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The geography of mortality in the Atlanta metropolitan area ☆

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Abstract

From exploratory spatial data analyses and geographically weighted regression (GWR), we found that previously hypothesized relationships between socioeconomic status (SES), race, urbanization and mortality were present and significant in the Atlanta metropolitan area for 1995–1999 and that the relationships between these predictors and mortality varied spatially, such that distinctive geographic patterns emerged. These patterns reflect the spatial processes operating in Atlanta for the past few decades, namely, rapid residential and commercial development in the outer portions of the metropolitan area and a concurrent movement of the affluent white population away from the central city, leaving behind a predominantly African American population with low SES. We also found that the relative influence of each predictor on mortality varied spatially, with SES demonstrating the most dominant influence in the majority of the study area and race demonstrating the most dominant influence in and near the City of Atlanta.

Keywords: Atlanta; Urbanization; Mortality; GIS; Geographically weighted regression

1. Introduction

Mortality rates reflect the overall health of populations. The objective of this study was to analyze the geographic distribution of mortality in the Atlanta metropolitan area, a rapidly growing city with a social environment greatly transformed since the 1980s. The purpose was to uncover spatial processes that account for geographic disparities in mortality rates.

Many public health studies show significant relationships between area social-demographic variables and several health-related outcomes. The studied dependent variables for health-related outcomes ranged from health risk behaviors such as smoking (Frolich, Potvin, Gauvin, & Chabot, 2002); adverse health outcomes such as low birthweight (Gorman, 1999; Krieger et al., 2003), obesity (Reidpath, Burns, Garrard, Mahoney, & Townsend, 2002), and cardiovascular disease (Jones & Duncan, 1995); and mortality (Huff & Gray, 2001). Other researchers established relationships between explanatory variables and health perception (Pampalon, Duncan, Subramanian, & Jones, 1999), the need for mental health services (Goldsmith, Holzer, & Manderscheid, 1998), and neighborhood social capital (Subramanian, Lochner, & Kawachi, 2002).

The range of sociodemographic variables hypothesized to influence health is also broad. Variables for which significant associations with health have been demonstrated include income (Gravelle, Wildman, & Sutton, 2002; Sturm & Gresenz, 2002), poverty (Braveman & Tarimo, 2002; Krieger et al., 2002; Krieger et al., 2003), wealth (Duncan, Daly, McDonough, & Williams, 2002), education (Krokstad, Kunst, & Westin, 2002; Muller, 2002; Osler & Prescott, 2003), occupation and employment status (Barnett, Armstrong, & Casper, 1997; Gregorio, Walsh, & Paturzo,

☆ The findings and conclusions in this report are those of the author(s) and do not necessarily represent the views of the Centers for Disease Control and Prevention.

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1997), housing tenure (Brimblecombe, Dorling, & Shaw, 1999), deprivation (Haynes & Gale, 2000), and socioeconomic status (Huff & Gray, 2001).

Composite measures of socioeconomic status (SES) are also used to assess its relationship to health outcomes (Huff & Gray, 2001; Reidpath et al., 2002). In addition, many studies included the well-known Townsend, Jarman, and Carstairs indices of deprivation from the United Kingdom (Carstairs & Morris, 1989; Jarman, 1983; Townsend, Phillimore, & Beattie, 1988). These indices were derived from a priori reasoning of factors causally associated with deprivation. Socioeconomic and deprivation indices also have the attractive quality of combining the effects of several potentially collinear variables into one construct. For the Atlanta study, this approach was used to assess the effect of socioeconomic status.

The degree to which an area is urbanized is another contextual variable for explaining geographic variations in health. Leviton, Snell, and McGinnis (2000) proposed two conceptual frameworks for research and practice relating to urban health promotion: (1) an urbanization framework and (2) an inner-city ecology framework. The urbanization framework refers to the population growth of an urban area: increases in the size of the urban area, increases in population density, increases in population heterogeneity, changes in population mobility, changes in the industrial base (including deindustrialization), emerging issues of social justice, and spatial proximity of the rich and poor. They argued that urbanization is accompanied by increased anonymity, less socializing with neighbors, less involvement in community associations, separation from familiar connections and social supports, loss of connectedness, and decreased trust of others. All these factors negatively affect health directly and indirectly.

Conversely, urbanization confers benefits that affect health through the increase in physical and human resources; affluent and middle-class neighborhoods; and easy access to diverse cultures, entertainment venues, and educational opportunities. However, crime, time pressure, high cost of recreational facilities, and disparate access to recreational facilities result in an unequal distribution of the benefits of urbanization among rich and poor. Likewise, the negative aspects of urbanization are not equally experienced by the population.

Leviton et al.'s (2000) inner-city ecology framework focuses on issues unique to central city areas: the concentration of the poor and minorities, deindustrialization, disinvestment in the downtown central business district, loss of inner-city jobs, and relative isolation of the population from amenities and job opportunities in the surrounding suburban areas. The result is a concentration in the inner cities of people with low incomes and low social status, both of which are well-known determinants of poor health and behaviors that increase morbidity and mortality.

In a study of metropolitan Tokyo, Japan, Tanaka, Takano, Nakamura, and Takeuchi (1996) found that mortality was positively correlated with several measures of urbanization, including population density, commercial-zone land area as a percentage of total land area, and urban land area as a percentage of total land area. These relationships held even after adjustment for income and education. However, Tanaka et al. noted that the relationship was not linear: as population density, urban area as a percentage of total area, and non-farmland and non-woodland area as a percentage of total land area increased, mortality decreased to a point; then mortality increased slightly as these indicators increased beyond that point. They also found that areas with a high proportion of residential land area and a low proportion of industrialized land area (i.e., suburbs) were related to low mortality rates. They concluded that residential-condition indicators concerning housing, land use, and local economic activities were related to age-adjusted mortality rates, both before and after they adjusted for the socio-economic levels of individual residents.

Verheij (1996) confirmed that urbanization has positive and negative effects on health, and that there are disparities in the distribution of positive and negative influences on health that result from urbanization. Others who found positive correlations between urbanization and health include Geronimus (2000) and McDade and Adair (2001); their results indicated significant, positive correlations between population density, social and material deprivation, and mortality.

Recent developments in tools and techniques for local spatial analysis provide new opportunities for using social science data to examine spatial relationships. In particular, since the mid-1990s the emphasis on local statistics and spatial analysis (Anselin, 1995; Fotheringham, 1997; Kirby, 1996) prompted re-examinations of associations between independent variables and outcomes of interest, which used to be studied using traditional analytic methods. Geographers cautioned that biases could be introduced when methods designed for analyzing non-spatial data are used to study geographically aggregated data (Brunsdon, Fotheringham, & Charlton, 1998; Fotheringham, 1997; Unwin & Unwin, 1998). For example, multiple regression techniques were commonly used to study relationships among data that were aggregated by geographic areas. This approach can lead to violations of the necessary assumptions for ordinary least squares (OLS) regression, namely the independence of observations and uncorrelated normal errors with constant variance. Because many if not most phenomena with a geographic component exhibit varying degrees of spatial autocorrelation, it is highly likely that these OLS assumptions are violated, which often results in underestimating confidence intervals for parameter estimates and an unduly high level of significance of the parameter estimates and in the overall regression model.

Another problem with using spatial, or global, regression techniques is that one must assume that the observed relationships between independent variables and the dependent variable are constant over space (Fotheringham, 1997; Fotheringham, Brunsdon, & Charlton, 2002). That is, one must assume no variation in the strength or in the significance of the relationship anywhere in the study area: the assumption of spatial stationarity. When dealing with aggregated socioeconomic data and other data derived from the study of human populations, this assumption of stationarity is often untenable (Fotheringham et al., 2002). Therefore, to accurately describe relationships among variables, it is advisable to use methods that account for nonstationarity in the data.

Because of the recent development of tools and techniques for local spatial analysis, we now can analyze both spatial patterns and, perhaps more importantly, the underlying processes involved in forming such spatial patterns. In this study of mortality in Atlanta, we used tools and techniques developed specifically to account for spatially autocorrelated data and for nonstationary statistical relationships. The purpose of this analysis was to understand the spatial processes, revealed by intra-urban patterns, in the relationship between sociodemographic and urbanization characteristics and mortality.

Atlanta was chosen for this analysis because it experienced rapid suburbanization during the last two decades of the 20th-century, typical of those cities described as "edge cities" (Garreau, 1991) and characterized by urban geographers as the "urban realms" model (Hartshorn & Muller, 1989). Atlanta also was chosen because of its historical pattern of racial residential segregation (Holloway & Wyly, 2001; Wyly & Holloway, 1999). Both spatial processes, land-use change and residential segregation, were hypothesized to have (1) an indirect influence on mortality through their influence on the spatial distributions of socioeconomic characteristics and (2) a direct influence on mortality through structural mechanisms of concentration of opportunity and the isolation of the predominant minority population.

2. Methods

We hypothesized that (1) census-tract–level[2] variables for socio-demographic characteristics and urbanization for metropolitan Atlanta, Georgia, in 1990, are spatially correlated, thus violating a major assumption for ordinary least squares regression and (2) the relationships between these independent variables and all-cause mortality exhibit spatial nonstationarity. Therefore, through the use of geographically weighted regression (GWR) we tested the hypothesis that socio-demographic characteristics and urbanization for metropolitan Atlanta, Georgia, in 1990, have significant and spatially varying relationships with all-cause mortality for 1995–1999.

[2] Census tracts are small, relatively permanent statistical subdivisions of a county, designed to be homogeneous with respect to their socioeconomic characteristics. Census tracts generally have between 2500 and 8000 persons (US Census Bureau, 2000). For the Atlanta study area, the mean population was 6131 persons per census tract.

2.1. Data sources

Mortality data were obtained from the Georgia Division of Public Health, in Atlanta; the data cover the 13 urban counties (Fig. 1) for 1980 – 1999. However, only data from 1995 to 1999 had a database field for the decedents' residential address, which is necessary for geocoding and computation of tract-level mortality counts and rates. Socioeconomic and demographic data were obtained from Geolytics, Inc., a retail provider of value-added US decennial census data. Specifically, US Census Long Form (SF-3) data were obtained for 1990. Because mortality data were available only for 1995–1999, we used 1990 census data and 1990 satellite imagery to preserve temporal ordering between independent and dependent variables. County boundary files were obtained from the Digital Environmental Atlas of Georgia, Version 2, published jointly by the Georgia Geologic Survey and the US Geological Survey. Census-tract boundary files were obtained from the US Census Bureau for 1990. Satellite imagery was obtained from the US Geological Survey, EROS Data Center, for 1990 (Scene ID: LT5019036037090268, Landsat 5, Thematic Mapper, Path 019, Rows 036-037 [50% offset], acquired September 25, 1990). The satellite image was used to derive land-use and land-cover data for the period of the research project. Black-and-white and color aerial photographs of portions of the metropolitan Atlanta area (particularly Gwinnett County, 1988 and 1989) were used for ground truthing of satellite-derived land-use and land-cover data for 1990. Road network data were obtained from the National Transportation Atlas Database: 2004, published by the US Department of Transportation, Bureau of Transportation Statistics, and from ESRI (Environmental Systems Research Institute, Redlands, CA). These data were used to assist in classification of land use and land cover.

The mortality data obtained from the Georgia Division of Public Health consisted of individual records of decedents along with their last known residential street address. To derive area-based counts and rates at the census-tract level, we geocoded (address-matched) the residential locations using a geographic information system (GIS). The original database contained 102,016 death records for the 13 counties of the study area. The mortality data were geocoded with two software packages and two street file databases in an effort to maximize address match rates. The first geocoding iteration was performed in ArcInfo 8.3™ (Environmental Systems Research Institute, Redlands, CA) by using the US Census Bureau's 2000 TIGER Line Files as the street matching file. Interactive matching was conducted on unmatched records. All records (matched and unmatched) were then geocoded with a second software application and database (Centrus Desktop 4.0 and Sagent Company's Address Coding Module). This improved the overall geocoding rate, particularly in rapidly developing areas, and served as a check on the accuracy of the geocoding results from ArcInfo/TIGER processing.

Fig. 1. Thirteen-County metropolitan Atlanta study area.

Both ArcInfo and Centrus allow interactive matching. The successfully matched addresses were merged from the ArcInfo and Centrus database information, resulting in match rates ranging from 83% (Paulding County) to almost 98% (Henry County). The match rate disparity generally is consistent with patterns of development; newer and more rapidly changing counties fared worse than did more established counties. The resulting file of geocoded deaths totaled 97,910 records, for an overall geocoding rate of 96.03%. This rate exceeds the 85% threshold demonstrated by Ratcliffe (2004) to be the minimum acceptable geocoding rate for address-based point pattern datasets.

The 444 census tracts (all the tracts within the 1990 boundary of the Atlanta metropolitan area), were reduced to an analysis set of 431 tracts, to remove four tracts that were unpopulated in 1990 and nine tracts in which the observed number of deaths during the 5 years (1995–1999) was less than 30.

2.2. Standardized mortality ratios

The mortality counts for each 1990 census tract were computed using ArcInfo 8.3, by spatially joining the point-level mortality data to the census tract boundary shapefile, a vector data format for geographic information systems software. Mortality counts were used in all subsequent regression analyses. However, we first wanted to assess spatial variations in mortality: to do so requires the computation of mortality rates to account for geographic variations in census tract populations. We began by computing crude mortality rates (number of deaths per 100,000 population) in the GIS using 1997 estimates of census tract populations. Because crude mortality rates are highly influenced by the age-structure of the population for whom they are computed, comparisons of crude rates between groups or areas can be misleading. This is especially problematic if some census tracts contain high proportions of elderly people and other census tracts contain low proportions of elderly people, because their risk of death is higher than young people's. Therefore, we used indirect age-adjustment procedures to calculate standardized mortality ratios (SMRs) (US Department of Health & Human Services, 2001), with estimated death rates per age-group for the US population in 1997 as the reference data. For crude rate and SMR calculations, we used 1997 as the reference year because it was the midpoint of the 5 years, 1995–1999.

By computing SMRs, we were able to make meaningful comparisons of mortality risk among census tracts. SMRs are calculated as a ratio of the observed number of deaths for a particular area divided by the expected number of deaths for that area:

$$\mathrm{SMR} = \frac{\text{Observed deaths}}{\text{Expected deaths}} = \frac{D}{\sum R_{si} \cdot P_i}, \tag{1}$$

where D is the total number of observed deaths in the population (in this case, each census tract), R_{si} is the age-specific death rate in age stratum i in the standard population, and P^i is the population of age stratum i in the observed population (each census tract). If a census tract has an SMR of 1.0, that census tract would have the same approximate mortality risk as that of the reference population (in this case, the 1997 US population). If the SMR is greater than 1.0, then the mortality risk is greater than that of the reference population. If the SMR is less than 1.0, the mortality risk is lower than that of the reference population. For example, a census tract with an SMR of 1.20 has a 20% higher mortality risk than that of the reference population; moreover, it is possible to compare mortality risks among census tracts in the Atlanta metro area: a census tract with an SMR of 1.20 has a 20% higher mortality risk than a census tract with an SMR of 1.00.

We then used the SMRs to explore spatial geographic patterns in mortality for metropolitan Atlanta (Fig. 2) and found that they follow a roughly north–south dichotomy. Most census tracts with relatively low mortality risk are in the northern arc of generally suburban areas (northern Fulton County, eastern Cobb County, northern DeKalb County, southern Forsyth County, and Gwinnett County), and the highest relative risks for mortality are concentrated in the inner core of the metropolitan area: the City of Atlanta and southeast DeKalb County. There are exceptions to this pattern, notably the low mortality risk in affluent Fayette County to the south of the metropolitan area and some pockets of elevated mortality risk in the outer arc of suburban tracts. The northern suburban tracts with high mortality risk are less affluent than the other northern suburban tracts, and they have a higher proportion of people from minority races. Examples of such areas are the cities of Smyrna and Marietta in Cobb County, Norcross and Buford in Gwinnett County, Newnan in Coweta County, Dallas in Paulding County, Douglasville in Douglas County, and Canton in Cherokee County.

2.3. Selection of independent variables

The remaining independent variables were obtained or derived from 1990 US census data, and were selected on the basis of a review of studies relating to mortality and other health outcomes. Of the variables reviewed in the previous section, we chose the following: (1) the percentage of population living below the federal poverty line in 1990;

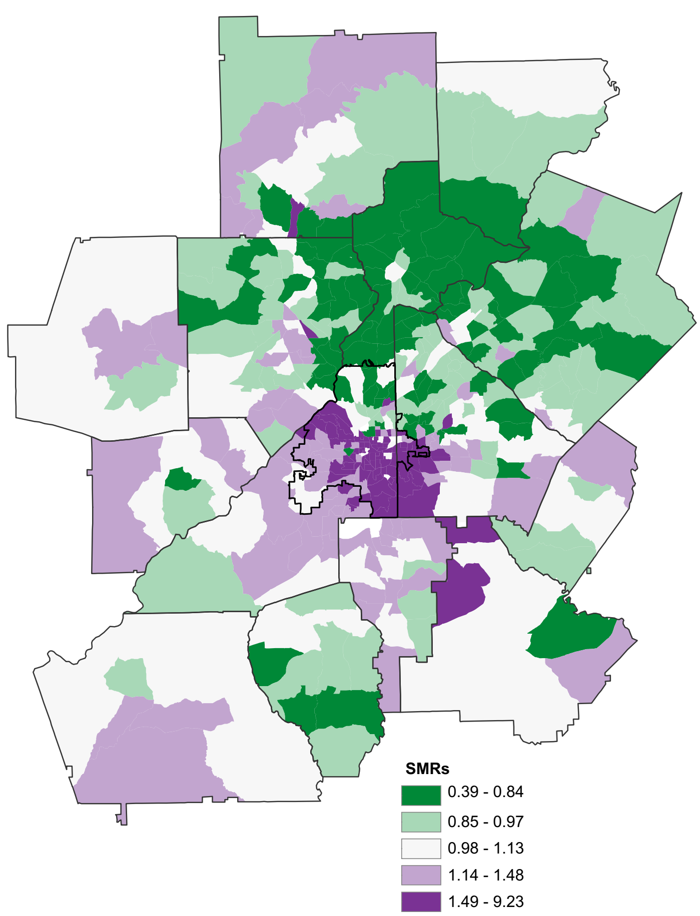

Fig. 2. Standardized mortality ratios (SMRs), metropolitan Atlanta, 1995–1999.

(2) the percentage of population over age 18 in the civilian workforce unemployed during the past year (1989); (3) the percentage of population in 1990 over age 25 with high school diploma or equivalent; (4) the percentage of housing units that were owner-occupied in 1990; and (5) the percentage of blacks in the total population in 1990. We chose these five variables because of the strength of their associations with health outcomes as demonstrated through public health research. These variables represent different constructs that have both independent and interactive effects on health risk behaviors and health outcomes: income, employment status, educational attainment, residential stability, and race. The 1990 sociodemographic variables are described in Table 1.

2.4. Urbanization variable

Land-use and land-cover data were derived from an unsupervised classification of remotely sensed satellite imagery of metropolitan Atlanta for 1990. The Landsat image was processed in ERDAS Imagine 8.7 (Leica Geosystems, Inc., Atlanta, Georgia) using the ISODATA procedure (Jensen, 1996), with classification accuracies (data not shown) exceeding the commonly accepted minimum accuracy standard of 85% for remotely sensed data (Anderson, Hardy, Roach, & Witmer, 1976). Six categories of land use and land cover were used: high-density urban, low-density urban, cultivated or exposed land, cropland or grassland, forested land, and water (Fig. 3). Areas in the high-density urban class were predominantly commercial and industrial areas, and areas in the low-density urban class were mostly residential areas.

After image classification, the extents of urbanized areas (high-density and low-density urban classes) were determined and expressed as percentages of the total land area for each census tract. There are many alternative definitions and measures of urbanization (Harris & Longley, 2000; Longley, Batty, & Shepherd, 1991), such as areas with populations or population densities exceeding predefined thresholds, and areas experiencing growth in urbanized land use above a predefined threshold rate. However, we chose the combination of high- and low-density urban land use as a percentage of total land area primarily to be consistent with Tanaka et al. (1996) use of urban land area as a percentage of total land area. This approach is similar to the conceptualization of urbanization from Kaplan, Wheeler, and Holloway (2004), in that it allows us to differentiate rural areas from urban areas within the study area. Yet, we differed from Kaplan et al. in that we measured land use at the pixel level (and summarized by zone – census tract), as opposed to computing the ratio of urban-to-total population by zone.

2.5. Socioeconomic status (SES) index

Because multicollinearity can be problematic for sociodemographic variables when included in subsequent multivariate regression models, we then examined correlation matrices (data not shown), which confirmed our reservations about multicollinearity. To avoid problems from multicollinearity, we constructed a socioeconomic status (SES) index through factor analysis, using the poverty, homeownership, high school completion, and unemployment variables. The SES index was scaled such that high values of the index correspond to low socioeconomic status and vice versa. We specifically excluded the urbanization and race variables because we wanted to analyze independently the effects of race and urbanization. In addition, since we were attempting to derive an index for socioeconomic status, we did not want to confound the effect of SES with the effect of race. We used SPSS 13 (© SPSS, Inc., Chicago, IL, 2004) to perform the factor analysis, using Principal Axis Factoring for factor extraction. We selected the first extracted factor, with an eigenvalue of 3.012, which explained 69.03% of total variance, as the factor to represent SES. No other factor's eigenvalue exceeded 1.000; therefore we used only the first extracted factor for subsequent analyses. Communalities and factor loadings are in Table 2. Eigenvalues and explained variance are in Table 3.

3. Analysis

3.1. Spatial autocorrelation

Because the SMRs for 1995–1999 (Fig. 2) exhibited a visually distinct spatial pattern, with areas of low mortality

Table 1
Descriptive statistics for variables, metropolitan Atlanta, 1990

Variable	Definition	Minimum (%)	Maximum (%)	Mean (%)	SD	Moran's *I*
Poverty	Percentage of population living below the federal poverty line, 1990	0.00	88.00	13.56	16.11	0.67
Homeownership	Percentage of housing units owner-occupied, 1990	0.00	90.11	47.50	22.81	0.52
High school graduation	Percentage of population over age 25 with high school diploma or equivalent, 1990	22.10	100.00	76.98	16.66	0.65
Unemployment	Percentage of population over age 18 in the civilian workforce unemployed during preceding year, 1989	0.00	41.00	6.38	5.43	0.55
Urbanization	Percentage of land area urbanized (high-density and low-density urban land use), 1990	3.47	100.00	40.48	23.05	0.83
Black population	Percentage of total population black, 1990	0.00	100.00	31.11	35.89	0.83

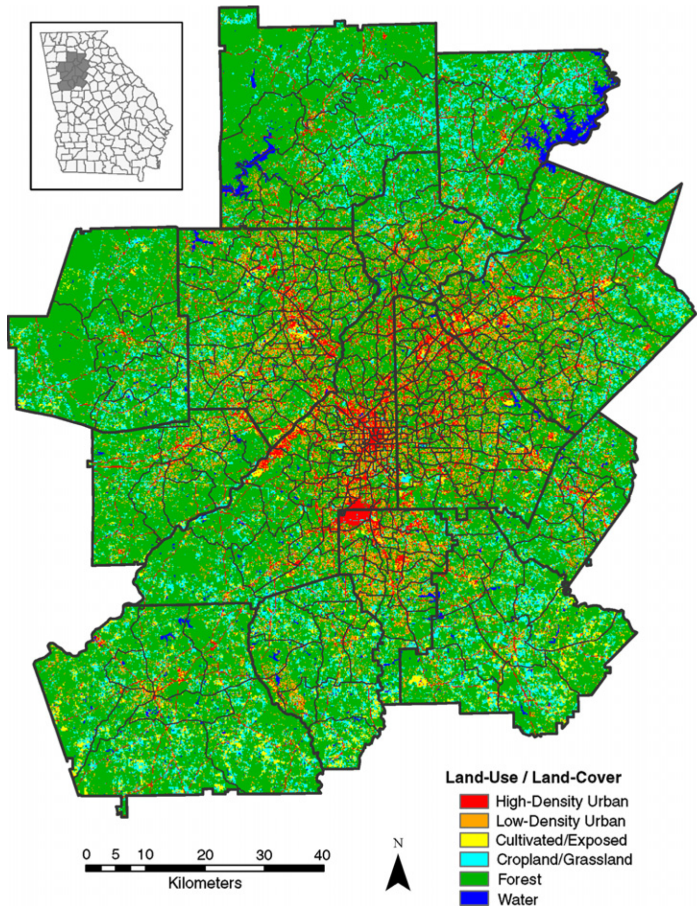

Fig. 3. Land-use/land-cover, metropolitan Atlanta, 1990.

Table 2
Communalities and factor loadings for SES index

Variable	Initial communalities	Extraction communalities	Factor 1 loadings
Poverty	0.827	0.987	0.994
Homeownership	0.422	0.361	−0.601
High school graduation	0.636	0.640	−0.800
Unemployment	0.744	0.773	0.879

concentrated in the northern arc and areas of high mortality concentrated in the urban core, we assessed the degree of spatial autocorrelation in the data. We performed exploratory spatial data analysis (ESDA) with GeoDa (Beta version 0.9.5-i) (Anselin, 2004). GeoDa contains many tools for ESDA, including global measures of spatial autocorrelation (Moran's I and Geary's C) and local indicators of spatial autocorrelation (LISAs) (Anselin, 1995) such as Local Moran's Indices:

$$I_i = z_i \sum w_{ij} z_j, \tag{2}$$

where z_j are observations, and w_{ij} is a weights matrix equal to $1/d_{ij}$ in which d_{ij} represents the Euclidean distances between the ith and jth points, where these points refer to the geometric centroids of the census tracts.

We found that the SMRs were spatially autocorrelated (Moran's $I = 0.38$). Not surprisingly, the Moran's I values for the independent variables were also high (Table 1), ranging from 0.52 for home ownership rates to 0.83 for urbanization as well as for the percentage of blacks in the total population. The latter value is especially congruent with historical patterns of residential segregation by race

Table 3
Total variance explained for SES factor analysis

Factor	Initial eigenvalues			Extraction sums of squared loadings		
	Total	Percentage of variance	Cumulative percentage	Total	Percentage of variance	Cumulative percentage
1	3.012	75.305	75.305	2.761	69.031	69.031
2	0.606	15.143	90.448			
3	0.263	6.563	97.011			
4	0.120	2.989	100.000			

in the Atlanta area (Holloway & Wyly, 2001; Wyly & Holloway, 1999). Spatially, this is manifested by extreme concentrations of black residential populations in the southern half of the City of Atlanta as well as southern DeKalb County and southern Fulton County.

Moran's I values indicate only the presence of spatial autocorrelation globally. That is, one is given a single overall indication of whether there is spatial autocorrelation in the dataset but no indication of whether there are local variations in spatial autocorrelation across the spatial extent of the data. To localize precisely the presence and magnitude of spatial autocorrelation, LISAs such as Local Moran's Indices are necessary. We computed Local Moran's Indices for an age-adjusted variant of the dependent variable (mortality counts) – SMRs – for each of the individual socioeconomic variables and for the urbanization and race variables.

In all cases we discovered distinctive patterns of localized spatial autocorrelation (Fig. 4). In all Fig. 4 maps, the dark red areas correspond to census tracts with high

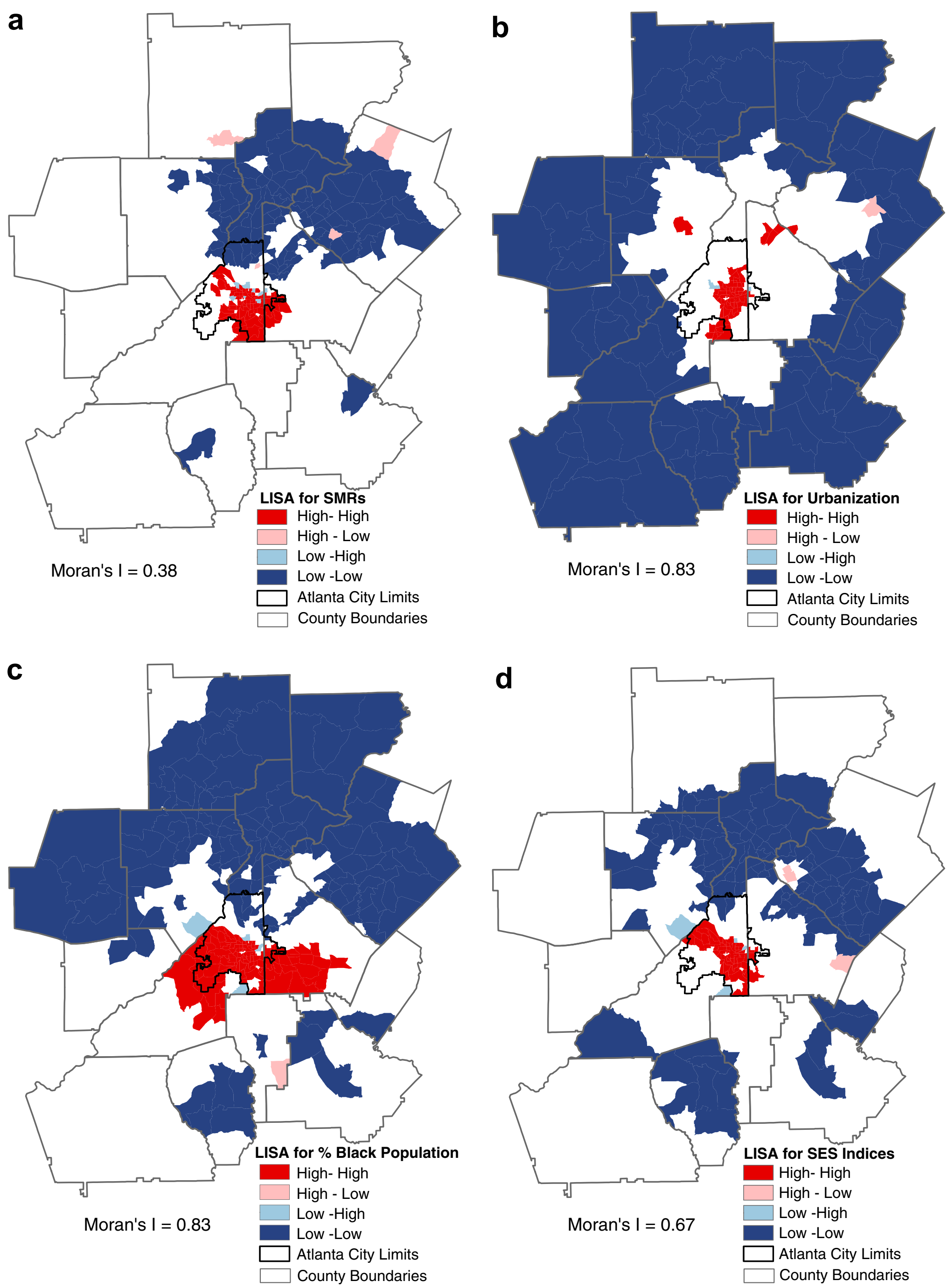

Fig. 4. LISAs for SMRs (a), urbanization (b), black population (c), and SES index (d), metropolitan Atlanta, 1995–1999.

SMRs and high degrees of localized spatial autocorrelation. Dark blue areas correspond to census tracts with low SMRs and high degrees of localized spatial autocorrelation. Light red areas correspond to census tracts with high SMRs that are spatial outliers; that is, these high SMR tracts are in areas in which there is a high degree of spatial autocorrelation of census tracts with low SMRs. Conversely, the light blue areas represent census tracts with low SMRs in close proximate location to census tracts with high degrees of spatial autocorrelation for high SMRs.

For the dependent variable, high concentrations of mortality (Fig. 4a) were observed in the City of Atlanta (depicted by a bold black polyline in all Fig. 4 maps); clusters of low mortality were observed in the northern arc of affluent suburban areas. The LISA for urbanization (Fig. 4b) is especially distinctive, with high concentrations of urbanization in the center of the study area (corresponding to the City of Atlanta) and low concentrations of urbanization in the outer rural and exurban fringes of the study area. This pattern is entirely consistent with the typical urbanization patterns for large metropolitan cities, where the central urban core is first developed and remains highly urbanized, then followed by a suburban fringe, and lastly by an outer, undeveloped rural ring.

The concentration of the black population for metro Atlanta is evident (Fig. 4c) in the broad band across the center of the study area, corresponding to the southern half of the City of Atlanta, southern DeKalb County, and portions of southern Fulton County. Conversely high concentrations of the white population are observed across the entire northern half of the study area along with some smaller concentrations scattered to the south of the study area and corresponding to highly affluent areas of Fayette, Henry, Clayton, and Rockdale Counties.

We computed the LISA for the SES index, to determine whether our initial concerns about spatial autocorrelation and spatial nonstationarity still pertained to our newly created independent variable. As we expected, the SES index variable (Fig. 4d) had a pattern of local spatial autocorrelation that was broadly representative of the combination of all four of the constituent variables: high concentration of high SES index values (i.e., low socioeconomic status) in the City of Atlanta and high concentration of low SES index values (high socioeconomic status) in the ring of affluent suburbs, with only a few spatial outliers in the study area. This analysis reinforced our hypothesis that the use of a global regression technique is inappropriate because we anticipated that the relationship between SES and mortality is spatially nonstationary.

The high degree of spatial autocorrelation in this dataset suggests that the use of traditional multivariate regression methods is inappropriate because of the violation of the assumption of independent observations. The distinctive patterns of local spatial autocorrelation suggest that there are underlying spatial processes in the study area that result in spatial nonstationarity of any relationships between the independent and dependent variables. These analyses supported our initial hypotheses regarding the data's spatial distribution. We then used regression analyses to test the hypothesis of a spatially varying relationship between the independent variables and mortality.

Initially we ran a series of Poisson regression models in Stata™ SE 9.2 (Statacorp, College Station, TX, 2006) with all-cause mortality (number of deaths per census tract, aggregated from 1995 to 1999) as the dependent variable. We used the following individual variables in the initial regression models to determine the specific effects of individual variables on the dependent variable: the percentage of the population living below poverty in 1990, the percentage of the population in 1990 aged 25 or older who had a high school diploma or equivalent, the percentage of the civilian work force aged 18 or older who was unemployed in the preceding year (i.e., 1989), the percentage of housing units that were owner-occupied in 1990, urbanized land as a percentage of total land area in 1990, and blacks as a percentage of the total population in 1990. Because age is a primary risk factor for death, we included the expected number of deaths as an offset variable. For each of the independent variables in the bivariate analyses, we found significant and intuitive relationships to mortality.

3.2. Geographically weighted regression

Geographically weighted regression (GWR) was developed by Brunsdon et al. (1998) and Fotheringham et al. (2002) to provide locally varying parameter estimates for regression models where spatially varying relationships are hypothesized. GWR is an extension of traditional regression techniques, which for an OLS or Gaussian regression model, can be expressed as:

$$y_i = \beta_0 + \sum_k \beta_k x_{ik} + \varepsilon_i, \tag{3}$$

where y_i and x_{ik} are the dependent and independent variables at point i, β_0 is a constant, β_k are parameters to be estimated, and ε_i is an error term at point i. The GWR extension of the Gaussian model takes the form:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \varepsilon_i, \tag{4}$$

where (u_i, v_i) denotes the coordinates of the ith point in space and β_0 and β_k are continuous functions of (u, v) at point i (Fotheringham et al., 2002). The GWR software program (version 3.0.16, © University of Newcastle, 2003) produces unique parameter estimates for all points i, by spatially weighting the observations according to their proximity to i. Observations closer to the ith point are given more weight than are observations further away. The weights are derived through a distance-decay function. To limit the number of data points considered for each local parameter estimate, a spatial kernel is used at the ith point. The kernel can be either fixed, in which case the bandwidth of the kernel is also fixed, and thus varying numbers of observations are weighted for the computation of each local parameter. This is not problematic for evenly distributed data points, but where there is great variability in data point density (as is the case for the metropolitan Atlanta census tracts, which vary considerably in areal extent), an adaptive kernel is more appropriate. With an adaptive kernel, an equal number of data observations are weighted and used for local parameter estimation. In addition to local parameter estimates, GWR also provides local goodness-of-fit measures and local residuals. The GWR model can be compared with the corresponding global regression model, through an F test and by comparison of Akaike Information Criteria (AIC), to determine whether the GWR model is a significant improvement.

We chose to implement an extension of the basic GWR regression technique: GWR Poisson regression (Fotheringham et al., 2002; Nakaya, Fotheringham, Brunsdon, & Charlton, 2005). Because mortality is a count variable, we used Poisson regression. The Poisson regression model can be expressed as:

$$\lambda_i = P_i \exp\left(\beta_0 + \sum_k \beta_k x_{ik}\right), \tag{5}$$

where λ_i is the mean of a distribution for a count y_i, where y_i is the dependent variable, the βs are regression functions, the xs are independent variables, and P_i is an offset used to account for a population at risk. The GWR extension to the Poisson model takes the form:

$$\lambda_i = P_i \exp\left(\beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i) x_{ik}\right), \tag{6}$$

where (u_i, v_i) denotes the coordinates of the ith point in space and β_0 and β_k are continuous functions of (u, v) at point i, as with the Gaussian GWR model (Fotheringham et al., 2002).

In our implementation of Poisson GWR, we used all-cause mortality as the dependent variable, the expected number of deaths as an offset variable, and the race, urbanization, and SES index variables as the predictors. We chose an adaptive bi-square kernel and calibrated bandwidth selection by cross-validation (convergence reached after nine iterations). Local parameter estimates were computed for each of the census tract areas by using their geometric centroids (measured in UTM Eastings and Northings) as the regression points. Local parameter estimates, residuals, local Z-values, and local R-square estimates were exported to ArcGIS™ 9 (Environmental Systems Research Institute, Inc., Redlands, CA, 2005) for mapping of spatial patterns.

4. Results

The spatial patterns of the parameter estimates from GWR are quite interesting (Fig. 5a–d). Although the global Poisson model provides an overview of the relationships between mortality and SES, urbanization, and race, GWR allows us to see how and where these relationships vary spatially and in magnitude and significance across the Atlanta metropolitan area. The intercept estimates are depicted in Fig. 5a. Without the influence of the model parameters, the predicted level of mortality is lowest in the general area of north Fulton County, north DeKalb County, and west Gwinnett County. Higher levels of mortality are predicted in the southern half of the City of Atlanta, south DeKalb County, north Henry County, north Clayton County, and to a lesser degree in the outlying counties to the west and north. In Fig. 5b, the local parameter estimates for the SES index suggest that low SES is particularly significant in estimating all-cause mortality in the northern suburbs of metropolitan Atlanta, and less significant and with a lesser absolute effect in the southern half of the study area. Interestingly, there is a small area along the Fulton/DeKalb border in which the effect of low SES is negatively associated with mortality.

In Fig. 5c, highly urbanized land areas are positively associated with high mortality in (1) portions of the City of Atlanta, (2) the urban areas of Gwinnett County (City of Norcross), which has a high percentage of Hispanics and Asians, and (3) the southernmost areas of the study area (including Henry County, Fayette County, Coweta County, and southern Fulton County). Conversely, highly urbanized land areas are negatively associated with high mortality in (1) the northernmost counties (Cherokee, Forsyth, northern Fulton), (2) an area in the east composed of portions of Rockdale, eastern DeKalb, northern Henry, and northeastern Clayton counties, and (3) an area of central Fulton County, including the extremely affluent Buckhead neighborhood.

The local parameter estimates for the race variable are depicted in Fig. 5d. The effects of race are particularly strong and significant in the center of the study area (City of Atlanta) and in the northern portion of the study area. In the former case, the population is predominantly black, and in the latter case, the population is overwhelmingly white. This suggests two dynamics: (1) in the inner city, structural processes resulted in the concentration of blacks in urban poverty and its associated lack of opportunity and (2) in the northern white suburbs (for example, Forsyth County), remnants of historical racism may still be operating to deny blacks the economic opportunities available to whites in these areas.

Local R-square estimates ranged from 0.73 in the southeastern corner of the study area to 0.96 in the northern and western portions of metropolitan Atlanta. This indicates a high degree of overall explanatory power for the GWR model, with some spatial variation, perhaps due to an unspecified variable that may have helped to improve the explanatory power of the model in the southeastern corner (e.g., portions of Rockdale and Henry counties). Spatial autocorrelation of the residuals was assessed by computation of the Moran's I index; for this model, Moran's $I = -0.03$, which is indicative of complete spatial randomness (CSR). We also checked for localized spatial autocorrelation of the residuals by computing Local Moran

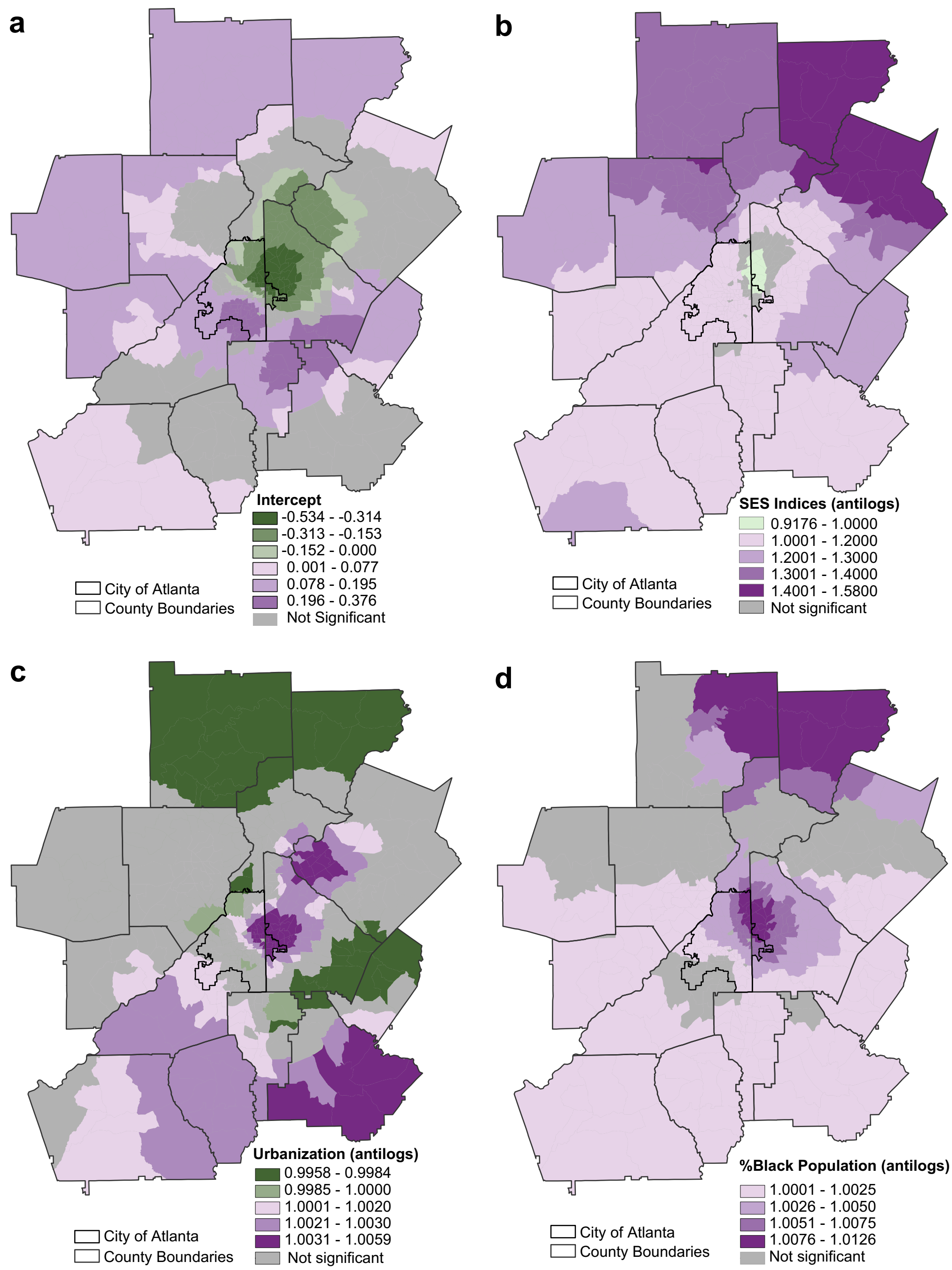

Fig. 5. GWR parameter estimates for Intercept (a), SES (b), urbanization (c), and black population (d), metropolitan Atlanta, 1990.

Indices in GeoDa. The results (data not shown) confirm that there are no localized areas in which clustering of high or low residuals were present.

GWR also produces a set of parameter estimates for a global Poisson model, to be used as a comparison with the local Poisson model. Table 4 contains the regression

Table 4
Global poisson parameter estimates

Parameter	Estimate	Standard error	*T*	Exp(B)	SD (Exp(B))
Intercept	−0.002	0.009	−0.231	0.998	0.009
PURB90	−0.001	0.000	−2.802	0.999	0.000
PBLK90	0.003	0.000	25.864	1.003	0.000
SES90	0.160	0.006	26.163	1.174	0.007

coefficients for the global Poisson regression model. The global Poisson model reached convergence after three iterations, with an AIC of 4034.94. The regression parameters of the global Poisson model suggest that increases in the socioeconomic status of a census tract, *ceteris paribus*, are associated with decreases in mortality rates. Increases in the degree to which an area is urbanized, *ceteris paribus*, are associated with decreases in mortality rates. Increases in the number of blacks as a percentage of total population, *ceteris paribus*, are associated with increases in mortality rates. The AIC of the GWR Poisson model, 2963.18, is a large reduction from the global model AIC, which indicates that the GWR model is an overall improvement over the global model. Furthermore, although the results from the global Poisson model provide an accurate summary of the overall relationships between the independent variables and mortality, they oversimplify and obscure the interesting and significant spatially varying relationships revealed through the GWR Poisson model.

5. Discussion

The spatially varying effect of each independent variable can be examined through local comparisons of the relative magnitudes of parameter estimates, whereas with a global regression model, the relative effect of each independent variable can be assessed only for the study area as a whole. By comparing relative magnitudes of parameter estimates, we can conceptualize the relative effects of the independent variables as a continuous function across space. Because we have three independent variables, six pair-wise comparisons are possible. Racial composition has a greater relative relationship to mortality than does urbanization in most of the northern two-thirds of the metropolitan area. Urbanization has a greater relative effect than racial composition in these two areas as well as in the southern third of the area. Racial composition and urbanization both have a greater relative effect than does SES in one small area along the Fulton–DeKalb border, including a portion of the City of Atlanta; otherwise, SES has a greater relative effect than racial composition and urbanization throughout the study area. Fig. 6 depicts these relationships.

The spatial distribution of parameter estimates for the effects of race (Figs. 5d and 6) are particularly interesting and can be interpreted through Geronimus's (2000) study on health problems unique to central cities. He argued that structural influences resulted in modern ghettos in central cities. Modern urban environments were developed under

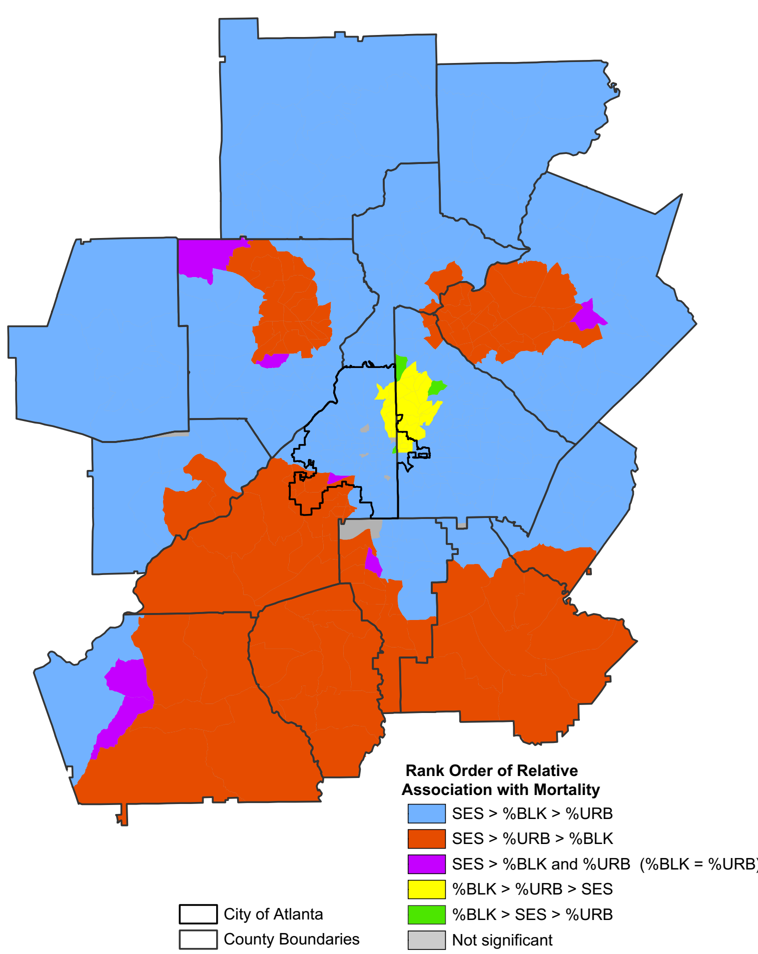

Fig. 6. Relative magnitude of association of independent variables to mortality.

the influence of race-conscious policies. For example, highway construction and public housing projects isolated black neighborhoods. Racial covenants, discriminatory mortgage lending practices, and racial steering prevented blacks from moving to newly developing suburban areas. White residents were offered government-subsidized low-interest home mortgage loans, which facilitated the migration of white residents to the suburbs. Publicly funded transportation projects provided convenient links between suburban homes, employment areas, and cultural or entertainment centers. Indeed, Holloway and Wyly found strong evidence to support the structural influences theory in metropolitan Atlanta (Holloway & Wyly, 2001; Wyly & Holloway, 1999). Meanwhile, economic restructuring led to a shift from a manufacturing to a service economy, which resulted in the loss of many high-paying unionized manufacturing jobs in the city and, eventually, high unemployment (Gong & Wheeler, 2002). The combined effect of housing policies and practices and economic restructuring was to prevent many blacks from escaping the poverty that resulted from the loss of jobs in the urban center. At the same time, few public and private funds were invested in central urban areas (e.g., funds to maintain and supervise infrastructure, public housing, and public parks). The inability of black residents to migrate from the central city, combined with the decline of these areas, led to a further decline in the quality and value of the housing stock. Therefore, a primary means of accumulating wealth (which is highly correlated with health outcomes) through home ownership was denied to blacks.

As Geronimus (2000) noted, these factors are important to health because of the strong association between health and poverty. People in poverty tend to be exposed to a greater extent than middle-class or wealthy people to social, psychosocial, and physical factors associated with increased morbidity and mortality. These factors include acute and chronic stress, overburdened or disrupted social supports, material deprivations, and exposure to hazards such as toxins or pollutants in the physical environment. The psychosocial stresses often lead to increases in unhealthy behaviors and a lowered ability to access health information, health services, or technologies that could protect them from exposure to health hazards or reduce their risk from such exposure. These negative influences resulting from poverty are often exacerbated for people from racial minorities, because their poverty often extends over their entire lifespan, thus suggesting a cumulative adverse health effect from being persistently disadvantaged.

The spatially varying relationships between urbanization and mortality are more challenging to explain. This may be due, in part, to limitations in our operational definition and measure of urbanization. Our measure is cross-sectional; we are not capturing land-use trends, such as suburban development or urban decline. Therefore, we may be characterizing different spatiotemporal dynamics with the same measure. On the one hand, we have a point-in-time reflection of suburban development in the previously rural outlying areas, where an increase in the proportion of urban land use would be expected to be associated with low mortality rates. On the other hand, we have a point-in-time quantification of the proportion of commercial and industrial land use in the inner city. What may be implicitly captured by our measure is the extent to which this latter area has experienced deindustrialization and decline. The financial resources to support industry and commerce may have been withdrawn over time, yet the physical infrastructure of commerce and industry (e.g., high-density urban land use) remain. Therefore, we may expect that in the inner city areas, those census tracts with high proportions of urban land use would be associated with high mortality rates.

Most of the outer fringe counties (e.g., Coweta, Cherokee, Forsyth, and Paulding) were rural in the 1980s. As urbanization began to spread, these areas became rapidly suburbanized as the growing (and generally affluent) population expanded outward in search of new residential opportunities. New suburban downtowns emerged (Hartshorn & Muller, 1989) especially in the northern tier of

Table 5
Land-use and land-cover statistics, metropolitan Atlanta, 1984–2000

Land-use/land-cover		1984	1990	2000
High-density urban	Hectares	67508	79733	96557
	Percentage of land area	6.45	7.61	9.28
Low-density urban	Hectares	64077	109366	174975
	Percentage of land area	6.12	10.43	16.72
Cultivated or exposed	Hectares	57614	43088	52144
	Percentage of land area	5.51	4.11	4.98
Cropland or grassland	Hectares	170924	118945	104890
	Percentage of land area	16.33	11.35	10.02
Forest	Hectares	668119	676258	595775
	Percentage of land area	63.84	64.52	56.90
Water	Hectares	18311	20736	21974
	Percentage of land area	1.75	1.98	2.10

Table 6
Changes in land-use/land-cover statistics, metropolitan Atlanta, 1984–2000

Land-use/land-cover		Change: 1984–1990	Change: 1990–2000	Change: 1984–2000
High-density urban	Hectares	12225	16824	29049
	Percentage change	18.11	21.10	43.03
Low-density urban	Hectares	45289	65609	110898
	Percentage change	70.68	59.99	173.07
Cultivated or exposed	Hectares	−14526	9056	−5470
	Percentage change	−25.21	21.02	−9.49
Cropland or grassland	Hectares	−51979	−14055	−66034
	Percentage change	−30.41	−11.82	−39.63
Forest	Hectares	8139	−80483	−72344
	Percentage change	1.22	−11.90	−10.83
Water	Hectares	2425	1238	3663
	Percentage change	13.24	5.97	20.00

metro counties (Gwinnett, northern Fulton, Cobb, and Forsyth). These emergent suburban downtowns in the northern counties as well as areas of the central core were easily accessible by automobile or public transportation from the northern suburbs. By 2000, the transition from rural to suburban land use had become quite clear from an analysis of remotely sensed satellite data. These changes are clearly reflected in land-use statistics, such as urban land use, derived from those satellite data (Tables 5 and 6).[3]

6. Conclusions

We found that previously hypothesized relationships between SES, race, and urbanization and mortality were present and significant in the Atlanta metropolitan area for 1995–1999 and that the relationships between these predictors and mortality varied spatially, such that distinctive geographic patterns emerged. This indicates there is a complex interaction of urbanization and the social environment across Atlanta, and these forces have differential, spatially varying, relative impacts on the health of Atlantans. These geographic patterns reflect the spatial processes that operated in Atlanta for the past few decades, namely, rapid residential and commercial development in the outer portions of the metropolitan area (especially to the north) and the movement of the affluent white population away from the central city, leaving behind a predominantly African–American population with low SES. Therefore, our ever-changing urban landscapes and the social forces that create them need to be studied in a broader context, one in which health and the conditions that influence health are considered. From a practical standpoint, urban planning, economic development, and policies that affect the social environment all need to be considered for their potential ramifications for the health of the population. In retrospect, if policymakers whose decisions influenced residential mortgage lending practices, transportation, and urban development in Atlanta had known about and considered the potential impacts of their decisions on the health of Atlanta residents, the spatial patterns that we see revealed through our GWR analysis, in which racial, social, and geographic health disparities[4] are glaringly revealed, quite possibly may have been averted.

This study demonstrates the usefulness of applying geographically weighted regression (GWR) analysis to mortality at the intra-urban scale. By using GWR, we are able to interpret local effects of race, SES, and urbanization on mortality. The global regression model fails to capture such detail, and therefore prevents us from being able to interpret the complex interplay of these contextual factors throughout the Atlanta area. In addition, this study highlights the application of LISA statistics to exploratory spatial data analysis for mortality. The relative ease of use of GeoDa and GWR as well as the increasing availability of GIS technology make these analytic tools and methods valuable for public health researchers.

Despite its usefulness, GWR has limitations. First, it assumes spatial nonstationarity for all variables, while in reality some explanatory processes may exhibit spatial stationarity. The present version (Release 3.0) of GWR does not allow for mixed (i.e., semi-parametric) models in the sense that some variables can be treated as stationary and others treated as nonstationary. Additionally, it cannot be used for spatially varying hierarchical models. Therefore, individual and area-level data cannot both be included in a GWR model. Wheeler and Tiefelsdorf (2005) caution against using GWR without giving consideration to potential repercussions of multicollinearity among exogenous variables, an issue they found to be problematic in a study of bladder cancer mortality. Furthermore, they demonstrate that local regression coeffi-

[3] Data for 1984 and 2000 were derived from Landsat TM and ETM+ imagery; imagery and LULC maps not shown.

[4] SMRs for the study area ranged from 0.39 (95% CI: 0.33–0.45) to 9.23 (95% CI: 6.77–11.69).

cients can be collinear, and they suggest that caution should be exercised in interpreting spatial patterns of GWR parameter estimates.

Recent research by Mei, Wang, and Zhang (2006) has shown that it is feasible to extend GWR to a Mixed Geographically Weighted Regression (MGWR) model. Lebreton (2005) offers an alternative to GWR, namely the neural coefficient smooth transition autoregressive (NCSTAR) model, in which local estimates are derived for every observation of the dataset as a nonlinear function of its geographical position and other variables. Furthermore, confidence intervals can be computed for NCSTAR estimates.

We chose to use an ecological approach because of data availability limitations as well as the desire to analyze influences on health that could be attributed to area effects. Accordingly, care must be taken not to attribute these relationships to individuals. Instead, these results suggest avenues for further research in order to better understand the complex relationships between the characteristics of individual people, their physical environment, and their individual behaviors. In addition, we need a better understanding of how these relationships affect health. By including individual risk behavior and health outcomes data, it would be possible through hierarchical modeling techniques to analyze more precisely such relationships and, more importantly, to suggest appropriate public health policies and interventions to improve the overall health status of the population and to reduce health disparities. With future enhancements to GWR or with alternatives such as MGWR or NCSTAR, it might be possible to study mixed models and geographically varying hierarchical models.

For a more comprehensive analysis of the relationship between the social and physical environments and health outcomes, a lifecourse approach (Kuh & Ben-Shlomo, 1997) may be helpful. This approach emphasizes the accumulation of health risks that result from lifelong exposures to adverse physical and social environments. Recent developments in Space Time Intelligence Software, or STIS, (Jacquez, Goovaerts, & Rogerson, 2005) may make possible the visualization and analysis of temporally dynamic geospatial data, that would be necessary for assessing the relationship between lifecourse data and health outcomes.

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