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Locating Spatial Variation in the Association Between Wildland Fire Risk and Social Vulnerability Across Six Southern States

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Abstract Wildland fire in the South commands considerable attention, given the expanding wildland urban interface (WUI) across the region. Much of this growth is propelled by higher income retirees and others desiring natural amenity residential settings. However, population growth in the WUI increases the likelihood of wildfire fire ignition caused by people, as humans account for 93% of all wildfires fires in the South. Coexisting with newly arrived, affluent WUI populations are working class, poor or otherwise socially vulnerable populations. The latter groups typically experience greater losses from environmental disasters such as wildfire because lower income residents are less likely to have established mitigation programs in place to help absorb loss. We use geographically weighted regression to examine spatial variation in the association between social vulnerability (SOVUL) and wildfire risk. In doing so, we identify "hot spots" or geographical clusters where SOVUL varies positively with wildfire risk across six Southern states—Alabama, Arkansas, Florida, Georgia, Mississippi, and South Carolina. These clusters may or may not be located in the WUI. These hot spots are most prevalent in South Carolina and Florida. Identification of these population clusters can aid wildfire managers in deciding which communities to prioritize for mitigation programming.

Keywords Wildland fire risk · Social vulnerability · Environmental hazards · Southeastern U.S. · Geographically weighted regression

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Introduction

The South contained eight of the ten fastest growing counties in the nation, in terms of percentage population increase from 2006 to 2007 (U.S. Census Bureau 2009). Moreover, greater than thirty million acres (12.15 million ha) of forest land in the South are projected to be converted to developed uses by 2040 (Wear 2002). The urban expansion that has already occurred throughout the region has created urban and suburban pockets in the wildland urban interface (WUI) [defined as "the area where houses meet or intermingle with undeveloped wildland" (Radeloff and others 2005), p.799]. This expansion heightens the contrast between rural, forested lands and the urban environment. When such growth occurs either in the short term or over longer time periods, it can destabilize rural community social, cultural, and environmental/ecological structures (Hurley and others 2008; Ghose 2004; Hurley and Walker 2004; Walker and Fortmann 2003; Faulkenberry and others 2000).

Such disruption is seen clearly in controversies involving residential and other constructions in wildfire-prone areas in the interface. Political ecologists charge that the aesthetic preferences of higher income groups for remote woodland living effectively elevate wildfire risks in rural areas. Risks can increase for both those with higher incomes and for more marginal populations living in and around the WUI (Collins 2008a; Collins and Bolin 2009; Rodrigue 1993). Collins (2008a) stresses that the mobility of middle and upper income groups creates disparities between "rich" and poor/working class communities in that state and market institutions such as local fire protection services and insurance act to buffer or insulate affluent WUI migrants from potential losses from wildfire; whereas lower socioe-conomic groups must absorb the increased risks created by growth in the WUI, as the former have fewer means to purchase or command the type of insulation readily available to higher income groups.

Kline and others (2004) addressed this claim indirectly by empirically testing the prevailing assumption that WUI growth had the effect of decreasing timber harvesting and forest management. Their examination of the effects of population growth and urban expansion in western Oregon WUI areas showed negative correlations between WUI development and intensive forest management on private lands. WUI development was associated with reduced thinning, planting, and stocking, resulting in increased fuel loadings. These factors may contribute to increased wildfire risk over time.

We hold the position, however, that more recent migrants to the WUI do not necessarily place undue hardships on place. Research has shown that rural in-migrants can enhance a place's social capital in that migrants oftentimes bring political savvy and organizational skills to rural communities (Fortmann and Kusel 1990). We also do not want to imply that longer-term rural residents, as a class, are "poor but virtuous" protectors of place; or, alternatively, that they lack human agency to effect social or political change, absence newcomers.

Rather than class differences, we maintain that irresponsible development, irrespective of whether this is fueled by wealthier newcomers or longtime residents, in and around wildlands threatens the ecological stability of those areas and burdens the larger society. Still, when this occurs, upper income populations are better insulated than poor people from financial burdens that may occur in the event of natural disaster because of the various forms of human and social capital possessed by the former strata (Lynn and Gerlitz 2006).

We stress that particular attention, in terms of wildfire mitigation and adaptation, should focus on places where socially marginal populations intersect with higher wildfire risk because these populations have the added vulnerabilities of lower capacity; yet poor and working class communities may be less likely than upper income communities to participate in wildfire protection programs. Indeed, research in the U.S. Southwest shows that census block groups (CBGs) comprised largely of lower income Navajo and Apache communities are less likely than majority white CBGs to participate in either state-sponsored grants to effect wildland fire mitigation, community wildfire protection programs, or the Firewise Community program (Ojerio 2008; Ojerio and others 2008a, b). Similarly, a report by the University of Oregon's Program for Watershed and Community Health (2003), p. 5 states: "The current mechanism for decisions about where [wildfire mitigation] grant funds go may favor communities with high value homes, better fire protection services, and, generally higher capacity to implement projects that reduce the risks to homes and communities. High capacity communities have…experience managing grants and programs and past successes in implementing fire protection services." These communities are contrasted with impoverished and lower income areas.

Building on the aforementioned research, we examine the influence of social vulnerability (SOVUL) on wildfire risk in six states in the U.S. South—Alabama, Arkansas, Florida, Georgia, Mississippi, and South Carolina. We estimate ordinary least squares (OLS) regression and geographically weighted regression models (GWR), both of which model wildfire risk as a function of a composite variable, SOVUL.

In the OLS model, we expect an inverse association between wildfire risk and SOVUL. As discussed, well-off populations are spearheading development in amenity-rich, wildlands in the South and elsewhere across the country (Cordell and Macie 2002, p. 20; Collins 2008b; Kline and others 2004; Ghose 2004; Johnson and others 2009; Andreu and Hermansen-Báez 2008).

To contrast, the more nuanced GWR models allow for an examination of possible spatial variation in the association between wildfire risk and SOVUL. GWR models would identify any clusters or sub-regions across the six-state region where the relationship between wildfire risk and SOVUL is positive. This identification is important, as it provides information on those places within a state where marginal increases in SOVUL result in increased fire risk. Again, these areas would be considered the highest wildfire risk class (hot spots) because biophysical risk of wildfire occurrence is compounded by social marginalization.

Wildfire Risk and SOVUL

A number of recent studies suggest that poorer communities or those with lower socio-economic profiles such as those prevalent in rural areas throughout the South would face greater wildfire risks than middle class or affluent communities (Ojerio 2008; Ojerio and others 2008a, b; Lynn and Gerlitz 2006; Mercer and Prestemon 2005). Some argue, even, against the notion of "natural disaster," insisting that all disasters have social origins (Davis 1999; Blaikie and others 2004). For instance, the oft-referenced consequences of Hurricanes Katrina in 2005 and of Gustav and Ike in 2008 in the U.S. South; and mudslides and wildfire devastation of homes in Southern California, are cited as either examples of state abandonment of impoverished persons or human disregard for ecologically sensitive topography and terrain. Both types of scenarios, whether primarily affecting poor or affluent populations, result from inadequate attention to the social roots underlying disaster.

Thus, wildfire occurrence is a type of disaster, which is a function of not only exposure to biophysical hazards, i.e., wildfire prone woodlands, but importantly, is also affected by the sensitivity of social groups to hazards. As Blaikie and others (2004), p. 7 emphasize: "…to understand [biophysical] disasters, we must not only know about the types of hazards that might affect people, but also the different levels of *vulnerability* (original emphasis) of different groups of people. This vulnerability is determined by social systems, not by natural forces."

We are aware of only two studies that have examined individual indicators of social vulnerability and wildfire risk in the South. In Florida, Butry and others (2002) found wildfires to occur more often in areas with higher income, older residents and a higher proportion of whites. These places tended to include privately owned, fragmented forests rather than intensively managed government holdings such as National Forests. Mercer and Prestemon (2005) also found an inverse relationship between poverty and wildfire ignition but a positive association between poverty and area of wildland burned and wildfire intensity, suggesting that once wildfires are ignited, poorer communities have fewer resources to extinguish fire. This latter finding is consistent with our supposition that SOVUL amplifies biophysical risk. It may also be that the relatively lower population densities in poor areas contributes to more areas burned because there are fewer persons or built structures, in an absolute sense, to impede wildfire once begun.

Outside of these investigations, we know of no research examining the association between wildfire risk and social vulnerability in the South despite the fact that social vulnerability pervades rural, forested areas of the region such as the Black Belt (Webster and Bowman 2008; Womack 2007, p. 42). Black Belt counties are defined as those with African–American populations greater than 33% (Wimberley and Morris 1997). The Southern U. S. also accounts for the greatest number of wildfires, when examined in the context of the entire U.S. (National Interagency Fire Center, Wildland Fire Statistics, n.d.). In 2007, 50% of all reported wildfires in the U.S. occurred in the 13 states of the U.S. Forest Service's Southern Region. In 2006, more than 50% of reported wildfires occurred in the South, and 42% of all large wildfires reported were in this region (Andreu and Hermansen-Báez 2008).

Objectives

Study objectives are to:

1. Model wildfire risk as a function of SOVUL
2. Examine possible regional or spatial variation in the relationship between wildfire risk and SOVUL
3. Map any spatial variation in the relationship and locate identifiable spatial clusters

Computation of Dependent and Independent Variables—Wildfire Susceptibility Index (WFSI) and Social Vulnerability (SOVUL)

The analysis was carried out at the CBG level. The CBG is the unit of analysis because it is the finest geographical scale at which both the fire risk data and socioeconomic data are available. Fire risk data are from the Wildfire Susceptibility Index (WFSI) developed by the Southern Group of State Foresters for the Southern Wildfire Risk Assessment (Buckley and others 2006a, b). WFSI incorporates terrain, surface fuels and canopy fuels, historical weather, historical fire occurrence, and fire behavior metrics to calculate a probability value between 0 and 1 (Buckley and others 2006a, b). The WFSI integrates the probability of an acre igniting (based on historical fire occurrence, with expected final fire size based on the rate of spread (ROS) in four weather percentile categories into a single measure of wildland fire susceptibility. Due to some necessary assumptions, mainly fuel homogeneity, it is not the true probability; however, since the value is determined consistently across the entire region, it provides a means for comparison and ordination of areas as to the likelihood of an acre burning.

WFSI includes three primary factors: (1) fire occurrence, (2) fire behavior, and (3) fire suppression effectiveness. Fire occurrence is expressed as a fire ignition rate measured in number of fires/1,000 acres per year as determined from historical fire occurrence records. As compiled for the Southern Wildfire Risk Assessment, the fire occurrence data does not differentiate fires by cause; however, wildfires throughout the South are largely human caused, approximately 93% (Buckley and others 2006a). Buckley and others (2006a, b) employ a roving window technique to generate a raster layer of fire occurrence from the point based fire records. This raster layer has a pixel size of 30 m × 30 m.

The second WFSI component, fire behavior, considers ROS, crown fire potential and flame length across a range of historical weather conditions expressed as low, moderate, high, and extreme conditions. Fire behavior calculations are performed by the FB3.DLL Windows software (commercial software licensed by Fire Program Solutions, LLC). Inputs to the fire behavior calculations such as topography and fuel type are provided as 30 m × 30 m raster layers while the weather conditions are considered uniform over a larger geographic area, referred to as a weather influence zone that are typically county size or larger.

The final component of the WFSI, fire suppression effectiveness, combines information from the historical fire records and the fire behavior calculations. The fire suppression effectiveness compares actual fire sizes to a theoretical fire size based on the fire behavior under steady conditions with no suppression activities. The combination of these three components yields the WFSI as a raster data layer with 30 m × 30 m pixels.

The analysis presented in this study was carried out at the CBG level. The fire risk data as expressed by the WFSI is converted from a 30 m × 30 m pixel raster data set to the CBG level by averaging all WFSI pixels within each CBG boundary.

Social Vulnerability

Data for the SOVUL variable were obtained from the 2000 U.S. Census Bureau's dataset summary file 3 for the CBG level. We included proportion of population below poverty, proportion of population 25 or older without a high school diploma, proportion African American, proportion of housing structures that are mobile homes, and proportion of occupied housing units that are renter occupied. Overall means ($N = 22{,}216$) for each of these variables are in Table 1. SOVUL at the CBG level was constructed by summing the respective proportions.

Our SOVUL index is specific to wildfire risk, as it includes variables that can have a direct bearing on wildfire preparedness, response, and recovery (Ojerio 2008; Ojerio and others 2008a, b). The wildfire and SOVUL literature indicates that variables such as these help distinguish those communities or subpopulations that would be most vulnerable to wildfire in social terms. For instance, persons below poverty and those with lower education levels typically have fewer efficacies in obtaining services or information about environmental protection (Collins 2005; Collins 2008a, b; Collins and Bolin 2009; Lynn and Gerlitz 2006; Program for Watershed and Community Health 2003). Also, race often figures into issues involving services and information access. Majority white, middle, and upper-class communities typically have a greater number of facilities and services compared to poorer, minority areas (Taylor and others 2007; Wolch and others 2002).

As well, mobile homes are less able to withstand natural disasters such as hurricanes because the building material is of lesser durability than constructed dwellings. This may also be the case with fire resistance. Mobile structures are less likely than constructed homes to be made of fire resistant materials (Cutter and others 2003). Finally, renters have less control over building materials, landscaping, fire insurance, or other safeguards against wildland fire, all of which could result in greater vulnerability for these residents (Cutter and others 2003).

Racial status tends to correlate positively with other socio-demographic and economic indicators included in our SOVUL—particularly poverty and education. However, we also believe that the descriptor "African American" or "Black" carries an additional weight beyond that of income or education. This relates to both overt and more subtle forms of discrimination from the larger society and

Table 1 List of socio-economic variables used to create the SOVUL index

Variables	Definition	Mean	Standard deviation
Poverty	Proportion of CBG population below poverty level	0.16	0.13
African–American	Proportion of CBG population African–American	0.26	0.30
Education	Proportion of CBG population with less than a high school education	0.25	0.15
Mobile home residence	Proportion of CBG population with mobile home residence	0.14	0.19
Renter	Proportion of CBG population with in rented housing	0.30	0.23

Correlations among SOVUL variables

	Poverty	African–American	Education	Mobile home residence	Renter
Poverty	1.00	0.63	0.64	0.04	0.56
African–American	0.63	1.00	0.45	−0.10	0.36
Education	0.64	0.45	1.00	0.26	0.30
Mobile home residence	0.04	−0.10	0.26	1.00	−0.28
Renter	0.56	0.36	0.30	−0.28	1.00

Cronbach alpha = 0.60

also to self-imposed racial segregation which continues defacto racial separation.

Each of the variables comprising SOVUL was selected based on a careful review of the SOVUL and disaster literature (Cutter and others 2000; Cutter and others 2003; Cutter and others 2009), much of which was specific to wildfire hazard (Lynn and Gerlitz 2006; Program for Watershed and Community Health 2003; Ojerio 2008; Ojerio and others 2008a, b; Collins 2005; Collins 2008a, b; Collins and Bolin 2009). From these studies we distilled the most consistent indicators of either SOVUL or a related concept—community capacity—that would bear on community efficacy. These are, again, poverty, race/ethnicity, education, homeownership, and condition of dwelling unit.

Because certain of these variables (race, education, income in particular) tend to correlate highly, we checked for multicollinearity among SOVUL variables using the variance inflation factor. The aim was to see whether standard errors were inflated, which could indicate multicollinearity. VIF factors were all less than three, which indicates low or moderate multicollinearity (Freund and Wilson 1998).

We assessed reliability of the index with coefficient alpha (Hatcher and Stepanski 1994, pp. 506–516). Coefficient alpha for SOVUL was 0.60 (raw variables), an acceptable reliability score for the social sciences (Hatcher and Stepanski 1994, p. 513) (Table 1). The raw score increases to 0.72 with the elimination of the mobile home variable. However, we retain it in the scale because it is a reliable indicator of housing quality, which can be an important wildfire deterrent. It appears that the race indicator (proportion black), education, poverty, and renter are measuring one dimension of vulnerability while mobile home residence may indicate another.

Convergent validity of SOVUL was assessed by examining the association between poverty and a version of the SOVUL index that did not include poverty (Hatcher and Stepanski 1994, pp. 331–332). Because the proportion of the population below poverty, alone, is a very defensible indicator of SOVUL as conceptualized in this article, we use it as a benchmark against which alternative assessments of SOVUL may be assessed. The correlation between SOVUL without poverty and SOVUL (with poverty) is 0.78, which indicates a strong correlation between these measures of SOVUL and hence lends validity to the SOVUL index.

Although SOVUL does not include other variables such as gender or age, we submit that it sufficiently captures the effects of these variables. For instance females, especially female-headed households, are more socially vulnerable because they are more likely than others to live in poverty. Historically, education levels also distinguished males and females, with males typically having more education. To account for gender differences resulting from educational differences, we also include education as a factor in the index.

We normalized the SOVUL because the raw SOVUL values among different CBGs would be inconsistent and therefore could bias the analysis. Following Wood and others (2010), we first normalized the individual census variables that composed SOVUL and then summed the normalized values to get the SOVUL for the analysis.

Model

Model estimation began with an examination of the linear relationship between wildfire risk (WFSI) and SOVUL using OLS. The regression model was specified as follows:

$$y_i = \beta_0 + \beta_1 x_i + e_i \tag{1}$$

where, y_i is wildlfire risk for the ith CBG of a given state, and x_{i} is SOVUL for the ith CBG of that state. Similarly, β_0 is the constant and β_1 is the coefficient to be estimated for SOVUL and e_i is the stochastic error term. We conducted a likelihood ratio test to see whether a pooled OLS regression for the region would fit better than separate regressions for individual states. The test statistic allowed us to reject the null hypothesis that the parameters were the same across the states (LR = 49662, df = 10, $P < 0.001$), suggesting that including a dummy state variable would not be sufficient to explain spatial variation.

Ordinary least squares is a global model, as it assumes that the estimated beta value or the relationship between dependent and independent variables holds the same everywhere within a given geographical range. To determine whether there is spatial variation within a given state, we employ a local (GWR) model that provides a SOVUL regression coefficient (beta) for each CBG within the state. These estimates allow us to compare the sign and size of coefficients among CBGs to see if the relationship holds the same everywhere.

The second stage involved estimating a GWR model (Fotheringham and others 2002). The GWR is a modified version of Eq. 1 as shown below:

$$y_i(u_i, v_i) = \beta_0(u_i, v_i) + \beta_1 x_i(u_i, v_i) + e_i(u_i, v_i) \tag{2}$$

where (u_i, v_i) represent the spatial location or the geographic coordinates of an observation (i.e., CBG). In our case, u_i and v_i are, respectively, the longitude and latitudes of the centroids of the ith CBG of a given state. The GWR fits this model to a group of observations near a given CBG, thereby yielding a separate parameter estimate for each CBG. In addition to separately estimating parameters for each observation, GWR puts more weight on observations nearer the ith CBG than those farther away. Note that the global regression model discussed above (OLS) neither allows parameters to vary over space nor accounts for geographical weighting, and therefore can estimate only a single parameter for the entire study area (for a state, in our case).

Regression coefficients estimated from the OLS model is given by Eq. 3.

$$\hat{\beta} = \left(X'X\right)^{-1}X'Y. \tag{3}$$

In contrast, the coefficients estimated from the GWR (Eq. 2) are given by

$$\hat{\beta}(u_i, v_i) = \left(X'w(u_i, v_i)X\right)^{-1}X'w(u_i, v_i)Y \tag{4}$$

where, $w(u_i, v_i)$ is the n x n spatial weight matrix that is unique for each observation or data location (i.e., CBG). While estimating the parameter for the ith location, the ith point itself gets the weight of one; whereas the weight attributed to other observation points (say the jth point), depends on the distance of that jth point from the ith point and a bandwidth.

The bandwidth, which helps define the optimal number of neighbors (i.e., CBGs), is either purposively set by the analyst or calculated through a cross-validation process. We used a cross-validation approach for this purpose. Details about this approach can be found in Fotheringham and others (2002). The idea of the weighting scheme is that weight values assigned to observations (CBGs) farther away from the ith point gradually decrease and become zero for those beyond a certain distance. As the standard errors are also estimated for each observation, t tests can be used to test the statistical significance of location specific parameters. This also allows selecting only the parameters that are statistically significant and appropriate for mapping.

For each state, both the OLS and GWR models were estimated. Local regression coefficients for a given CBG were paired with the CBG location (latitude, longitude) to carry out a test of spatial variability of parameters. This is also called the test of spatial non-stationarity. A spatially non-stationary variable means that it does not stay the same over space. This test uses a Monte-Carlo simulation technique to compute the experimental significance level that can confirm whether the observed variation in the parameter is just by chance. The test is based on Hope (1968) and is available with the GWR 3.0 program (Fotheringham and others 2002).

Results

Table 2 presents results from the global, OLS regressions for each state and the region as a whole. Regression coefficients were statistically significant at the 5% level for the whole region and all states except Alabama and Mississippi. Also, there was some variation among the states in terms of the significance, size and sign of SOVUL. For example, in South Carolina SOVUL had a positive effect on wildfire risk, WFSI; whereas the effect was opposite in the remaining states. The global model thus shows an interstate difference in the relationship between these two variables. Comparison of OLS coefficients among the states shows that Florida, Arkansas, and Georgia exhibited remarkably stronger evidence for negative relationships between fire risk and SOVUL compared to Mississippi and Alabama. South Carolina had a more direct relationship between these two variables. This suggests that wildfire risk in South Carolina communities is more sensitive to SOVUL; but overall, OLS results support our supposition that the statewide association between SOVUL and wildfire risk is negative.

A summary of GWR results for each state is presented in Table 3. The adjusted R-Square indicates that the model fits well in each state. The table also shows five variables summarizing coefficients for the parameter estimates for a given state—minimum, lower quartile, median, upper quartile, and maximum values. These statistics allow a comparison of minimum and maximum parameter values in each state, which show how greatly the coefficient varies within the state and help explain the spatial variation in the relationship.

An F-test was conducted to see whether employing the local model (GWR) improved the analysis and results over the OLS global model. F-test results are presented in Table 4. Statistically significant F-tests for each state permit us to reject the null hypothesis that there is no improvement of the GWR model over the OLS one. The strongest F-test value is for the Florida data. This test supports our use of a locally weighted regression model here.

In addition, a test of non-stationarity was conducted using a Monte-Carlo simulation test of significance; results are also presented in Table 4. Highly significant test

Table 2 Region and statewide OLS regression coefficients: WFSI regressed on SOVUL (Global model)

S.No.	State	OLS coefficient	T ratio	Number of CBGs
1	Alabama	−0.000060	−1.234259	3329
2	Arkansas	−0.000525	−5.020923**	2069
3	Florida	−0.002904	−7.768543**	9088
4	Georgia	−0.000163	−2.054058***	4788
5	Mississippi	−0.000061	−1.532636	2147
6	South Carolina	0.000962	8.642123**	2858
7	Southeast Region	0.003343	−19.140000**	22216

Significant at 1% (***) and 5% (**) level, respectively

Table 3 State-wise summary of coefficients from the GWR regression (Local model) of wildfire risk against SOVUL

State	Model goodness of fit	Coefficient summary				
	Adj. R-square	Minimum	Lower quartile	Median	Upper quartile	Maximum
Alabama	0.49	−0.00129	−0.00011	−0.00002	0.00006	0.00404
Arkansas	0.31	−0.01058	−0.00027	−0.00008	−0.00000	0.00736
Florida	0.55	−0.02154	−0.00366	−0.00167	−0.00013	0.02659
Georgia	0.47	−0.00306	−0.00032	−0.00007	−0.00000	0.00768
Mississippi	0.43	−0.00098	−0.00011	−0.00001	−0.00019	0.00211
South Carolina	0.46	−0.00275	−0.00030	−0.00009	0.00055	0.00397

Table 4 Results from F-test for GWR improvement and Monte-Carlo simulation test for spatial variability of coefficients

	States	F-test statistic	Monte-Carlo test
1	Alabama	32.911***	0.000***
2	Arkansas	10.266***	0.000***
3	Florida	120.277***	0.000***
4	Georgia	44.946***	0.000***
5	Mississippi	18.076***	0.000***
6	South Carolina	24.977***	0.000***

*** Significant at 1% level

parameters again allow us to reject the null hypothesis that the spatial variation in the parameters is insignificant, suggesting that the relationship between wildfire risk and SOVUL varies over space in each state.

Census block group regression coefficients estimated by GWR are mapped in Figs. 1 through 6. Readers interested in detailed maps with additional reference layers may get maps from the first author. Figure 1 shows that in Alabama, there are few portions of the state with a significant association between WFSI and SOVUL. A group of CBGs slightly northwest of Birmingham (marsh red cluster near cities of Jasper and Cordova, not labeled). There are a few more red CBG clusters along the Mississippi and Florida border around the Mobile Bay area in the southwestern corner exhibiting a positive effect of SOVUL on wildfire risk. Communities along I-65 north of Mobile (in dark navy blue color) exhibited a cluster of significant and negative relationship between SOVUL and wildfire risk.

In Arkansas, clusters were located in the northern portion of the state, along the Missouri border (Fig. 2). The cluster around Mountain Home, Bull Shoals Lake, and Buffalo River State Park (cities not labeled) was quite significant revealing a positive relationship between SOVUL and WFSI. Communities north of the Ozark National Forest and east of Fayetteville, including Berryville, Eureka Springs (not labeled) formed the clusters with a significant and negative relationship. A similar cluster was forund in the Northeast that included communities such as Pocahontas and Maynard (not labeled).

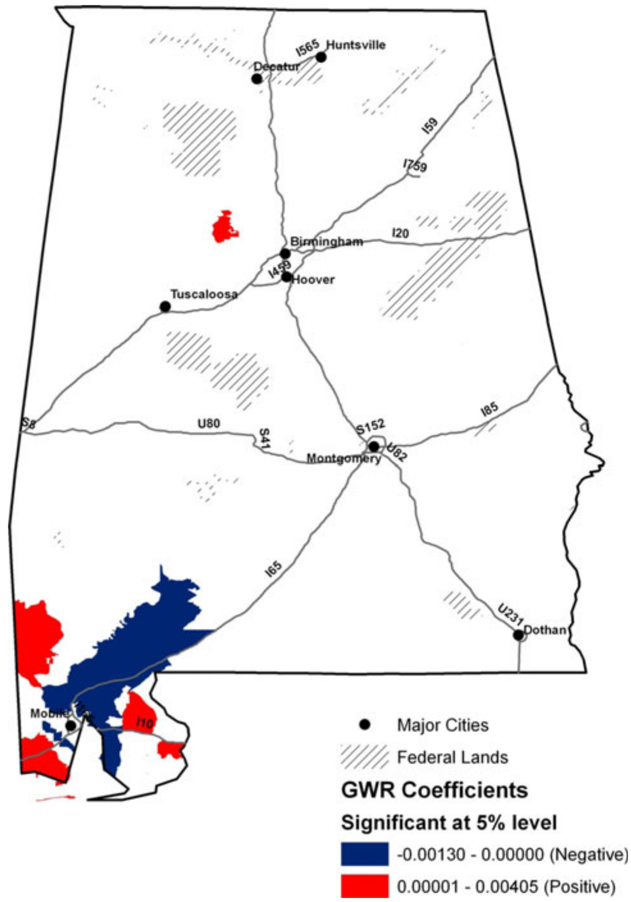

Fig. 1 Geographically weighted regression clusters for Alabama

The coefficients in Florida varied from as low as −0.021, mostly along the Eastern bay of the peninsula portion of the state and the portion in between Cape Coral and West Palm Beach (in dark blue), to as high as 0.027 in the Western portions of the peninsula and communities around Lake Okeechobee (in marsh red) (Fig. 3). Notably, the relationship is significant primarily in the peninsular portion of the state. CBG clusters around the Spring Hills areas, west of I-75; rural areas west of Port St. Lucie, the Ockechoobee area, and rural areas east of Naples around state and federal land areas exhibit a positive effect of SOVUL on WFSI.

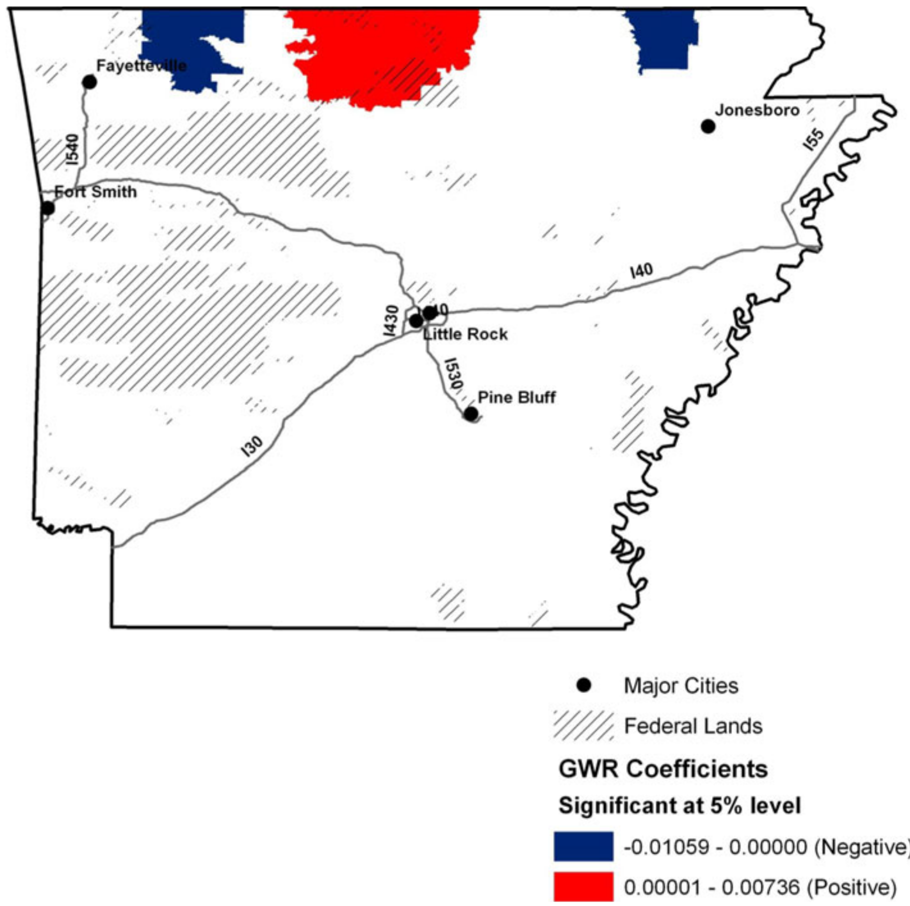

Fig. 2 Geographically weighted regression clusters for Arkansas

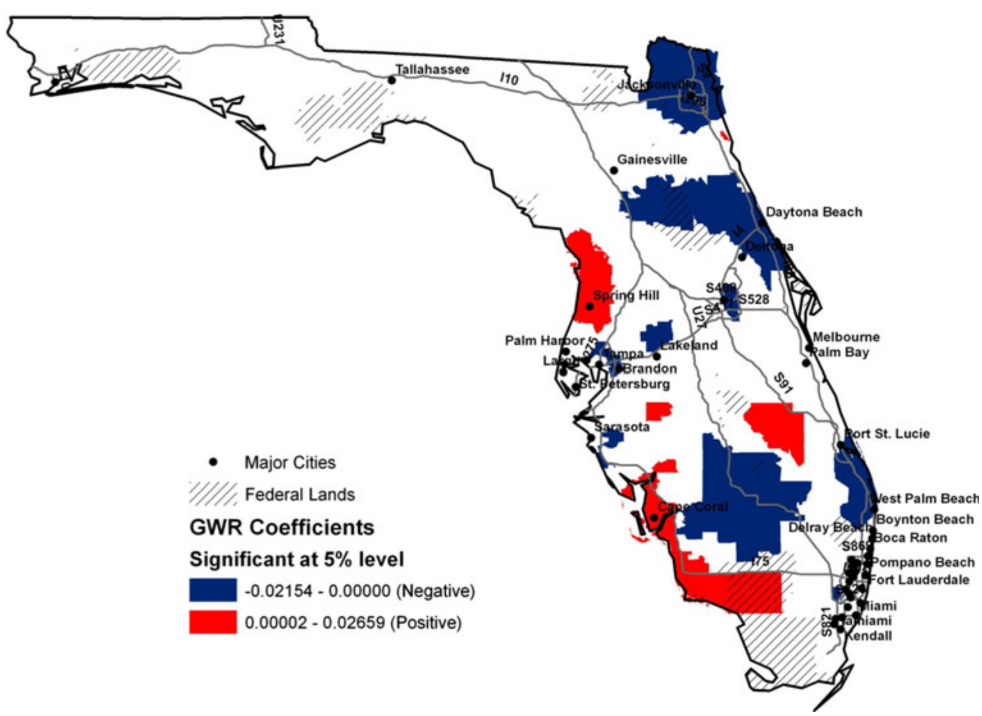

Fig. 3 Geographically weighted regression clusters for Florida

Larger groups of CBGs near Jacksonville, Daytonna Beach, and south of Gainesville stretching along the Ocala National Forest, West Palm Beach, and the area north of Everglades National Park reveal a negative relationship between the variables. In general, a positive effect of SOVUL on fire risk was more evident in CBGs located in relatively rural areas, whereas the negative effect was observed around urban areas in the state (with the big dark blue cluster, north of the Everglades as an exception), which is not surprising.

In Georgia, the regression coefficient value ranged from −0.0030 to 0.0077 (Fig. 4). There are two big CBG clusters showing positive coefficients. The first one lies in the north-central part of the state stretching down from the Tennessee border to Canton (near Atlanta). The other one lies in the southeastern part and includes areas like Jesup, Brunswick, and Hinesville (not labeled). Again, these are the areas where wildfire risk is highly sensitive to SOVUL. Three remarkable clusters of CBGs with a negative relationship were observed in the state. Those included areas between I-20 and I-75 in the northwestern corner, areas along I-85, east of highway 441 in the northeastern part, and communities along the South Carolina border just north of Savannah.

Interestingly, most of the CBGs with significant interaction between wildfire risk and SOVUL in Mississippi lie south of Interstate I-20 (Fig. 5). CBGs with a positive relationship between WFSI and SOVUL form big clusters in communities surrounding the Homochitto National Forest. Red clusters are also seen just Southwest of Bienville National Forest, in communities in and around Raleigh, Mendenhall, and Magee; and in some rural communities in between Interstates I-59 and I-10 in the southern end of the state. This cluster and a similar group of CBGs near Gulfport encompass rural, poor communities. Other positive clusters were found just Northwest of the Holly Springs National

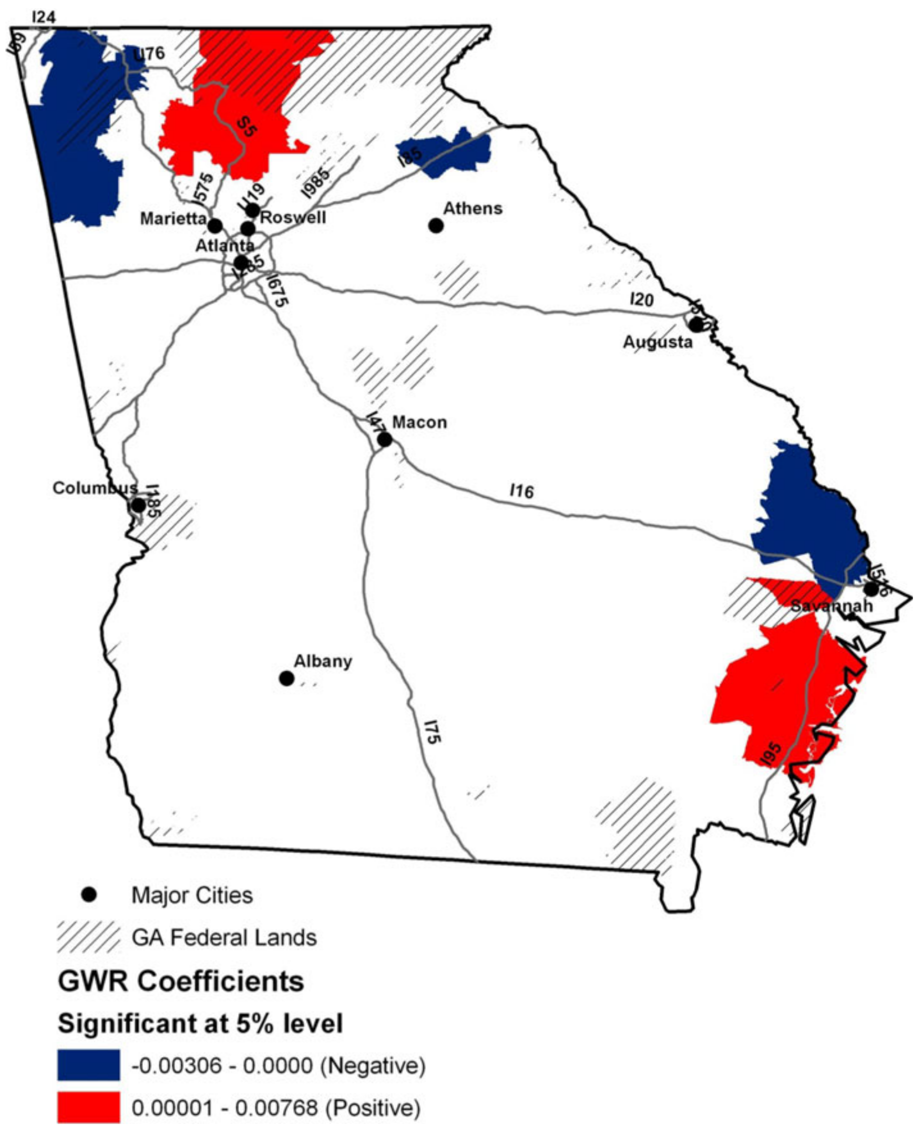

Fig. 4 Geographically weighted regression clusters for Georgia

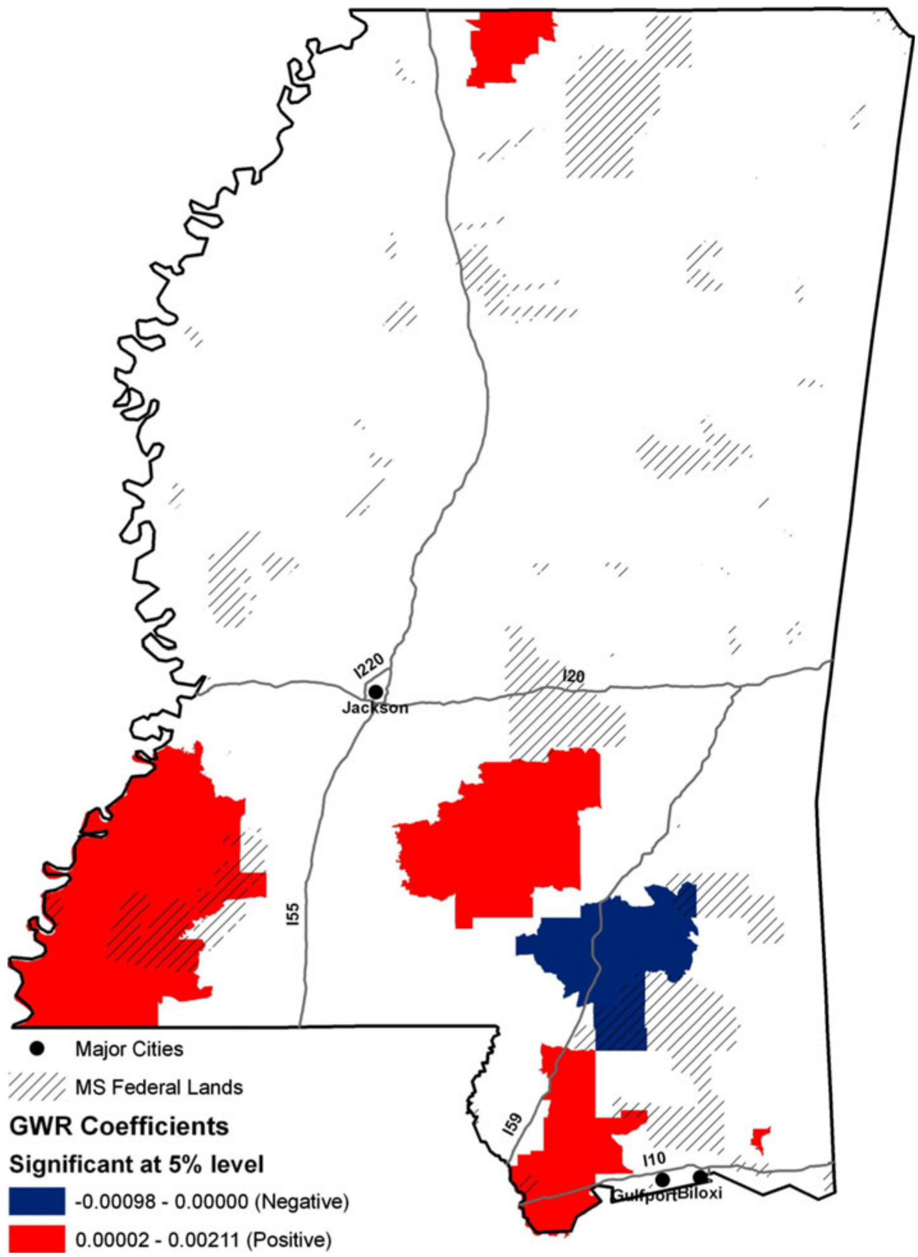

Fig. 5 Geographically weighted regression clusters for Mississippi

Forest in the north along the Tennessee border. These areas include suburban communities of Memphis including Byhalia, Mt. Pleasant and Olive Branch.

In contrast, CBGs with a negative relationship between fire risk and SOVUL were found in relatively developed or urbanizing areas as along the city of Hattiesburg and surrounding agricultural communities. This is consistent with our previous observation in Florida, where relatively rural areas exhibited positive and relatively urban areas exhibited negative associations.

In South Carolina (Fig. 6), significant clusters reveal some noteworthy observations. First, CBGs with statistically significant interaction between fire risk and SOVUL lie mostly in the eastern half of the state. Second, results for this state differ from the other five states because the amount of land area with a significant and positive relationship between wildfire risk and SOVUL exceeds areas with a negative relationship. Third, areas with a negative relationship were found around the Florence area. Fourth, the areas with a positive relationship were mostly found near the coastal areas in the east (mostly to the east of I-95). A wide and long cluster stretching from Savanna to Myrtle Beach showed a positive relationship between WFSI and SOVUL. There were some other notable clusters in the urbanized areas near Columbia, Savannah, Florence, and Augusta, Georgia.

Ecological fallacy is a concern when analyzing relationships between aggregate data, like those in this study.

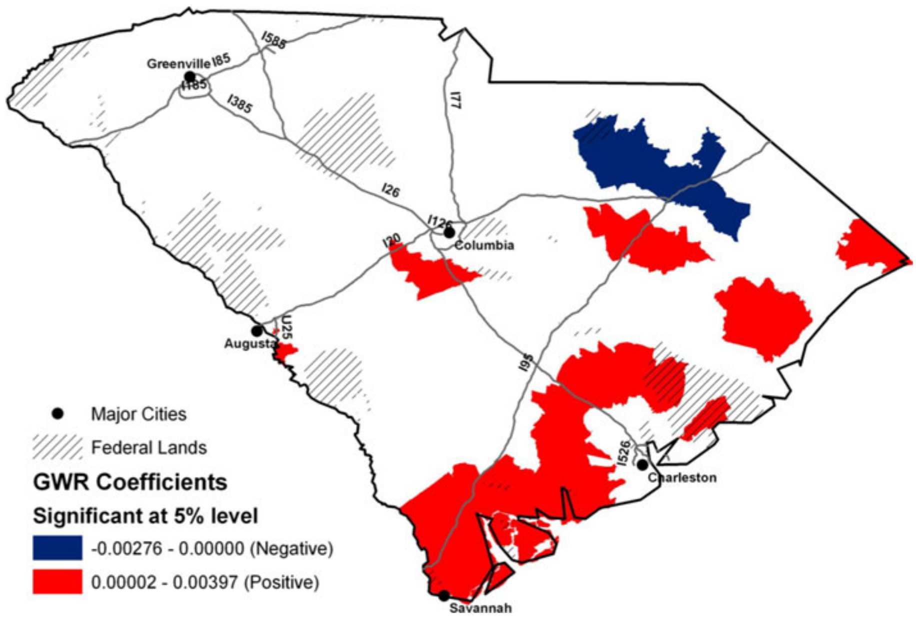

Fig. 6 Geographically weighted regression clusters for South Carolina

To check whether the statistics hold constant among different scales, we ran the regression analysis at two additional levels, the census tract and county level in Alabama (insignificant relationship at CBG level) and South Carolina (significant relationship at CBG level). In both states, the relationship seen in the CBG level analysis was consistent with results from the census tract and county level analysis, suggesting that the implication of our results would be the same regardless of the scale of analysis. We presented the CBG level analysis because this would allow us to map the relationship and potential hotspots at the finest level possible.

Conclusion

Rural areas in the United States and elsewhere face increasing pressure from human induced disturbances (Radeloff and others 2005). Although wildfire risk counts among these concerns, we know little about how the socioeconomic well-being of local people interacts with wildfire in wildland proximate areas. Empirical findings from this study shed some light on this relationship and offer some important policy implications that are relevant in wildfire management, land management, and forestry.

Consistent with Mercer and Prestemon (2005) and Butry, Pye, and Prestemon's (2002) results for Florida, findings generally show an inverse association between wildfire risk and SOVUL for all states except South Carolina. However, as the analysis moved beyond the simple regression models and adopted a spatially varying parameter model, it successfully detected local level variation between wildfire risk and SOVUL. The GWR model confirmed that the relationship varies by location, which demonstrates that the negative relationship does not hold everywhere; that is, in states where there is an overall inverse relationship between wildfire risk and SOVUL, we locate some areas within these states where SOVUL interacts positively with wildfire risk.

Identified hot spots could be targeted by state and federal agencies to implement community-based wildfire mitigation initiatives such as Community Wildfire Protection Plans (CWPPs), Firewise USA communities, or other mitigation programming; as these communities must contend with both biophysical and social risk factors. We suspect that community-level mitigation programs such as Firewise and CWPPs would be more prevalent in middle and upper income communities. Conversations with state fire managers in Florida, for instance, stressed that the state provides extensive wildfire mitigation information and programming; but that managers oftentimes encounter residents in fire-prone wildlands who demonstrate indifferent attitudes towards mitigation because of the false belief that their properties would not be affected by wildfire. We acknowledge such frustrations but counter that managers should also be cognizant of the differential capitals (human, social, financial) possessed by communities. In some cases, the synergy of higher skill, education, and income levels combine to insulate communities from fire risk; whereas other communities, struggle with complacency and also lack of information and services.

Along these lines, Florida wildland fire managers have expressed an interest in assessing constraints residents face in becoming more involved in community wildfire mitigation programming and planning. A next phase in this research effort would be to coordinate with state forest managers in specific "hot spot" communities across the South to identify barriers or constraints to more effective resident engagement with existing wildland fire mitigation programming and to solicit ideas on resident methods of mitigating the same.

The University of Oregon's Center for Watershed and Community Health (CWCH) provides some guidelines for assisting poor, rural communities in developing mitigation plans (in the Pacific Northwest) (Program for Watershed and Community Health 2003). Ojerio (2008); Ojerio and others (2008a, b) provide similar strategies. CWCH recommends mapping the relationship between poverty and wildfires by identifying poverty distributions within a geographical area; identifying community capacity, in terms of insurance and fire protection; and pairing these with estimates of actual wildfire risk. Also, participatory community mapping can identify where mitigation services appear on the ground. Ojerio (2008), Ojerio and others (2008a, b) stress the need for collaboration between fire mitigation planning and available social services. Social service agencies could provide useful information about socially vulnerable populations and how best to engage them; these agencies could also suggest alternative methods of contacting poor communities, such as working through religious organizations.

A crucial component of mitigation planning is funding. Without financial or technical aid, poor communities may find it difficult to implement strategies. Ojerio (2008), Ojerio and others (2008a, b) suggest drawing from indirect sources, not specific to wildfire mitigation, when direct funding is not available, for instance, the Federal Emergency Management Agency grants for evacuation or mapping.

Specific objectives for our research team would be to map the intersection of socially vulnerable populations, wildfire risk, and mitigation programs (Firewise, CWPPs, state and federal grants) for all of the 13 Southern states (Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, and Virginia). This information could be incorporated into future wildfire assessments in the southern U.S., thus contributing a valuable social science dimension to this effort.

Lastly, a few caveats should be noted. First, the fire risk data we used did not distinguish between risks caused by human activities or other anthropogenic sources from natural sources. Second, while we used an index variable to minimize the problem with the mutlicollinearity issue, other issues may have some effects. Regarding normality, we checked for outliers, and less than 1% of the observations had outliers, which we assumed did not affect our results substantially. We found that the OLS model suffered from spatial autocorrelation. However, we discuss our results from the GWR model which itself is a locally weighted regression that uses a moving window approach to identify local sub-samples of observations and computes coefficients for every observation unit (i.e., CBG). In defining the neighborhood sample of a given CBG, the model provides higher weight to nearby observations than those farther away, and is therefore expected to control for inherent spatial interactions. It should be noted that the GWR model improved the spatial autocorrelation substantially. For example, the magnitude of Moran's I was reduced by 41% (Arkansas), 40% (Georgia), 34% (Florida), 48% (Mississippi), 46% (South Carolina). While we suspect there could still be some spatial interaction remaining even in the GWR residuals, we assume the effect may be very minimal. Correcting this in a GWR framework is rather complicated and none of the spatial econometrics software is currently capable of handling this. There are a handful of user-written codes available, but they are still in the alpha or beta version at this time; and their reliability is yet to be well-established in the spatial econometrics literature.

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