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Neighborhood characteristics and depressive symptoms of older people: Local spatial analyses

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ABSTRACT

Depressive symptoms in community-dwelling older people significantly increase the risk of developing clinically diagnosable depressive disorders. Knowledge of the spatial distribution of depressive symptoms in the older population can add important information to studies of neighborhood contextual factors and mental health outcomes, but analysis of spatial patterns is rarely undertaken. This study uses spatial statistics to explore patterns of clustering in depressive symptoms using data from a statewide survey of community-dwelling older people in New Jersey from 2006 to 2008. A significant overall pattern of clustering in depressive symptoms was observed at the state level. In a subsequent local clustering analysis, places with high levels of depressive symptoms near to other places with high levels of depressive symptoms were identified. The relationships between the level of depressive symptoms in a place and poverty, residential stability and crime were analyzed using geographically weighted regression. Significant local parameter estimates for the three independent variables were observed. Local parameters for the poverty variable were positive and significant almost everywhere in the state. The significant local parameters for residential stability and crime varied in their association with depressive symptoms in different regions of the state. This study is among the first to examine spatial patterns in depressive symptoms among community-dwelling older people, and it demonstrates the importance of exploring spatial variations in the relationships between neighborhood contextual factors and health outcomes.

Introduction

The prevalence of elevated depressive symptoms among community-dwelling older people in the United States ranges from 8% to 16% (Berkman et al., 1986; Blazer, Burchett, Service, & George, 1991; Stallones, Marx, & Garrity, 1990; Steffens, Fisher, Langa, Potter, & Plassman, 2009). These symptoms increase the risk of developing clinically diagnosable depression as well as the likelihood of experiencing other functional impairments and comorbidities (Beekman, Deeg, Braam, Smit, & Van Tilburg, 1997; Schäfer et al., 2010; Unützer et al., 2000). The overwhelming majority of research studies focus on understanding predictors of depressive symptoms such as an individual's age, gender, race, socioeconomic status, and functional abilities. In the past decade, recognition that factors such as socioeconomic status also have social dimensions directed attention toward examining the ways in which characteristics of the environment, most notably the neighborhoods where people live, affect depressive symptoms.

Reviews by Truong and Ma (2006), Kim (2008), and Mair, Diez Roux, and Galea (2008) consistently find evidence that better neighborhoods are associated with better mental health in the general population and that neighborhood characteristics retain their significant association with depressive symptoms even after accounting for individual characteristics. The extent to which these findings reflect the situation for older people remains unclear. Yen, Michael, and Perdue (2009) suggest that neighborhood characteristics should have even greater salience for older people because, compared to younger people, they spend more time during the day in their neighborhoods. Yet, empirical studies have yielded conflicting reports, with some finding evidence for significant independent variation in mental health due to neighborhood poverty controlling for individual characteristics (Everson-Rose et al., 2011; Kubzansky et al., 2005; Ostir, Eschbach, Markides, & Goodwin, 2003) while others find that contextual effects were mitigated when individual characteristics were controlled (Aneshensel et al., 2007; Hybels et al., 2006).

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The majority of studies linking depressive symptoms and neighborhood characteristics have been atheoretical, although three distinct conceptual models have attempted to explain the mechanisms by which neighborhood characteristics affect mental health. Detailed by Truong and Ma (2006), these models focus on structural characteristics, neighborhood disorder, and environmental stress. The structural characteristics model focuses on the characteristics of the population living in an area, such as the percentage of residents living below poverty, their ethnic distribution, percentage of female-headed households, and the rate of population turnover. The neighborhood disorder model posits that indicators of physical (e.g., dilapidated houses, abandoned buildings, vandalism, and litter) and social incivilities (e.g., public drunkenness, corner gangs, street harassment, drug trade, and noisy neighbors) cause depressive symptoms to increase. The environmental stress model examines the balance between the stressors to which people in a geographic area are exposed (e.g., crime) and the resources to which they have access (e.g., health services). However, the mechanisms by which neighborhood characteristics influence the depressive symptoms experienced by older people remain undefined.

Multilevel modeling has been the main analytical technique used in research examining the relationships between neighborhood characteristics and depressive symptoms (Mair et al., 2008), and is has contributed significantly to our understanding of the importance of neighborhood contextual effects. Studies using multilevel methods have yielded modest, but consistent evidence that neighborhood conditions, particularly neighborhood socioeconomic status, significantly influences the health of older adults (Yen et al., 2009).

Multilevel modeling analyses have made research on health more geographic, by placing individuals in defined neighborhoods and accounting for conditions in those places. Research using local spatial statistical methods enables us to investigate spatial variability in neighborhood conditions, in health outcomes, and in the relationships between neighborhood conditions and outcomes across areas. Although the presence of spatial autocorrelation in neighborhood-level socioeconomic status has important conceptual and methodological consequences (Chaix, Merlo, & Chauvin, 2005; Chaix, Merlo, Subramanian, Lynch, & Chauvin, 2005), testing for spatial clustering of neighborhood characteristics and associated spatial dependences or spatial lag effects is not elemental to multilevel models. It is known, for example, that areas of low socioeconomic status are often geographically clustered (Dorling & Pritchard, 2010; Holt, 2007; Orford, 2004), and that significant spatial autocorrelation biases parameter estimates unless it is accounted for. Addressing this issue, spatial statistical analysis can provide more accurate standard error estimates of risk factor effects for neighborhood conditions and health outcomes. The need to examine dependencies across groups in multilevel analyses, including spatial dependencies, has been recognized as an important issue in advancing research on multilevel determinants of health (Diez Roux, 2008).

There is a growing trend toward more spatially extensive research in health social science, evidenced by research that draws data from many communities at the same time. With this trend, there is increased interest in understanding spatially varying processes in health (Congdon, 2011; Holt & Lo, 2008; Nakaya, Fotheringham, Brunsdon, & Charlton, 2005). Using global and local statistics can lead to a completely different level of insight into area-level characteristics and health outcomes (Fotheringham, Brunsdon, & Charlton, 2002). So-called "global" statistics summarize data for entire study areas such as cities, provinces, or countries. Local statistics summarize data for individual places within these larger study areas. Two types of local spatial analysis are especially relevant to research on depressive symptoms in the elderly: 1) local clustering analysis to establish that significant local patterns in depressive symptoms exist, and 2) geographically weighted regression analysis to investigate whether the associations between area characteristics and depressive symptoms vary from place to place.

Spatial clustering analysis is widely used in health geography and epidemiology, but its application to the study of mental health conditions is limited. Few studies have addressed the issue of spatial clustering and neighborhood effects for depressive symptoms among older people. Yet, research has often uncovered differences in spatial patterns of different types of mental health problems. In a study of Nottingham residents who were 15–59 years of age diagnosed with schizophrenia, affective psychosis, or non-psychotic mental disorders, standardized incidence rates and Poisson probabilities were mapped revealing significant "polynuclear" patterns (clusters) (Giggs, 1986). Clusters of areas with high rates were observed in both central city neighborhoods and in suburban areas. Geostatistical modeling to compare spatial patterns in mental disorders due to psychoactive substance use and neurotic disorders among all persons aged 40 to 69 residing in Malmö, Sweden, revealed that the disorders exhibited different spatial distributions. Mental disorders due to substance use showed greater neighborhood variation than neurotic disorders (Chaix et al., 2006). Further, the relationships between neighborhood characteristics and mental health were variable. Individual risk of substance use disorders was associated with measures of neighborhood deprivation and neighborhood social disorder, but only neighborhood deprivation was associated with neurotic disorders (Chaix et al., 2006).

These studies provide the rationale for research using local spatial statistics to explore depressive symptoms in older adults. Cluster analysis to understand where there are concentrations of individuals with depressive symptoms is important to the design of improved service delivery and intervention studies. When individuals in need of services are clustered in large numbers in particular communities, it may be easier and less expensive to deliver services to them because of the large number of potential clients to support services. When individuals in need of services are isolated and spread across a number of communities, it may be more difficult to identify people in need of services. Different service delivery strategies might be needed if the local population is too small to support a local service program without subsidy requiring people in need of service to travel for care. The approach to treatment itself, individual versus group therapy, for example, might be influenced by the geographic pattern of need.

Interventions to address depressive symptoms by focusing on employment, housing, poverty, and violence have been tested, although they are few in number (Gottlieb, Waitzkin & Miranda, 2010). Analyses of spatially varying processes can yield important information for intervention design by showing whether the factors associated with depressive symptoms themselves vary across communities, suggesting that interventions need to be tailored to communities. An important issue in evaluating interventions is assessing efficacy and effectiveness. The efficacy of interventions is tested in particular contexts. A deeper level of understanding of spatial variability in the role of contextual factors can help us more properly evaluate where an intervention may be successful by helping us to identify the appropriate places to target specific types of interventions.

In this study, we used local statistics to identify local clusters of places in New Jersey where older people report high or low levels of depressive symptoms. We sought to answer three main research questions: 1) is there evidence of spatial clustering in depressive symptoms among older community residents in New Jersey? 2) where are clusters of older people with high or low levels of depressive symptoms found? 3) do the relationships between depressive symptoms and neighborhood-level characteristics vary across places? We predicted that older people with depressive symptoms cluster geographically. Our analysis focuses on two neighborhood structural characteristics (percentage of people living in poverty and residential stability) and one indicator of incivility (crime), selected based on conceptual and empirical work pointing to their association with depressive symptoms (Aneshensel et al., 2007; Curry, Latkin, & Davey-Rothwell, 2008; Kubzansky et al., 2005; Ostir et al., 2003). We extend previous work seeking to understand how rates of poverty, residential stability, and crime explain variance in depressive symptoms by hypothesizing that relationships between depressive symptoms and these neighborhood conditions vary spatially.

Methods

Sample

The sample for the study was drawn from the ORANJ BOWL℠ (Ongoing Research on Aging in New Jersey – Bettering Opportunities for Wellness in Life) panel that includes 5688 people, who completed interviews between November, 2006 and April, 2008. The ORANJ BOWL protocols were reviewed and approved by the University of Medicine and Dentistry of New Jersey's Institutional Review Board. Eligibility criteria for inclusion required that participants be between the ages of 50 and 74, living in New Jersey, and able to participate in a 1-h English language telephone interview. Panel members were recruited by telephone cold calling using list-assisted random-digit-dialing (LA-RDD) procedures. Coverage of residential POTS numbers for sample population represented by the panel's sample is estimated as 95%. The demographics of this sample make coverage loss very small due to the growing incidence of cell phone-only households (Blumberg & Luke, 2007). Based on American Association for Public Opinion Research standards, ORANJ BOWL achieved a response rate of 58.76%, and a Cooperation Rate of 72.9%, rates consistent with or higher than the average response rates in RDD efforts during this same time.

Comparison of characteristics of ORANJ BOWL respondents with those of all persons age 50-74 living in New Jersey reveals that they have similar racial composition, rates of being born in the state, and marital status distributions. The ORANJ BOWL sample has a slightly higher proportion of females (63.7%–53.3%) and a slightly higher percentage of individuals with advanced secondary degrees (18.5%–14.8%). It under-represents persons of Hispanic descent, as participants were restricted to those fluent in English (Pruchno, Wilson-Genderson, Rose, & Cartwright, 2010).

For the purposes of the analyses that follow, 134 ORANJ BOWL participants were excluded from the sample because they were missing data for one or more variables used in the study, including census tract of residence and depressive symptoms. Based on the remaining 5554 participants included in the sample, there were 1355 census tracts in the state with at least one ORANJ BOWL participant out of a total of 1994 land-area census tracts from the 2000 census.

Measures

Residential location

Residential locations were coded at the census tract level. Because the ORANJ BOWL surveys were conducted from 2006 to 2008, census tracts defined for the 2000 census were used.

Depressive symptoms

Other studies investigating spatial patterns and processes in mental health outcomes have relied on data from the medical care system to assess mental health status (Chaix et al., 2006; Giggs, 1986). These studies acknowledge that differential access to mental health care and patterns of diagnosis may influence the patterns of health outcomes observed. In contrast, the measure of depressive symptoms used in our research was derived from self-report using the 10-item short form of the Center for Epidemiologic Studies Depression Scale (CES-D) (Andresen, Malmgren, Carter, & Patrick, 1994). Each item was scored on a four-point scale ranging from none of the time (0) to most of the (3) yielding scores ranging from 0 to 30. For census tracts with one eligible participant (235 of 1355 tracts), the participant's depressive symptoms score was used. For census tracts with more than one eligible participant (1120 out of 1355 tracts), the mean of the individual CES-D scores of participants was used as the tract-level measure of depressive symptoms. The mean number of participants in tracts with more than one eligible participant was 4.8 and the range was 2–31.

Neighborhood characteristics

Neighborhood characteristics were measured using 3 variables quantifying socioeconomic status and social processes for each tract. Socioeconomic status was represented by the percentage of people in each tract who were living below the poverty level as reported in the 2000 U.S. Census. As shown in Fig. 1a, poverty was highly concentrated in several communities across the state, especially in the major cities of Newark, Trenton, and Camden. In about 6% of tracts with ORANJ BOWL participants, the poverty rate exceeded 25%.

Residential stability was operationalized as the percentage of the population in each tract who had been living in their present dwelling for five years or more as reported in the 2000 U.S. Census. Fig. 1b shows the geographical pattern of residential stability across the state. In close to 12% of tracts with ORANJ BOWL participants, less than 50% of the 2000 population five years or older resided in the same dwelling as in 1995.

The Uniform Crime Report prepared by the State of New Jersey, Division of State Police Uniform Crime Reporting Unit, for the year ending December 31, 2006, was the source for crime data. The total number of the seven major offenses (murder, rape, robbery, aggravated assault, burglary, larceny theft, and motor vehicle theft) reported per 1000 people was used as the crime measure. The distribution of the number of crimes per 1000 people is shown in Fig. 1c. In about 8% of tracts with participants, the crime rate exceeded 800 crimes per 1000 residents.

Analytic strategy

The analysis was included three steps; all were implemented using ArcGIS 10 software (ESRI, 2010). In the first step, we used global Moran's I to test for a significant pattern of spatial autocorrelation in depressive symptom scores at the census tract level in the entire state (Moran, 1950). A statistically significant positive value for Moran's I is a sign that census tracts with similar depressive symptom scores are clustered together. A statistically significant negative value for Moran's I is a sign that census tract depressive symptoms scores are higher or lower than scores in neighboring tracts. As a global measure, Moran's I does not identify individual clusters; it provides insight into the statistical significance of the observed pattern of values. If neighborhood context affects depressive symptoms, we would expect to find some evidence of significant local clusters across tracts in the state.

In the second step, we used a local measure of spatial autocorrelation, the Local Indicator of Spatial Autocorrelation or LISA

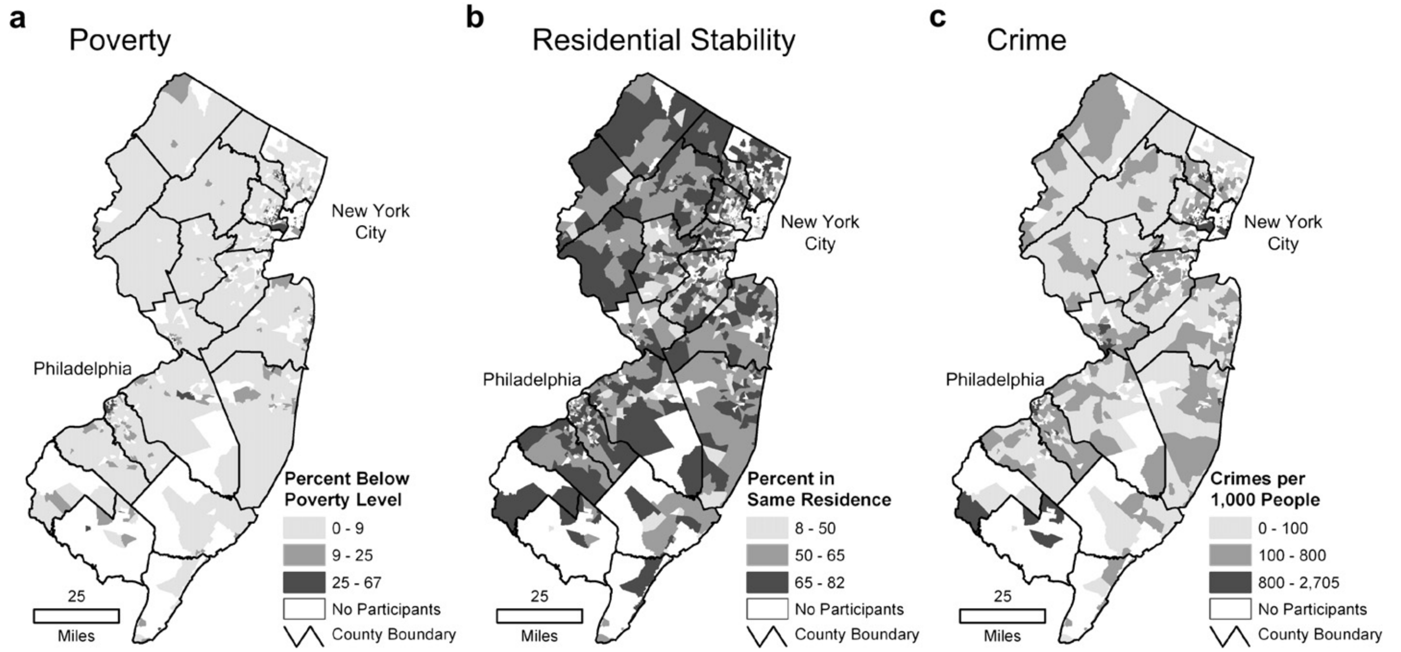

Fig. 1. Neighborhood contextual variables analyzed for relationships with depressive symptoms.

statistic, to identify particular census tracts with high and low depressive symptoms. The LISA statistic is a local version of the Moran's *I* (Anselin, 1995). In a study region that is divided into areas, the LISA statistic for area *i* is:

$$I_i = z_i \sum_{i \neq j} w_{ij} z_j$$

where z_i represents the value of the depressive symptoms in area *i*, z_j are in deviations from the mean, and w_{ij} are spatial weights measuring the nearness of areas *i* and *j*. The summation over *J* is such that only values for neighboring areas are included. LISA essentially measures the statistical correlation between the value in area *i* with the values in nearby areas. LISA values close to zero indicate little or no statistical association among neighboring values. A positive LISA statistic identifies a spatial concentration of similar values. These may be high values that represent high depressive symptoms scores – a high–high cluster or hot spot – or of low depressive symptoms scores – a low–low cluster or cold spot. When the LISA statistic is negative, there is a spatial cluster of *dissimilar* values, such as an area with high depressive symptoms score surrounded by areas with low scores. For this analysis, a spatial weights matrix was developed based on tract proximity. The 50 nearest tracts based on Euclidean distance were identified as the neighbors for calculation of the LISA statistic. ArcGIS 10 software was used to manage the census tract data and tract measures, to calculate Moran's *I*, and to create the spatial weights matrix and use it to compute LISA statistics.

In the third and final step of the analysis, we first used Ordinary Least Squares regression to examine the extent to which poverty, residential stability, and crime explained depressive symptoms in the ORANJ BOWL sample. Then, to explore spatial variability in the relationships between depressive symptoms and poverty, residential stability, and crime, we used Geographically Weighted Regression (GWR). GWR extends the basic regression model to analyze a set of places and provides locally varying R-square values and parameter estimates (Fotheringham, Charlton, & Brunsdon, 1998). The model takes the form:

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

where y_i is the dependent variable for observation *i*, x_{ik} is the value of the independent variable *k* for observation *i*, β_0 and β_k are continuous functions of (u_i,v_i), the spatial coordinates of the *i*th observation, at point *i*, and e_i is the error at point *i*. The analysis yields a regression for each place.

This method has been used effectively in health research (Holt & Lo, 2008; Mennis & Jordan, 2005). We used a variable kernel to define the local area of each tract with the kernel extent based on a specified number of nearest neighbor tracts. As in the local clustering analysis, we chose the 50 nearest neighbor tracts. We used the number of ORANJ BOWL participants in each census tract as a weight because the dependent variable was an average of the depressive symptom scores of participants in each tract.

Results

The value of Moran's *I* was 0.032601, indicating an overall pattern of positive spatial autocorrelation or clustering in depressive symptom scores by tract. Given the corresponding z-score of 6.647955, the likelihood that the observed pattern could have occurred by chance is less than 1%. There are areas in New Jersey where the mean depressive symptoms scores of ORANJ BOWL

Table 1
Localized clusters of depressive symptoms based on LISA statistic.

Cluster type	Number of tracts (%)	Number of participants (%)
Unclustered	1190 (87.8)	5129 (92.3)
High–High	69 (5.1)	188 (3.4)
Low–Low	45 (3.3)	111 (2.0)
High-Low	26 (1.9)	62 (1.1)
Low–High	25 (1.9)	64 (1.2)
Total	1355 (100.0)	5554 (100.0)

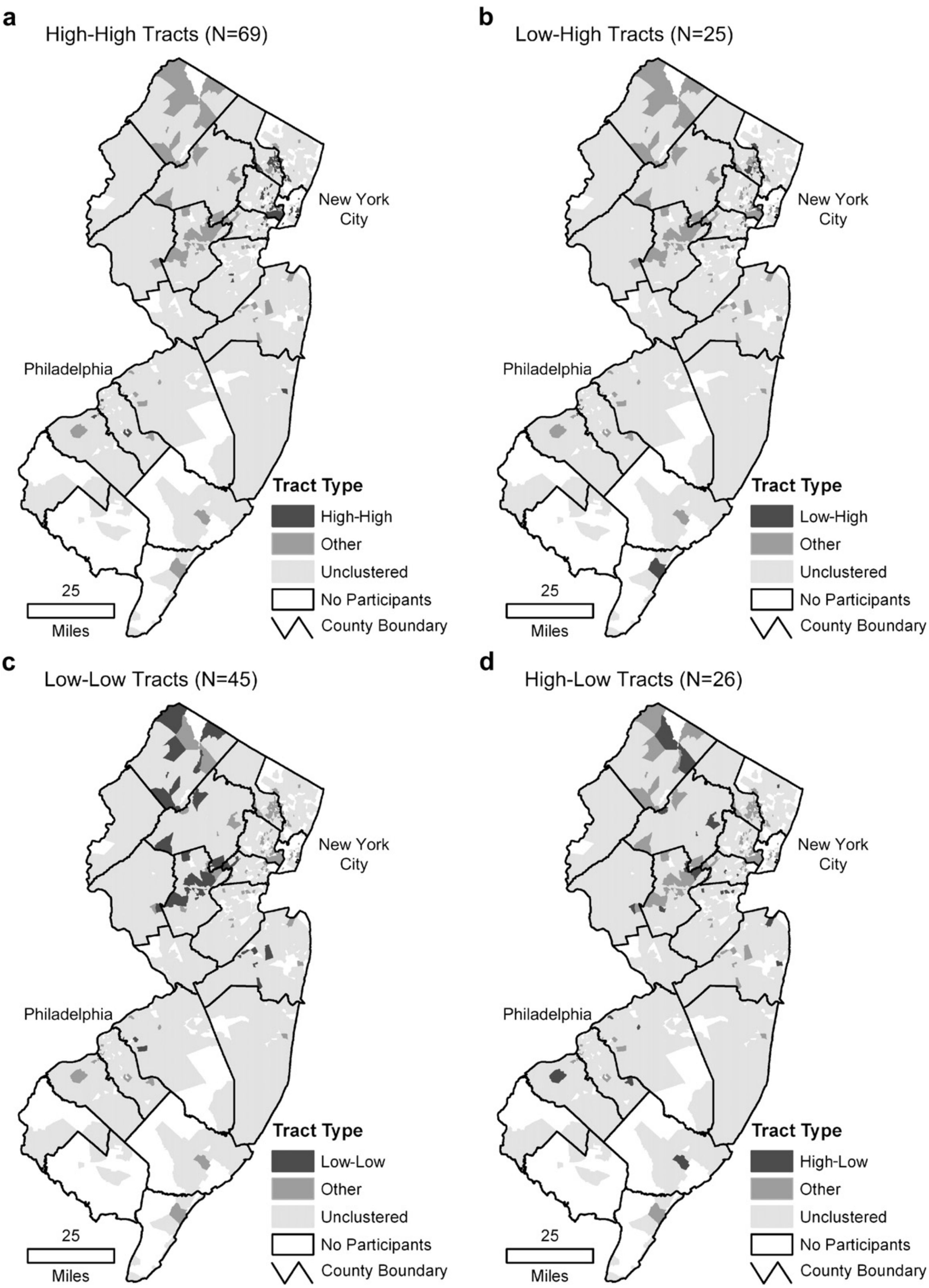

Fig. 2. Localized clusters of depressive symptoms by census tract type based on LISA statistics for census tracts in New Jersey, 2006–2008.

participants at the tract level are similar, and these areas are identified through the local clustering analysis.

The LISA analysis identified five groups of census tracts based on the local relationships between the tract's mean depressive symptoms score and the scores of neighboring tracts (Table 1). For most of the tracts with participants (about 88%), there was no statistically significant relationship between the mean of depressive symptoms of participants residing in the tract and the level of depressive symptoms in neighboring tracts (Unclustered). About 92% of ORANJ BOWL participants resided in these tracts. The mean level of depressive symptoms of the individual ORANJ BOWL participants residing in these tracts was 5.6.

For some tracts, however, there was a statistically significant indicator of positive local spatial autocorrelation. For 5% of the tracts including 3.4% of ORANJ BOWL participants, a high level of depressive symptoms was observed in the tract and the level of depressive symptoms in neighboring tracts was also high (High–High). The mean level of depressive symptoms of the individual ORANJ BOWL participants residing High–High tracts was 12.3. For 3.3% of tracts including 2.0% of participants, a low level of depressive symptoms was observed in the tract and the level of depressive symptoms in neighboring tracts was also low (Low–Low). The mean level of depressive symptoms of the individual ORANJ BOWL participants residing in Low–Low tracts was 1.7.

For the remaining tracts, the indicator of local spatial autocorrelation was statistically significant but negative. For 1.9% of tracts including 1.1% of participants, the tract level of depressive symptoms was high but the levels in neighboring tracts were low (High–Low). The mean level of depressive symptoms of the individual ORANJ BOWL participants residing in High–Low tracts was 13.1. For the other tracts (1.9%) including 1.2% of participants, the tract level of depressive symptoms was low but the levels in neighboring tracts were high (Low–High). All but four of these tracts were located adjacent to High–High tracts in the northeastern part of the state. The mean level of depressive symptoms of the individual ORANJ BOWL participants residing in Low–High tracts was 2.3.

Tracts in these various groups (e.g., High–High, Low–High) were located in different areas of the state. Most of the tracts with significant measures of local spatial autocorrelation were located in northern region of the state (Fig. 2). Many High–High tracts were located in the northeastern part of the state, a highly urbanized area close to New York City, in Passaic, Essex, and Hudson counties or adjacent to these counties in Bergen and Union (Fig. 2a). All but four of the Low-High tracts were interspersed among High–High tracts in this region of the state (Fig. 2b). Many of the Low–Low tracts formed a band to the west in Sussex, Morris, and Somerset counties (Fig. 2c). The High–Low tracts were found near this band of Low–Low tracts and in scattered locations in the southern part of the state (Fig. 2d). Outside the areas identified by these groups, there was a more even distribution of individuals with depressive symptoms. More than half of the 1355 census tracts with study participants (737 tracts) had at least one participant with a depressive symptom score greater than or equal to 10, and these tracts were spread across the sate and located in every county.

The Ordinary Least Squares regression analysis using poverty, residential stability, and crime to explain average depressive symptoms indicated that only the parameter for poverty ($b = 10.523633$, $p < 0.05$) was significant in this model. The residential stability ($b = 0.764700$, $p > 0.48$) and crime ($b = 0.000279$, $p > 0.36$) parameters were not significant. In contrast to the OLS results, the Geographically Weighted Regression found that the degree to which poverty, residential stability, and crime explain depressive symptoms varies from place to place in the state, as indicated by the range in R-square values (Fig. 3). Poverty, residential stability, and crime account for more variation in depressive symptoms in a swath of census tracts stretching from the northeast to the southwest regions of the state than in other areas. In this area, including about 80% of all census tracts analyzed, the independent variables explained 5%–18% of the variation in average depressive symptoms.

The spatial patterns of the parameter estimates of the local GWR regressions are presented using two maps (Fig. 4). For each parameter, the map on the left shows the spatial patterns of the parameter estimate. The map on the right shows the areas where the parameter value is significant. The estimates for the intercept parameter (Fig. 4a left) reveal that the predicted level of depressive symptoms without the influence of area residential stability, crime, and poverty is highest in the northeast region of the state and decreases as the distance from this region increases. Local intercept estimates were statistically significant for tracts in the north and central regions of the state (Fig. 4a right). When parameter estimates for the three independent variables used in the analysis are mapped, different patterns emerge for each variable.

Poverty was positively associated with depressive symptoms everywhere in the state (Fig. 4b left). Furthermore, the local parameter values were significant for 80% of the tracts, almost everywhere in the state (Fig. 4b right). Poverty can be considered a "global variable" in its association with depressive symptoms. The role of poverty is significant almost everywhere in the state given the other contextual variables.

Residential stability was significantly negatively associated with average depressive symptoms in many places in the northern part of the state (Fig. 4c). This means that areas with higher levels of residential stability had lower levels of depressive symptoms. In

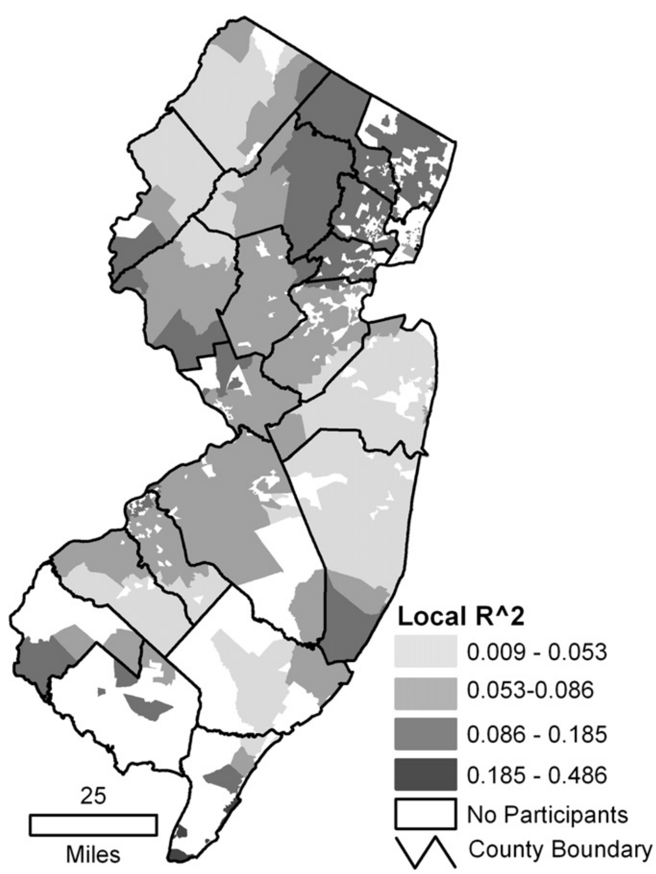

Fig. 3. Geographically weighted regression local R square values mapped for census tract observations from the analysis of residential stability, crime, and poverty as independent variables predicting average level of depressive symptoms.

many tracts in the southern part of the state, however, residential stability was positively associated with average depressive symptoms. In these areas, higher levels of residential stability were associated with higher levels of depressive symptoms, but the parameter values were not significant.

In about 60% of census tracts, crime rate per 1000 was positive providing evidence that higher crime is associated with higher levels of depressive symptoms in most places (Fig. 4d left). The crime parameters were significant for a group of 215 (18%) tracts located in the center of the state (Fig. 4d right). Crime was positively associated with depressive symptoms in all of these tracts.

The results for residential stability and crime indicate that these variables, in contrast to the poverty variable, are "local" variables in their associations with depressive symptoms. There is variability in the role they play in that, given the other contextual variables; they are significantly associated with depressive symptoms only in some places.

The age and sex of ORANJ Bowl participants whose depressive symptoms were analyzed were explored in relation to the significance of the regression parameters (Fig. 4). Q–Q plots were made to compare the age distribution of ORANJ Bowl participants in the area where a parameter was not significant to the age distribution of participants in the area where the parameter was significant (Isaaks & Srivastava, 1989, pp. 24–28). The percent of participants who were female in the area where a parameter was not significant was also compared to the percent of participants who were female in the area where a parameter was significant. The areas where the parameter was not significant are not different from the areas where the parameter was significant in its association with depressive symptoms in the age distribution (Fig. 5). Again, the sex distributions were not different, except for the intercept parameter where the area with significant intercepts has a slightly lower proportion of females than the area where the intercepts were not significant (Table 2).

Discussion

These analyses revealed that there is evidence of overall clustering in depressive symptoms reported by older adults in New Jersey. Local spatial analysis was key in uncovering the locations of significant clusters. Places where people with high levels of depressive symptoms lived were often proximate to other places where people with high levels of depressive symptoms lived. These findings suggest that neighborhood contextual factors influence mental health outcomes in older people. Moreover, our analyses found that neighborhood poverty, residential stability, and crime had differential relationships with depressive symptoms across local areas in New Jersey.

Examination of local spatial autocorrelation in depressive symptoms and local spatial variability in associated contextual factors provides important and complementary information to that offered by multilevel models about how neighborhood

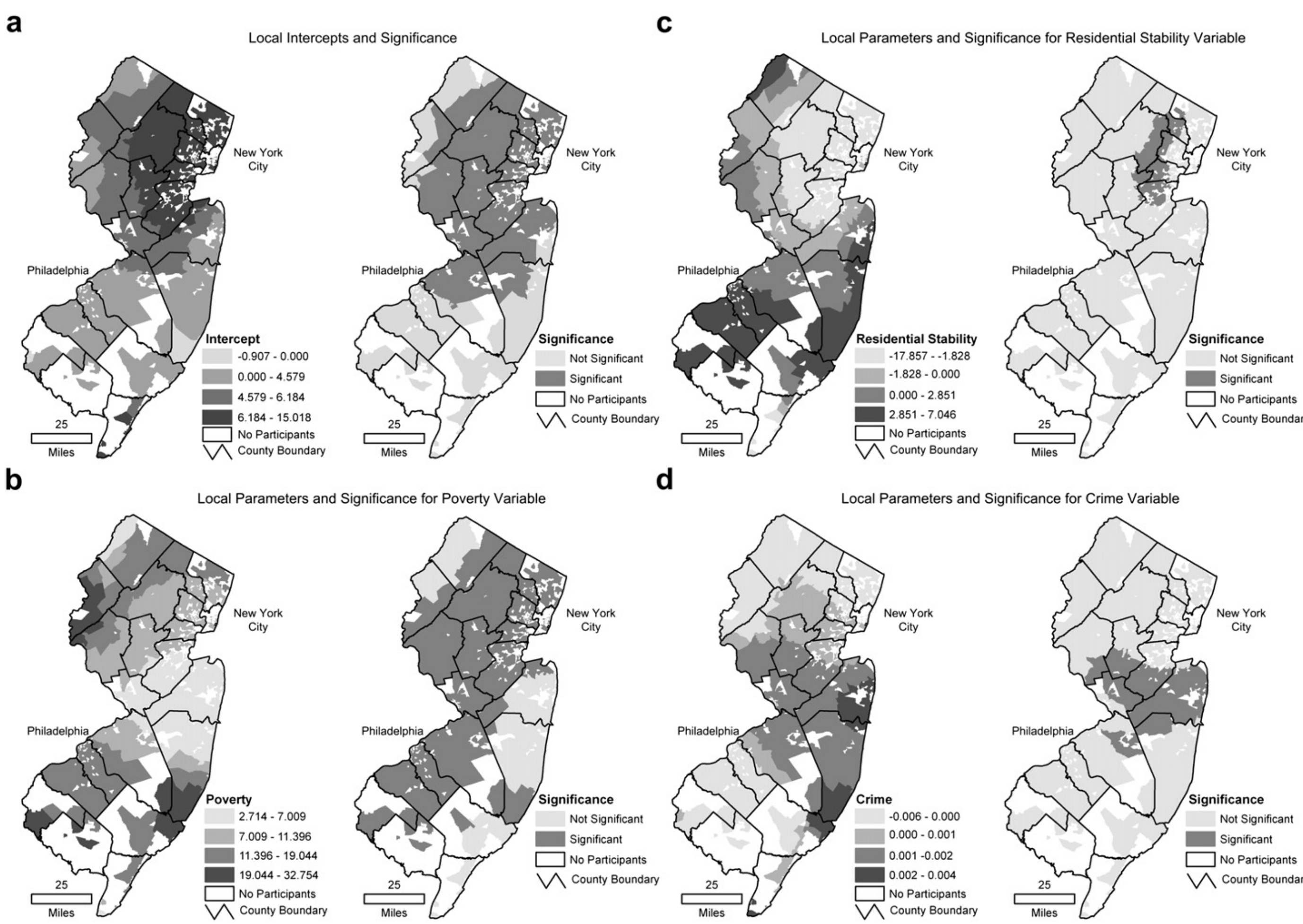

Fig. 4. Geographically weighted regression parameter values and significance mapped for census tract observations from the analysis of poverty, residential stability, and crime as independent variables predicting average level of depressive symptoms.

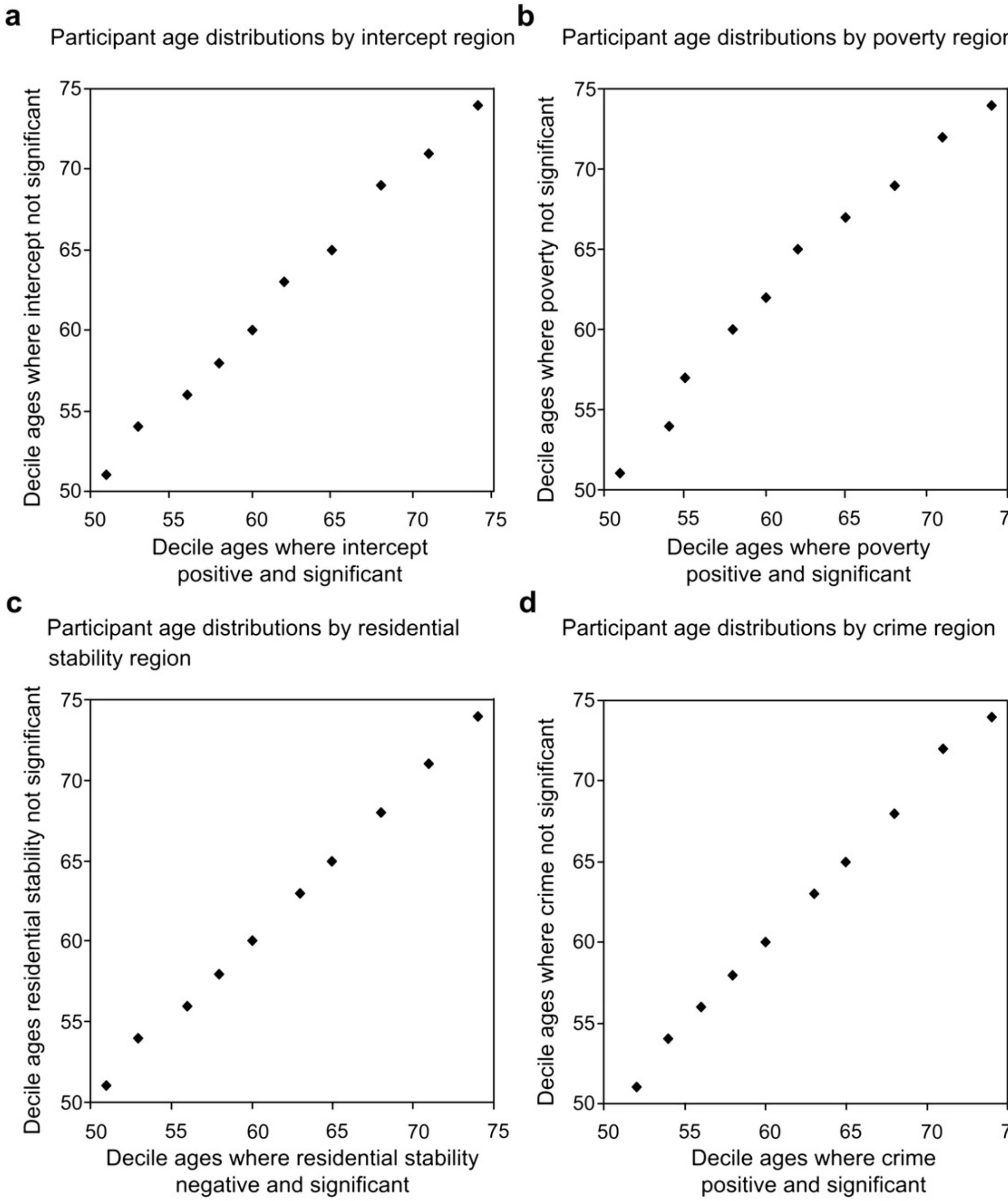

Fig. 5. Q–Q plots of participant age distributions in areas where geographically weighted regression parameter values are not significant versus significant.

characteristics influence health. Our finding of significant spatial autocorrelation in the relationships between depressive symptoms and neighborhood characteristics suggests that failing to utilize spatially-oriented methodologies may result in biased parameter values in explanatory models. Global models can be designed to incorporate spatial effects to address this problem (Chaix, Merlo, & Chauvin, 2005).

Our findings suggest that there may be multiple processes affecting the depressive symptoms experienced by older people. In some places across New Jersey, a variety of neighborhood factors were associated with the prevalence of depressive symptoms or the relative absence of such symptoms in individuals. In other places, neighborhood factors do not appear to play a significant role. In the locations where spatial clustering of individuals with depressive symptoms is observed, particular configurations of neighborhood characteristics come together in place as in this study to increase the likelihood that a cluster of individuals with high or low depressive symptoms relative to neighboring areas exists. These configurations may differ from place to place. The operation of spatially varying processes provides one explanation for inconsistent results in the research on neighborhood contextual factors and health conducted in single community settings.

Table 2
Participant sex distributions in areas by geographically weighted regression parameter significance.

Parameter	Area	Sex of participants (% female)
Intercept	Not significant	65.9
	Significant	62.8
Poverty	Not significant	64.3
	Significant	63.4
Residential stability	Not significant	63.5
	Significant	63.8
Crime	Not significant	63.5
	Significant	63.7

The results of the geographically weighted regression analysis indicate that spatially varying processes operate in New Jersey with respect to the relationships between local contextual variables and depressive symptoms in older people. The significant positive intercept values in the northeastern region of the state near New York City point to higher levels of depressive symptoms in that region regardless of local residential stability, crime, or poverty. Significant local parameter estimates for the residential stability and crime variables were observed, but they were found in different areas of the state. Residential stability parameters were significant in a zone in the northeastern part of the state along Interstate 287. The communities in this region are relatively affluent suburbs in the New York metropolitan area. The relationship between residential stability and depressive symptoms among older people is negative in this region, suggesting that high percent in the same residence is associated with lower levels of depressive symptoms in this area. High residential stability can occur in different types of communities. In some cases, it may be associated with residents aging in place in communities with strong local supports, but in other cases, it may be associated with residents who are trapped in deteriorating communities. In communities where there is high residential stability because residents cannot relocate, residential stability might be associated with higher levels of depressive symptoms.

Significant crime parameters were found in a band of census tracts across the central portion of the state. In these areas, for a given level of residential stability and poverty, higher crime rates were associated with higher levels of depressive symptoms. This region of the state is characterized by low poverty, but includes a number of tracts with low residential stability and crime rates above 100 per 1000 residents. Possible connections between higher crime in areas of lower residential stability and depressive symptoms in older adults warrant further investigation.

Understanding spatially varying relationships in neighborhood conditions and depressive symptoms also provides insight into the spatial scales at which processes may be operating. The parameter estimates for poverty were distinctive in that the relationship between poverty and depressive symptoms was positive in every tract such that higher poverty was associated with higher depressive symptoms. The highest significant associations between poverty and depressive symptoms were found in census tracts just north of Atlantic City on the southeast coast and along the border with Pennsylvania in the northwestern part of the state. The relationship between poverty and depressive symptoms was significant almost everywhere in the state. This is consistent with the literature on neighborhood contextual factors and health, which identifies poverty as a key neighborhood contextual variable in many studies.

These findings have important policy implications. Significant variables such as poverty showing little regional variation highlight problems that might best be addressed at a statewide level in New Jersey. Significant variables such as residential stability and crime showing strong local variation point to problems that might best be addressed at the local level based on the situations in particular regions. During the time period when the ORANJ BOWL survey was conducted, the New Jersey Department of Health and Senior Services published a blueprint for healthy aging (New Jersey Department of Health and Senior Services, 2007). Mental health, particularly depression among those 60 or older, was addressed in the report, with recommendations for developing programs at the community level. The report highlighted a model program, Healthy IDEAS, for identification and management of depressive symptoms in older adults. Developed and implemented in Houston (Quijano et al., 2007), Healthy IDEAS relies on community-based case managers in agencies providing a range of social services to older adults with chronic illness and functional limitations to deliver the intervention. In New Jersey, the program has been implemented in parts of Essex and Union counties, both counties in the northeast where local clustering analysis identified significant High–High clusters of older residents with depressive symptoms.

Healthy IDEAS is one of several interventions originating in local communities that the Centers for Disease Control and Prevention points to as evidence-based programs local communities might adopt (Centers for Disease Control and Prevention and National Association of Chronic Disease Directors, 2009). Whether or not these interventions work equally well in all local contexts is an important question. In particular communities where older adults with depressive symptoms are concentrated, it may be easier and less expensive to deliver services. In other areas, such as the southeastern part of the state where individuals in need of services are isolated and spread across a number of communities, the need for services might not be as visible and different service delivery strategies may be needed to tailor programs to local conditions.

This study has several limitations. The outcome considered is depressive symptoms based on self-report, not depression based on clinical diagnosis. Although the research is more geographically extensive than many studies, which report on analyses for only a single city, our analysis covers only one state. The clustering and geographically weighted regression analyses were conducted for data at the tract level. Some census tracts had only one survey participant. With these limitations, the research advances our understanding of neighborhood influences on the health of older individuals and the methods available to explore them.

Conclusions

Evidence of depressive symptoms in community-dwelling older people is a cause for concern because they are an important factor in multi-morbidity patterns in older people and affects patterns of care. Research has shown that neighborhood contextual factors influence depressive symptoms in some communities, but this research has rarely documented whether or not there are spatial concentrations of older people with varying levels of depressive symptoms in particular communities.

Spatial statistical methods can be used to identify significant global and local patterns in health outcomes, including mental health outcomes. Some individuals with depressive symptoms reside in areas where others also exhibit these symptoms, but other individuals with depressive symptoms live in areas where most people are not depressed. On the other hand, there is evidence of individuals with few depressive symptoms living in areas where people are depressed. Attention to these spatial patterns and the neighborhood characteristics associated with them can contribute to our understanding of depression and resilience and to the design of contextual interventions.

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References

Andresen, E., Malmgren, J. A., Carter, W. B., & Patrick, D. L. (1994). Screening for depression in well older adults: evaluation of a short form of the CES-D. *American Journal of Preventive Medicine, 10*(2), 77–84.

Aneshensel, C. S., Wight, R. G., Miller-Martinez, D., Botticello, A. L., Karlamangla, A. S., & Seeman, T. E. (2007). Urban neighborhoods and depressive symptoms among older adults. *Journal of Gerontology: Social Sciences, 62B*(1), S52–S59.

Anselin, L. (1995). Local indicators of spatial autocorrelation: LISA. *Geographical Analysis, 27*(2), 93–115.

Beekman, A. T. F., Deeg, D. J. H., Braam, A. W., Smit, J. H., & Van Tilburg, W. (1997). Consequences of major and minor depression in later life: a study of disability, well-being and service utilization. *Psychological Medicine, 27*(6), 1397–1409.

Berkman, L. F., Berkman, C. S., Kasl, S., Freeman, D. H., Leo, L., Ostfeld, A. M., et al. (1986). Depressive symptoms in relation to physical health and functioning in the elderly. *American Journal of Epidemiology, 124*(3), 372–388.

Blazer, D., Burchett, B., Service, C., & George, L. K. (1991). The association of age and depression among the elderly: an epidemiologic exploration. *Journal of Gerontology: Medical Sciences, 46*(6), M210–M215.

Blumberg, S. J., & Luke, J. V. (2007). Coverage bias in traditional telephone surveys of low-income and young adults. *Public Opinion Quarterly, 71*(5), 734–749.

Centers for Disease Control and Prevention and National Association of Chronic Disease Directors. (2009). *The state of mental health and aging in America issue Brief 2: Addressing depression in older Adults: Selected evidence-based programs*. Atlanta, GA: National Association of Chronic Disease Directors.

Chaix, B., Leyland, A. H., Sabel, C. E., Chauvin, P., Råstam, L., Kristersson, H., et al. (2006). Spatial clustering of mental disorders and associated characteristics of the neighbourhood context in Malmö, Sweden, in 2001. *Journal of Epidemiology and Community Health, 60*(5), 427–435.

Chaix, B., Merlo, J., & Chauvin, P. (2005). Comparison of a spatial approach with the multilevel approach for investigating place effects on health: the example of healthcare utilisation in France. *Journal of Epidemiology and Community Health, 59*(6), 517–526.

Chaix, B., Merlo, J., Subramanian, S. V., Lynch, J., & Chauvin, P. (2005). Comparison of a spatial perspective with the multilevel analytical approach in neighborhood studies: the case of mental and behavioral disorders due to psychoactive substance use in Malmö, Sweden, 2011. *American Journal of Epidemiology, 162*(2), 171–182.

Congdon, P. (2011). Spatial path models with multiple indicators and multiple causes: mental health in US counties. *Spatial and Spatio-temporal Epidemiology, 2*(2), 103–116.

Curry, A., Latkin, C., & Davey-Rothwell, M. (2008). Pathways to depression: the impact of neighborhood violent crime on inner-city residents in Baltimore, Maryland, USA. *Social Science & Medicine, 67*(1), 23–30.

Diez Roux, A. V. (2008). Next steps in understanding multilevel determinants of health. *Journal of Epidemiology and Community Health, 62*(11), 957–959.

Dorling, D., & Prichard, J. (2010). The geography of poverty, inequality and wealth in the UK and abroad: because enough is never enough. *Applied Spatial Analysis and Policy, 3*(2–3), 81–106.

ESRI (Environmental Systems Research Institute. (2010). *ArcGIS 10*. Redlands, CA: ESRI.

Everson-Rose, S. A., Skarupski, K. A., Barnes, L. L., Beck, T., Evans, D. A., & Mendes de Leon, C. F. (2011). Neighborhood socioeconomic conditions are associated with psychosocial functioning in older black and white adults. *Health & Place, 17*(3), 793–800.

Fotheringham, A. S., Brunsdon, C., & Charlton, M. E. (2002). *Geographically weighted regression: The analysis of spatially varying relationships*. Chichester, UK: Wiley.

Fotheringham, A. S., Charlton, M. E., & Brunsdon, C. (1998). Geographically weighted regression: a natural evolution of the expansion method for spatial data analysis. *Environment and Planning A, 30*(11), 1905–1927.

Giggs, J. A. (1986). Mental disorders and ecological structure in Nottingham. *Social Science & Medicine, 23*(10), 945–961.

Gottlieb, L., Waitzkin, H., & Miranda, J. (2010). Depressive symptoms and their social contexts: a qualitative systematic literature review of contextual interventions. *International Journal of Social Psychiatry, 57*(4), 402–417.

Holt, J. B. (2007). The topography of poverty in the United States: a spatial analysis using county-level data from the Community Health Status Indicators Project. *Preventing Chronic Disease, 4*(4), A111.

Holt, J. B., & Lo, C. P. (2008). The geography of mortality in the Atlanta metropolitan area. *Computers, Environment and Urban Systems, 32*(2), 149–164.

Hybels, C. F., Blazer, D. G., Pieper, C. F., Burchett, B. M., Hays, J. C., Fillenbaum, G. G., et al. (2006). Sociodemographic characteristics of the neighborhood and depressive symptoms in older adults: using multilevel modeling in geriatric psychiatry. *American Journal of Geriatric Psychiatry, 14*(6), 498–506.

Isaaks, E. H., & Srivastava, R. M. (1989). *An introduction to applied geostatistics*. New York: Oxford University Press.

Kim, D. (2008). Blues from the neighborhood? Neighborhood characteristics and depression. *Epidemiologic Reviews, 30*, 101–117.

Kubzansky, L. D., Subramanina, S. V., Kawachi, I., Fay, M. E., Soobar, M.-J., & Berkman, L. F. (2005). Neighborhood contextual influences on depressive symptoms in the elderly. *American Journal of Epidemiology, 162*(3), 253–260.

Mair, C., Diez Roux, A. V., & Galea, S. (2008). Are neighbourhood characteristics associated with depressive symptoms? A review of evidence. *Journal of Epidemiology and Community Health, 62*(11), 940–946.

Mennis, J. L., & Jordan, L. (2005). The distribution of environmental equity: exploring spatial nonstationarity in multivariate models of air toxic releases. *Annals of the Association of American Geographers, 95*(2), 249–268.

Moran, P. A. P. (1950). Notes on continuous stochastic phenomena. *Biometrika, 37*(1/2), 17–33.

Nakaya, T., Fotheringham, A. S., Brunsdon, C., & Charlton, M. (2005). Geographically weighted Poisson regression for disease association mapping. *Statistics in Medicine, 24*(17), 2695–2717.

New Jersey Department of Health and Senior Services. (2007). Blueprint for healthy aging in New Jersey. Trenton: State of New Jersey.

Orford, S. (2004). Identifying and comparing changes in the spatial concentrations of urban poverty and affluence: a case study of inner London. *Computers, Environment and Urban Systems, 28*(6), 701–717.

Ostir, G. V., Eschbach, K., Markides, K. S., & Goodwin, J. (2003). Neighborhood composition and depressive symptoms among older Mexican Americans. *Journal of Epidemiology and Community Health, 57*(12), 987–992.

Pruchno, R. A., Wilson-Genderson, M., Rose, M., & Cartwright, F. (2010). Successful aging: early influences and contemporary characteristics. *The Gerontologist, 50*(6), 821–833.

Quijano, L. M., Stanley, M. A., Petersen, N. J., Caseado, B. L., Steinberg, E. H., Cully, J. A., et al. (2007). Health IDEAS: a depression intervention delivered by community-based case managers serving older adults. *Journal of Applied Gerontology, 26*(2), 139–156.

Schäfer, I., von Leitner, E.-C., Schön, G., Koller, D., Hansen, H., Kolonko, T., et al. (2010). Multimorbidity patterns in the elderly: a new approach to disease clustering identifies complex interactions between chronic conditions. *PLoS ONE, 5*(12), e15941.

Stallones, L., Marx, M. B., & Garrity, T. F. (1990). Prevalence and correlates of depressive symptoms among older U.S. adults. *American Journal of Preventive Medicine, 6*(5), 295–303.

Steffens, D. C., Fisher, G. G., Langa, K. M., Potter, G. G., & Plassman, B. L. (2009). Prevalence of depression among older Americans: the aging, demographics and Memory study. *International Psychogeriatrics, 21*(5), 879–888.

Truong, K. D., & Ma, S. (2006). A systematic review of relations between neighborhoods and mental health. *The Journal of Mental Health Policy and Economics, 9*(3), 137–154.

Unützer, J., Simon, G., Belin, T. R., Datt, M., Katon, W., & Patrick, D. (2000). Care for depression in HMO patients aged 65 and older. *Journal of the American Geriatrics Society, 48*(8), 871–878.

Yen, I. H., Michael, Y. L., & Perdue, L. (2009). Neighborhood environment in studies of health of older adults. *American Journal of Preventive Medicine, 37*(5), 455–463.