall age-adjusted (via direct standardization) stroke death rate was 23 per 100,000 person-years of risk, using the 2000 US standard population; the rates were 51 for African Americans and 16 for whites, or about 3.2 times higher for African Americans than for whites.

Small Area Modeling

The 3.2 times higher stroke death rate for African Americans represents a summary across the southeast. We investigated local variations in racial disparity, in terms of both magnitude and geography. As noted previously, moving from larger to smaller geographic units provides increased geographic resolution with an accompanying loss of statistical precision. Statistical solutions to this problem typically involve the use of random effects to “borrow strength” across estimates, improving local precision by incorporating information from other local estimates. Such methods have been used for small-area analysis,¹⁷ multilevel models,¹⁸ and disease mapping.¹⁹

The most widely applied form of Bayesian models for disease mapping provides spatial smoothing of unstable local rates via the use of spatially structured county-level random effects after a conditionally autoregressive (CAR) prior distribution. Such models were

introduced by Clayton and Kaldor²⁰ and placed in a fully Bayesian setting by Besag et al.¹³ In such models, a county's rate estimate is smoothed on the basis of its neighbors' rates, with "neighbors" typically defined as adjacent counties. The software package WinBUGS (MRC Biostatistics Unit, Cambridge, UK) provides a commonly used and convenient platform for fitting such models.

Recent extensions of such disease mapping models focus on the simultaneous modeling of more than 1 set of rates on the same set of small areas using random effects defined by a multivariate CAR (multiCAR) prior distribution. Such models allow a local rate to be simultaneously smoothed toward neighboring rates and smoothed toward other rates in the same local area. Most applications involve the simultaneous estimation of local rates from several diseases, and such models can also be fit within WinBUGS.

In our application, we extend the multiCAR approaches of Carlin and Banerjee,²¹ Gelfand and Vounatsou,²² and others^{23–26} from modeling local rates for multiple diseases to simultaneously modeling local rates for the same disease (stroke) across different racial subpopulations. We use the resulting race-specific, age-adjusted, and spatially smoothed rate estimates to calculate county-level measures of racial disparity in stroke mortality.

Model Specification

Let Y_{ijk} denote the number of stroke deaths and N_{ijk} the number of person-years at risk for stroke death in county, i for race group j in age stratum k during the study period. We model the log relative risk of stroke death in county i for group j (ie, summed over age strata, with k suppressed) via a Poisson regression with random effects:

$$Y_{ij} | \theta_{ij} \stackrel{ind}{\sim} \text{Poisson}(E_{ij} \times \theta_{ij}),$$

and

$$\log(\theta_{ij}) = \alpha_j + x_{ij}^T \beta_j + U_{ij},$$

where E_{ij} is the expected number of stroke deaths in county i for group j , θ_{ij} is the relative risk of stroke death in county i for group j compared with the reference risks, which here are the race-specific overall stroke death rates across all age groups and all counties in the study area, and x_{ij} county-level covariates with corresponding parameters β_j . In some cases the x_{ij} will not be race specific, that is, we will have $x_{ij} = x_i$ for all j . The U_{ij} denotes county- and race-specific random effects and are spatially structured via a multiCAR prior, including the U_{ij} results in spatial smoothing toward a local mean rate. (See chapter 9 of Waller and Gotway for additional details and references.¹⁹) The maximum likelihood estimate of θ_{ij} is

the standardized mortality ratio for group j in county i : $\hat{\theta}_{ij} = \frac{Y_{ij}}{E_{ij}}$. The E_{ij} s are regarded as fixed and known, whereas the Y_{ij} s are regarded as random and conditionally independent of one another given the θ_{ij} s. The E_{ij} are calculated via indirect, internal standardization,²⁷

where the internal standard is race-specific. Thus, all model output is age adjusted.

Calculation of the E_{ij} is a 2-step process: First let $\pi_{jk} = \frac{\sum_{i=1}^I Y_{ijk}}{\sum_{i=1}^I N_{ijk}}$ and then calculate $E_{ij} = \sum_{k=1}^K N_{ijk} \pi_{jk}$. Details on choice of prior distributions and implementation are provided in supplementary material (eAppendix, <http://links.lww.com/A723>). We ran several variants of our model to investigate 2 questions: (1) Is there benefit to using the multiCAR prior distribution versus competing approaches? and (2) Given the answer to the first question, do either or both of the potential covariates (poverty and rurality) belong in the final model? To answer the first question, we compared the multiCAR model with (a) the basic null model in which there is no spatial variation (ie, each racial group gets its own rate estimate, which does not vary by county) and (b) a model in which different, independent CAR priors were used for each racial group, thereby prohibiting intracounty smoothing of rate estimates across racial groups. To answer the second question, we compared a model without covariates with models with only poverty, only rurality, and both poverty and rurality as county-level explanatory variables. Table 1 describes these models and provides deviance information criterion²⁸ results for each model (a penalized measure with lower values denoting better fit). Note that in this table, models 1 to 3 pertain to the first question of interest, and models 3 to 6 address the second question.

Measuring Disparity

Following the recommendations of NCHS Methodological Issues in Measuring Health Disparities,²⁹ we calculate 2 measures of racial disparity by county, 1 relative and the other absolute. Our model produces the posterior distribution of θ , a matrix of relative risks for 755 counties by 2 racial groups. We convert these relative risks to indirectly age-standardized rates $\lambda_{ij} = c_j \theta_{ij}$, where the c_j are crude, race-specific rates.²⁷ Our disparity

measures for county i are, therefore, defined as $\delta_i^{(r)} = \frac{\lambda_{i2}}{\lambda_{i1}}$ for the relative measure and as $\delta_i^{(a)} = \lambda_{i2} - \lambda_{i1}$ for the absolute measure. The linear transformation $(\delta_i^{(r)} - 1) \times 100$ of our $\delta_i^{(r)}$ yields the relative disparity measure in Methodological Issues in Measuring Health Disparities. (See also Harper and Lynch.³⁰) The relative measure is the rate ratio of the estimated rate for African Americans in county i divided by the estimated rate for whites in county i . Consequently, a value of $\delta_i^{(r)}$ exceeding 1 indicates a higher relative age-adjusted stroke death rate in county i for African Americans compared with whites, with (for example) a value of 2.0 corresponding to a 2-fold racial disparity in stroke death rate ratio. For the absolute measure, a value of $\delta_i^{(a)}$ greater than 0 indicates a higher absolute rate for African Americans in county i than for whites in county i , and therefore, a disparity in the stroke death rates. We obtain posterior inference for the δ 's by examining the Markov chains of transformed values from θ , estimating quantities by their median posterior value.

Results

As mentioned in Model Specification, we ran several variants of our model to investigate whether there was any benefit to using the multiCAR prior distribution versus competing

approaches, and to decide which covariates to include in a final model. First, we present results adjusted only for age; this demonstrates the benefit of the multiCAR approach. Second, we present covariate-adjusted results when using the multiCAR approach and examine the impact of adding poverty and rurality into the model. Table 2 summarizes these models and provides deviance information criterion to allow comparisons across models.

CAR Versus MultiCAR

The values in Table 1 indicate the age-adjusted multiCAR model (model 3) yielded the best (lowest) for the deviance information criterion among the age-adjusted models, besting models 1 and 2. Insight into superior fit of model 3 can be gleaned by comparing the unmodeled intracounty correlation between African Americans and white rates in the independence model (model 2) with the explicit modeling of such correlation in the multiCAR model (model 3). In model 2, the race-specific rate estimates for African Americans and whites were derived independently, which effectively modeled intracounty correlation of African American and white rates as 0. However, inspection of these race-specific rate estimates revealed substantial correlation (Spearman correlation coefficient >0.6), despite the prohibition of intracounty smoothing. In model 3, we allowed for intracounty correlation and obtained a posterior median correlation coefficient of 0.89, with a 95% credible interval (CI: 0.66, 0.97). Further, as a result of explicitly modeling the intracounty correlation between African American and white rates in model 3, the width of the CIs for relative disparity were reduced on average about 60% compared with the CIs from model 2, and about 40% for absolute disparity, indicating more precise estimation of disparity in model 3 than model 2.

Covariates

Comparison of the deviance information criterion values for models 4 to 6 in Table 1 indicated that model 6 (containing both poverty and rurality and the multiCAR prior distribution) provides the best fit to the data. Maps of county-level poverty percentages and urban-rural codes are presented in Figure 1.

The effect measures and CI for models 4, 5, and 6 (see Table 2) indicate that for both African Americans and whites, county-level stroke death rates increase as county-level percentages of poverty increase, and rural counties had higher stroke death rates than urban counties. Based on parameter estimates from model 6, a 10-point increase in the county-level percentage of residents below poverty (about the size of the 8-point interquartile range of the county-level poverty distribution) corresponds to a 6% increase in the stroke death rate for African Americans and a 12% increase for whites; the death rates for rural areas were higher than urban areas by 11% for African Americans and 14% for whites.

Maps of Racial Disparity in Stroke Death Rates

The maps in Figures 2 and 3 each present the relative and absolute measures of racial disparity in stroke death rates before (Fig. 2) and after (Fig. 3) adjustment for poverty and rurality. Comparison of the legends for the preadjustment measures of racial disparity with the corresponding postadjustment measures does not show much change. However, visual comparison of the maps of age-adjusted racial disparity with the corresponding maps of

covariate-adjusted racial disparity indicates noticeable changes in the geographic patterns, particularly for relative racial disparity. In addition, the age-adjusted maps of Figure 2 appear somewhat smoother than the covariate-adjusted maps of Figure 3, which reflect more local variations in racial disparity in stroke mortality.

Looking at the disparity estimates in Figures 2 and 3, relative racial disparity ranged from a rate ratio of 2.3 to 3.3 among the 755 counties, and the magnitude of absolute disparity ranged from 19 to 47 excess deaths per 100,000. Geographic patterns of racial disparity in stroke death rates differed for relative versus absolute racial disparity. Counties with the largest relative racial disparities were primarily in the eastern portion of the southeast (North Carolina, South Carolina, and sections of Georgia and Florida), although there were several high relative-disparity counties in western and southern Louisiana. Counties with the largest absolute racial disparities were concentrated primarily in the western portion of the southeast (Arkansas, Louisiana, and Mississippi), with high-absolute disparity counties scattered along the coastal plain of Georgia and South Carolina.

Maps of Stroke Death Rates by Racial Group

Our model allows us to obtain simultaneous estimates of other quantities of interest. Figures 4 and 5 provide maps of race-specific stroke death rates, both age adjusted (Fig. 4) and covariate adjusted (ie, adjusted for poverty and rurality; Fig. 5). These may be thought of as the component maps of Figures 2 and 3, respectively. The maps in Figures 4 and 5 show similar geographic patterns for African Americans and whites (comparing across groups within each figure), with counties in the top quintile of stroke death rates located primarily in the states along the lower Mississippi River Valley Basin (eg, Arkansas, Louisiana, and Mississippi) along with high-rate counties scattered among the states of South Carolina and Georgia. The ranges of stroke death rates for African Americans and whites, however, varied widely, with nonoverlapping county distributions between whites (11–28 deaths per 100,000) and African Americans (32–73 per 100,000).

Discussion

The results of this study highlight the pervasiveness and geographic heterogeneity of racial disparities in stroke mortality in the southeast among residents aged 35 to 64, consistent with earlier work.⁹ For the region as a whole, without adjustments and before modeling, stroke death rates were 2.8 times higher among African Americans than whites, with component rates 48 and 17 deaths per 100,000, respectively, for a gap of 31 deaths per 100,000. After modeling, the estimated stroke death rates for African Americans were at least double the rates for whites for all counties in the study—both before and after adjusting for poverty and rurality—with measures of relative racial disparity reaching as high as 3.3. County-level measures of absolute disparity between African Americans and whites ranged from 19 to 45 excess stroke deaths per 100,000 even after adjusting for poverty and rurality. There was no overlap in the race-specific county-level stroke death rates, with the lowest rate among African Americans (32 per 100,000) exceeding the highest rate for whites (28 per 100,000).

These results underscore the importance of examining racial disparities in both absolute and relative terms, as recommended by NCHS.²⁹ Some researchers have favored absolute

measures, arguing that measures such as excess deaths more directly indicate the potential impact of a successful intervention.³¹ Despite similar race-specific geographic patterns of stroke death rates, there were striking differences in the geographic patterns of absolute versus relative racial disparity. The concentration of large absolute racial disparities primarily in the western portion of the southeast reflects the high stroke death rates in the states along the lower Mississippi River Valley Basin. The higher rates for both racial groups in this subregion contribute to the larger absolute disparities. On the other hand, the concentration of counties with the largest relative racial disparities in the eastern portion of the southeast reflects a variety of patterns of race-specific stroke death rates: Some counties had high rates for both African Americans and whites, others had high rates only for African Americans, and still others had low rates for both African Americans and whites (eg, much of Florida). Both measures of racial disparity are important and neither tells the complete story alone.

For both African Americans and whites, our results are in keeping with studies on the association of stroke mortality or incidence with poverty or rurality.^{32–34} Stroke death rates in our study increased with increasing poverty levels (a 10 percentage-point increase in the level of poverty corresponded to a 7% increase in stroke death rates for African Americans and a 12% increase for whites) and were higher in rural areas compared with urban areas (on average 11% higher for African Americans and 14% higher for whites). These findings reinforce the importance of addressing the deleterious health effects of poverty^{35–37} and rurality.³⁸ A recent study of regional and rural patterns in health status among older adults reported that after controlling for individual level characteristics, negative health effects of rural residency were found only in the southern region of the United States.³⁸ The authors hypothesized that the cumulative risk associated with residence in rural areas of the south may operate through mechanisms of available resources, norms, culture, and chronic stress.

Our models used race-specific parameter estimates for the effects of poverty and rurality. Although adjustment for rurality and poverty (and resultant differences in the relative and absolute disparity maps) could be implemented with nonrace-specific parameters, we believe the flexibility afforded by race-specific parameter estimates to be a strength of our approach. Models that do not use race-specific parameters would force an assumption that the effects are identical for African Americans and whites, a restrictive assumption generally and a dubious one for these data.

Indeed, our results suggest that the magnitudes of association for poverty and rurality with stroke mortality differ by race, with poverty and rurality having a greater impact on stroke death rates among whites than African Americans. The effect measures were larger for whites than African Americans, with a posterior probability of over 90% that the effects of poverty differed by race, and over 75% that the effects of rurality differed by race. A racial difference in the impact of poverty and rurality on stroke mortality could be a function of differential exposure to poverty and rurality experienced by the 2 race groups. Exposure to a narrower range of poverty levels for African Americans could result in a smaller effect measure. In fact, within the southeast, 27% of African Americans lived in counties in which 20% or more of the residents are below the Federal poverty line, whereas only 9% of whites lived in these counties. Hence, African Americans were concentrated more heavily in the

poorer counties. For African Americans in these poorer counties, an additional increase in poverty may have had a smaller impact on the already high risk of stroke they experienced due to the high levels of poverty.

The limitations of this study include the modifiable area unit problem and the cross-sectional study design. The modifiable area unit problem refers to the fact that the scale of aggregation in the data may not match the scale of true association.³⁹ Studies have found that when examining the effects of poverty levels on health, geographic units smaller than a county (eg, census tracts) are often preferable because of the high degree of heterogeneity of poverty that can exist within counties and other larger geographic units.⁴⁰ However, because of confidentiality issues the county is the smallest geographic unit for which we were able to obtain all data elements. Analyses at the county level are in accord with the level at which funding and intervention strategies are often implemented. Our finding of associations between county-level poverty and rurality with race-specific stroke death rates suggests that the between-group heterogeneity is large enough at the county level to be important, but does not rule out the possibility that the associations may be different, stronger, or more informative at a different geographic level. Consequently, we specifically limit the inferences we draw from these data to such aggregate associations.

The cross-sectional study design limits our ability to assess the historical conditions that contributed to the existing levels of poverty and rurality, as well as the social and geographic mobility of the decedents. Variation in all of these factors could have important implications for the impact of poverty and rurality on racial disparities in stroke mortality at any given point in time. If appropriate data were available, our methodology could be extended to handle such spatio-temporal data, perhaps as in Waller et al.⁴¹

To more fully understand the geographic patterns of racial disparity in stroke mortality, additional studies are needed to examine the impact of other contextual characteristics (including racial residential segregation^{42–50}) and the joint affects of individual and contextual characteristics.^{51–53} Furthermore, studies are needed to investigate potential pathways that could result in differential opportunities for African Americans and whites to live stroke-free lives. Such pathways might include differential access to quality health care (especially high blood pressure treatment and control); jobs with appropriate health care benefits and working environments conducive to promoting health; quality education; job markets resilient to economic downturn; safe recreational facilities; healthy diets; and living and working environments free from tobacco advertisements.

Our Bayesian approach for estimating small-area racial disparity in mortality offers many useful features. First and foremost, the Bayesian formulation provides posterior inference for all model parameters, including the race-specific county death rates and the county-level absolute and relative disparity measures. By building posterior samples of rates and disparity measures based on the Markov chain Monte Carlo samples of model parameters, the estimates derive from 1 model-fitting exercise and incorporate all modeled sources of uncertainty. In contrast, approaches based on plugging in race-specific race estimates to provide estimates of absolute or relative disparity often ignore the variability associated with estimation of the rate estimates, and treat them as known quantities. Our approach also

includes the ability to model covariate and correlation structures, thereby enabling model-based estimation of associations between covariates (eg, county-level poverty and rurality) and health outcomes, and any inherent spatial correlation remaining in our observations.

By using a multiCAR approach that also borrows strength across racial groups, rather than the standard CAR approach that borrows only from neighboring geographic units, we were able to increase the precision of our estimates while maintaining the geographic resolution of the analysis. The use of the multiCAR prior also resulted in more conservative estimates of disparity by explicitly modeling the positive intracountry correlation of the race-specific rates, compared with models that ignore this intracounty correlation.

Because we applied the multiCAR model to 2 different populations (African Americans and whites), rather than 2 diseases on 1 population as is more usual, it was particularly important to assess the potential for Simpson Paradox,⁵⁴ wherein associations observed at the aggregate level may differ from those at the individual level. However, after thorough investigation based on checks recommended by Pickle and White we found that our data did not violate the proportionality assumption and therefore were not susceptible to Simpson Paradox.⁵⁵

In conclusion, our study documents both absolute and relative racial disparity in stroke mortality, and the pervasiveness of this disparity across the southeastern United States. Such estimates add a local perspective to understanding and ultimately eliminating such disparities. Much research into the causes of racial disparity in health in the United States has focused on individual attributes.^{44,48,56} However, there is a growing recognition of the importance of contextual characteristics in local health disparities.^{44,46,57,58} As David Williams has written: “Effective effort to reduce racial disparities in health status should seriously grapple with ... targeting interventions not only at individuals but also at the geographic context within which they live.”⁴⁶

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

The authors would like to acknowledge G. Ishmael Williams and Kurt Greenlund of the Centers for Disease Control and Prevention for their assistance with data preparation and other contributions to this manuscript.

Supported by Environmental Protection Agency “Science to Achieve Results” (STAR) Fellowship 91589901-0, an Association of Schools of Public Health and Centers for Disease Control and Prevention Public Health Fellowship S22/22-CCD03-015, and National Institute of Environmental Health Sciences Grant R01-ES07750.

The findings and conclusions in this report are those of the authors and do not necessarily represent the official position of the Centers for Disease Control and Prevention. Trade names are provided for informational purposes only and do not constitute an endorsement by the Centers for Disease Control and Prevention or the US Department of Health and Human Services.

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Figure 1. County-level poverty (left) and rurality (right), southeastern United States. The maps depict county-level percentages of residents below the Federal poverty level and rurality based on the USDA rural-urban classification.

Figure 2. Age-adjusted relative (left) and absolute (right) racial disparity in stroke mortality, aged 35–64, southeastern United States, 1999–2002. The maps depict estimates of county-level relative and absolute racial disparity in stroke death rates adjusted only for age.

Figure 3.

Covariate-adjusted relative (left) and absolute (right) racial disparity in stroke mortality, aged 35–64, southeastern United States, 1999–2002. The maps depict estimates of county-level relative and absolute racial disparity in stroke death rates adjusted for age, poverty, and rurality.

Figure 4.

Age-adjusted stroke death rates, African Americans (left) and whites (right) aged 35–64, southeastern United States, 1999–2002. The maps depict estimates of county-level stroke death rates adjusted only for age.

Figure 5. Covariate-adjusted stroke death rates, African Americans (left) and whites (right) Aged 35–64, southeastern United States, 1999–2002. The maps depict estimates of county-level stroke death rates adjusted for age, poverty, and rurality.

Table 1
Model Selection Based on Deviance Information Criterion

Type of Adjustment Type of Smoothing	Model	Notation	DIC
Age-adjusted models			
No smoothing (race-specific intercept only)	1	α_j	7652.96
Within-map smoothing only (independent CAR priors)	2	$\alpha_j + U_i^I$	7092.31
Within-and across-map smoothing (multiCAR prior)	3	$\alpha_j + U_i^M$	7073.18
Covariate-adjusted models			
Within-and across-map smoothing (multiCAR prior)	4	$\alpha_j + Pov + U_i^M$	7073.18
Within-and across-map smoothing (multiCAR prior)	5	$\alpha_j + Rur + U_i^M$	7060.44
Within-and across-map smoothing (multiCAR prior)	6	$\alpha_j + Pov + Rur + U_i^M$	7056.67

The term α_j denotes a race-specific intercept. The U_i are county-specific random effects that result in local (U) smoothing. The superscripts I and M reflect models that use only within-map smoothing (the I model) or that use within-and across-map smoothing (the M model.) The terms “Pov” and “Rur” denote the county-level covariates “percent below poverty” and “rurality,” respectively, and CAR and multiCAR are described in Small-Area Modeling. All results are age adjusted through calculation of the expected counts, E_i (see text).

DIC indicates deviance information criterion.

Table 2
Relative Risk Estimates of Effects of Poverty and Rurality on Stroke Death Rates

Effect	Group	Median (95% CI)		
		Model 4	Model 5	Model 6
Poverty	African Americans	1.110 (1.051–1.171)	—	1.068 (1.008–1.131)
	White	1.186 (1.124–1.251)	—	1.123 (1.060–1.190)
Rurality	African Americans	—	1.141 (1.072–1.211)	1.110 (1.036–1.188)
	White	—	1.192 (1.131–1.255)	1.142 (1.079–1.208)

Estimates are changes in the explanatory variable, specifically a 10-point increase in a county's percentage below poverty for the poverty variable, or simply the effect of rurality for the other explanatory variable. All results are age adjusted through calculation of the expected counts, E_i (see text).

CI denotes credible interval.