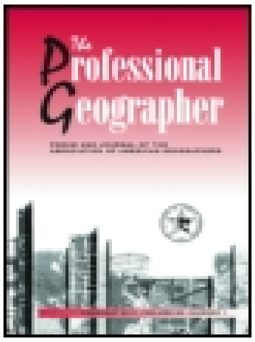

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The combination of crime mapping and geospatial analysis methods has enabled law enforcement agencies to develop more proactive methods of targeting crime-prone neighborhoods based on spatial patterns, such as hot spots and spatial proximity to specific points of interest. In this article, we investigate the spatial and temporal patterns of the neighborhood crimes of aggravated assault and larceny in 297 census tracts in Miami–Dade County from 2007 to 2015. We use emerging hot spot analysis (EHSA) to identify the spatial patterns of emerging, persistent, continuous, and sporadic hot spots. In addition, we use geographically weighted regression to analyze the spatial clustering effects of sociodemographic variables, poverty rate, median age, and ethnic diversity. The hot spots for larceny are much more diffused than those for aggravated assaults, which exhibit clustering in the north over Liberty City and Miami Gardens and in the south near Homestead, and the ethnic heterogeneity index has a moderate and positive effect on the incidence of both larceny and aggravated assaults. The findings suggest that law enforcement can better target prevention programs for violent versus property crime using geospatial analyses. Additionally, the ethnic concentration of neighborhoods influences crime differently in neighborhoods of different socioeconomic status, and future studies should account for spatial patterns when estimating conventional regression models. **Key Words: aggravated assault, crime, emerging hot spots analysis, geographically weighted regression, larceny.**

犯罪製图与地理空间方法的结合，让法律执行单位能够根据诸如热点和对于特定兴趣点的空间距离之空间模式，针对具有犯罪倾向的邻里，发展更为先发制人的方法。我们于本文中，探讨迈阿密—戴德县 2007 年至 2015 年之间，在二百九十七个人口统计单元中，加重伤害与窃盗的邻里犯罪之时空模式。我们运用浮现的热点分析 (EHSA) 来指认浮现、反覆、持续和零星的热点。此外，我们运用地理加权迴归，分析社会人口变因、贫穷率、年龄中位数和族裔多样性的空间集群效应。窃盗的热点，较加重伤害更为分散，并集中于自由城与迈阿密花园的北部，以及邻近霍姆斯特德的南部，而族裔异质性指标则同时对窃盗和加重犯罪事件具有中等与正向的影响。研究结果显示，法律执行运用地理空间分析对暴力实施预防计画，较财产犯罪效果更佳。此外，邻里的族裔集中，在不同社经地位的邻里中，对犯罪产生不同的影响，而未来的研究在评估传统迴归模型时，应将空间模式纳入考量。 **关键词：加重伤害，犯罪，浮现的热点分析，地理加权迴归，窃盗。**

La combinación del mapeo del crimen y los métodos de análisis geoespacial ha habilitado a las agencias de aplicación de la ley a desarrollar métodos más proactivos para enfocar su mayor atención sobre barriadas con propensión criminal con base en patrones espaciales, tales como los puntos calientes y a la proximidad espacial a puntos de interés específico. En este artículo investigamos los patrones espaciales y temporales en la criminalidad vecinal de asalto agravado y hurto, en 297 distritos censales del Condado de Miami–Dade, de 2007 a 2015. Usamos el análisis de puntos calientes emergentes (EHSA) para identificar los patrones espaciales de puntos calientes emergentes, persistentes, continuos y esporádicos. Además, usamos regresión geográficamente ponderada para analizar los efectos de agrupamiento espacial de variables sociodemográficas, la tasa de pobreza, edad media y diversidad étnica. Los puntos calientes relacionados con hurto están mucho más dispersos que los relacionados con asalto agravado que exhiben agrupamiento en el norte sobre Liberty City y Miami Gardens y en el sur cerca a Homestead, y el índice de heterogeneidad étnica tiene un efecto moderado y positivo sobre la incidencia tanto de hurto como de asaltos agravados. Los hallazgos obtenidos sugieren que la aplicación de la ley debería enfocarse preferencialmente en programas de prevención del crimen violento contra el crimen contra la propiedad, usando análisis geoespaciales. Adicionalmente, la concentración étnica en los vecindarios influye el crimen de modo diferente en vecindarios de diferentes estatus socioeconómicos, y los estudios futuros deben tomar en cuenta los patrones espaciales cuando se esté operando con modelos convencionales de regresión. **Palabras clave: asalto agravado, crimen, análisis de puntos calientes emergentes, regresión geográficamente ponderada, hurto.**

Although the average crime rate in the United States has generally been decreasing since 1992 (Zimring 2007; Baumer and Wolff 2014), the recent incidents of high-profile use of force by law enforcement in several metropolitan areas have shifted public, political, and scholarly attention to the subsequent increase in crime in these areas (Davey and Smith 2015; Federal Bureau of Investigation 2015; James 2015). Often, this public and political discourse posits that increase in crime is due to immigration by ethnic and racial minorities (Latinos in particular), who are argued to have greater criminal involvement, to form deviant subcultures, and to engage in antisocial behavior (Portes 1999; Rumbaut and Ewing 2007). The

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current body of empirical literature, however, has found that the relationship between neighborhood immigrant and racial and ethnic concentration is inconsistent, with several recent studies finding that neighborhoods with a greater Latino immigrant concentration actually have lower crime rates (Lee and Martinez 2002; Nielsen, Lee, and Martinez 2005; Ousey and Kubrin 2009; Peterson and Krivo 2010; Ramey 2013).

In response to the current state of urban crime patterns, numerous misconceptions about the relationship between immigrant ethnicity and crime, and the ambiguity of the findings in the scholarly literature, it is necessary to conduct further investigations into the relationship between immigration and ethnic and racial concentration and crime using a large sample of neighborhoods in a large metropolitan area. As such, this study examines spatial patterns of larceny and aggravated assault in Miami–Dade County from 2007 to 2015 with a sample of 297 census tracts using choropleth maps, emerging hot spot analysis (EHSA), and geographically weighted regression (GWR) analysis. Furthermore, we use diurnal analyses to illustrate how crime patterns vary over time differently for larceny and aggravated assault within each day and over the course of a week.

Crime Analysis Review

Immigrants have long been perceived to correspond to a rise in crime. It is often uncertain, however, whether a greater immigrant concentration is significantly related to increases in property and violent crime. Several recent studies have indicated that crime rates are either not or negatively related with Latino immigration in parts of the United States (Lyons, Velez, and Santoro 2013; Ramey 2013). These studies reason that immigrants generally desire to maintain their immigrant visas and status, form dense social networks with high social capital, tend to have greater family intactness than white or black families, and seek steady employment in the secondary labor market, all of which provide a mitigating effect on criminal involvement and aggregated crime rates in ethnic enclaves (Portes and Rumbaut 2006; Ousey and Kubrin 2009; Ramey 2013).

To provide a theoretical background and to interpret the geospatial analyses in this study, we turn toward the theories of crime of social disorganization and routine activity. First, social disorganization theory proposes that residential inequality, economic disadvantage, and racial and ethnic heterogeneity lead to high rates of crime. A more recent extension of social disorganization theory (Sampson, Raudenbush, and Earls 1997; Sampson 2012) posits that collective efficacy, defined as social cohesion among neighbors and their willingness to intervene when witnessing crime, is also a strong predictor of reduced crime rates. It has been shown that there is a strong negative correlation between high collective efficacy and homicide rates, along with a statistically significant local spatial autocorrelation between the two (Anselin et al. 2000; Getis 2010). Analyses of the crime-mitigating effects of collective efficacy from spatially enabled models help to account for interdependencies between nearby neighborhoods and other factors through local Moran's I tests for clustering neighborhood violence, social disorganization, and other collective efficacy variables (Morenoff, Sampson, and Raudenbush 2001).

Second, routine activity theory states that crime occurs when there are (1) suitable targets such as valuable property, (2) motivated offenders, and (3) lack of capable guardians to supervise and intervene on witnessing crime over time and space (Cohen and Felson 1979; Brown, Halcli, and Webster 1999). Spatial regression models show that in general, routine activity theory is a better predictor of crime than social disorganization theory (Pratt and Cullen 2005; Andresen 2006). Overall, these two theories suggest that greater racial heterogeneity will result in higher rates of crime because less cohesive social networks will be formed (i.e., provide guardianship) in neighborhoods to intervene when witnessing suspicious behavior (i.e., motivated offenders). Additionally, neighbors will share less information on crime prevention with neighbors because they might have lingual and cultural dissimilarities that reduce communication and social interactions. Furthermore, increased economic disadvantage (i.e., poverty) might increase neighborhood crime because it reduces the extent to which neighbors can engage intra- and extracommunity resources such as law enforcement, political entities, and social organizations to intervene to reduce community crime and disorder (Bursik 1988; Sampson 2012). We examine the applicability of these two theories in the context of Miami–Dade County.

Geospatial analysis techniques have been widely used to analyze crime patterns at various spatial scales, which include kernel density and hot spot mapping. Although kernel density maps lose the exact location of crimes as a result of spatial aggregation, this anonymization makes them a valuable resource for operational purposes and for sharing the spatial patterns of crime rates with the public (Ratcliffe 2004; Ye et al. 2015). Another technique, prospective hot-spotting, developed by Bowers, Johnson, and Pease (2004), attempts to provide a risk map for future crime through a combination of past crime incidence and propensity of crime to occur within 400 m of a recently burgled location. In another study, street profile analysis was used, which incorporates street networks into maps to create more effective illustrations of streets with the highest crime rates, instead of a hot spot map where a single hot spot covers a wide area (Spicer et al. 2016). Furthermore, the analysis of spatial patterns of burglaries in Wuhan City, China (Wu et al. 2014), and gun assaults in Houston, Texas (Wells, Wu, and Ye 2011), revealed the spatial clustering of repeat offenses by the same offender. Thus, geospatial analyses have been successfully used to study spatial patterns of crime patterns in various urban areas.

Crime in Miami

Miami–Dade is an ethnically diverse county with large, segmented communities of Hispanic and Latino immigrants, as well as sizable black and white populations (Portes and Rumbaut 2006). Therefore, Miami–Dade County is particularly suitable as a metropolitan context to study crime patterns that can be generalized to other major U.S. cities, demonstrating the external validity of the findings for two reasons. First, drawing from the extensive work of Sampson (2012) and a meta-analysis by Pratt and Cullen (2005) on macrolevel predictors of crime, the statistical significance and effect size of structural predictors of crime including economic disadvantage, residential instability, and racial and ethnic heterogeneity do not vary substantially across cities. As such, we extend this logic to determine whether Latino immigrant concentration also shows similar levels of significance and magnitude beyond the Miami–Dade context. Second, as has been found in Portes and Rumbaut's (2006) work on ethnic enclave economies and more recently in Ramey's (2013) study of the immigration and crime relationship across 8,628 census tracts in eighty-four U.S. cities, areas with large Latino immigrant populations provide revitalization to the neighborhood structure by increasing the availability of secondary labor market jobs, enhancing social capital resources, and maximizing social cohesion among community residents. Because these intervening factors drawn from social disorganization theory have been found to similarly reduce crime across U.S. cities in diverse geographic areas, we examine whether our findings can be similarly generalized beyond the Miami–Dade context.

Specifically in Miami–Dade, existing research has suggested that contemporary forms of immigration contribute to "deleterious social and economic conditions" that encourage crime (Lee and Martinez 2002). From 1985 to 1995 the homicide rate in Miami was among the highest in the nation, corresponding to the end of a two-decades-long surge of immigration. Using drug-related homicide as a proxy for drug violence and markets, it was found that the ethnic composition of Miami neighborhoods had no significant influence on determining drug market activity; however, economic deprivation is a significant predictor (Martinez, Lee, and Nielsen 2004).

Therefore, in this study we analyze the long-term spatial and temporal trends of two types of crime, larceny and aggravated assaults, in Miami–Dade County from 2007 to 2015 at the census tract level. In addition, we examine the role of various sociodemographic variables, including ethnic diversity (i.e., heterogeneity), poverty rates, and age on the local-level spatial patterns of the occurrences of larceny and aggravated assault. This article contributes to the body of extant literature in two ways. First, we integrate elements from social disorganization theory and routine activity theory with geospatial methods to explain and interpret our findings. Second, we evaluate crime patterns with GWR to examine how spatial heterogeneity affects the statistical significance and effect size of the Latino immigrant concentration, racial concentration, and both larceny and aggravated assault.

Data and Methods

Data with geographic locations for every crime reported to the Miami–Dade Police Department (MDPD) jurisdiction from 2007 to 2015 were obtained from the MDPD. The files contained seventy distinct codes for various crime types in Miami. Preliminary analysis of all of the crime data revealed the highest incidence for larceny-based crimes (299,581 total incidences), followed by aggravated assaults (29,911 total incidences). We used the UCR definition of aggravated assault and define larceny as a composite of seven separate codes: stolen property, pocket picking, purse snatching, shoplifting, theft from a coin machine, theft from a building, and theft from all others. We then filtered the original data to create data sets containing exclusively those two categories of crimes to do a census tract–level analysis.

The MDPD jurisdiction does not cover the entire county, so a tract-level analysis requires that the tracts be matched to only the jurisdiction of the department. The police district spatial extent data were downloaded from Miami–Dade GIS services (Miami–Dade County 2016). There are four districts that extend far west into the Everglades, an uninhabited area. Therefore, our final study area boundary was determined by the Urban Development Boundary (UDB) in the northwest and midwest, Everglades National Park boundary in the south, in view of no significant population in the Everglades, and the boundary of the Port of Miami in the east (Figure 1A).

Florida census tract data were downloaded from the U.S. Census Bureau for the 2010 decennial U.S. Census, consisting of 297 tracts within the MDPD jurisdiction (U.S. Census Bureau 2016). Next, the demographic data were added from the 2010 U.S. Census to the census tracts, which included population density, median age, poverty, and all racial and ethnicity-related demographic attributes. For numerical attributes such as population, we multiplied the proportion field calculated earlier by the different attributes to get an estimate of the included data for each clipped census tract. The average tract population was 5,420 people but with a high degree of variance—population sizes ranged from a few tracts containing 210 to a maximum of 11,966 people (Table 1). Finally, we calculated the crime counts at the census tract level (Figures 1B and 1C). The average number of aggravated assaults at the census tract level was 100 with a standard deviation of 154; for larceny it was 1,013 with a standard deviation of 1,132.

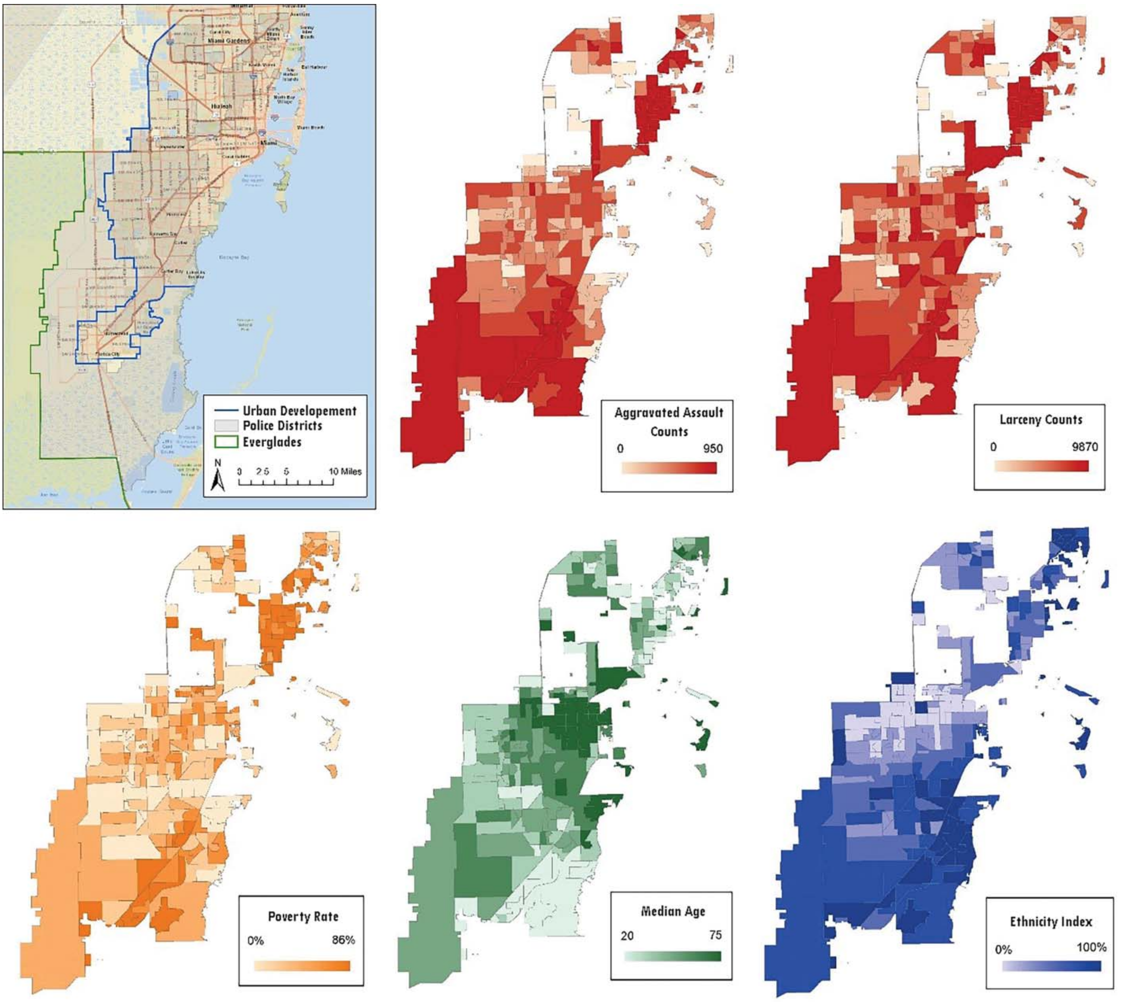

Figure 1 *Census tract–level distribution of (A) general layout of the study area; (B) aggravated assaults; (C) larceny; (d) poverty rate; (e) median age; and (f) ethnic diversity index. Census tracts are clipped on the west and south by the Urban Development Boundary and the Everglades. (Color figure available online.)*

To understand the relationship between reported crimes and sociodemographic characteristics, we took into consideration poverty rate (Figure 1D), median age (Figure 1E), and the ethnic diversity index (Figure 1F) at the census tract level. The ethnic diversity index was calculated by the following equation, which is based on the more widely used Blau's index of heterogeneity (Blau 1977):

$$\begin{aligned}\text{Ethnic Diversity Index } = 1 - \Big[&(\text{Hispanic})^2 + (\text{White})^2 \\ &+ (\text{Black})^2 + (\text{Asian})^2 \\ &+ (\text{Native American})^2 \\ &+ (\text{Pacific Islander})^2 \\ &+ (\text{Other})^2\Big],\end{aligned}$$

where each ethnicity is represented by an ethnic diversity index representative of all of the different ethnicities recognized by the census. Due to the substantial variation in ethnic composition across the county and having one of the highest concentrations of foreign-born population in the entire country, the ethnic diversity index represents the spatial patterns of ethnic diversity in the study area.

To examine the spatial clustering of larceny and aggravated assault, we used EHSA1 to reveal the spatial patterns of crime incidences across Miami–Dade County. This technique identifies the spatial patterns of point clustering trends over a given period of time, in the form of intensifying, persistent, diminishing, sporadic, oscillating, and historical hot and cold spots. An EHSA has two sets of parameters for (1) a space–time cube and (2) the actual analysis. A space–time cube is a netCDF file representing points in *XY* coordinates with a *Z*-coordinate for time. We calculated the EHSA based on a time cube with a time interval of twelve months. The output maps are limited to four types of hot spots (new, consistent, intensifying, and persistent) to simplify visual analysis (Esri 2016).

We next used GWR to examine the role of various sociodemographic variables on crime incidence. This method takes into consideration spatial nonstationarity in the relationships between different variables across space (Fotheringham, Charlton, and Brunsdon 1998; Fotheringham and Brunsdon 1999; Fotheringham, Brunsdon, and Charlton 2000). It is estimated using a subset of data close to the point location being predicted. The equations used for calculating the GWR for larceny and aggravated assault are given here:

$$\begin{aligned}\text{Larceny }(x,y) = {} & \beta 0(x,y) \\ & + \text{Ethnic Diversity Index }(x,y) \\ & + \text{Poverty }(x,y) + \text{Median Age }(x,y) \\ & + \varepsilon(x,y)\end{aligned}$$

$$\begin{aligned}\text{Aggravated Assault }(x,y) = {} & \beta 0(x,y) \\ & + \text{Ethnic Diversity Index }(x,y) \\ & + \text{Poverty }(x,y) \\ & + \text{Average Age }(x,y) + \varepsilon(x,y),\end{aligned}$$

where (x, y) are coordinates for individual crime locations and $\beta(x, y)$ is a vector of the location-specific parameter estimates. This method takes into consideration the local variations in rates of change with resulting coefficients calculated by the model that are specific to each location (Brunsdon, Fotheringham, and Charlton 1996). Specifically, the parameter estimates are calculated with a weighting method in which the contribution of an observational site to the analysis is weighted in accordance with its spatial proximity to the specific location being considered. We also used Akaike's information criterion correction (AICc) and an adaptive kernel for optimal bandwidth and number of neighbors. Therefore, the contribution of an observation in the analysis is not constant but a function of its relative location. This technique has been successfully used to examine the spatial patterns of violent crime, such as in the case of Portland, Oregon (Cahill and Mulligan 2007).

Maps of the derived parameters, which included the local R^2 values and the local beta coefficients for each of the independent variables, were used to identify the spatial patterns of the role of different independent variables on the incidences of larceny and aggravated assault in Miami–Dade County. The local R^2 values ranged between 0.0 and 1.0, which when mapped allow us to visualize the spatial variations in the performance of the GWR model and indicate where the local regression model fits the actual crime occurrences well.

Results

To investigate the temporal variations of crimes across Miami–Dade census tracts, we first report the results of the daily hourly analysis of larceny and aggravated assault.[2] The overall hourly patterns of crime reveal the middle of the day as the peak time for larceny, which coincides with normal working hours (Figure 2A). The temporal patterns of aggravated assaults, however, peaked in the after-dark hours, close to midnight. We next plotted the time of crime during the entire day for each day of the week separately. On weekdays there is a higher crime incident rate during daytime hours, whereas on weekends there is a spike late at night (Figure 2B). If we look at Monday and Wednesday, there is a clear increase in both types of crime during the daytime hours from 6 a.m. to 4 p.m. In contrast, on Friday there is a higher rate for both types of crimes during the late-night hours from 4 p.m. to 6 a.m. Our results are similar to those observed in other cities such as Houston, Texas, where similar spikes in crime were observed during the evening hours (7 p.m.–2 a.m.) as well as midday to early-evening hours (1 p.m.–7 p.m.; Gao et al. 2014). Similar results were also found in the case of armed robberies in Houston from 1990 to 1999, when half of all robberies occurred between 5 a.m. and 6:13 p.m. and the other half between 6:13 p.m. and 4:59 a.m. (Felson and Poulsen 2003). Additionally, we found higher rates of crime during weekends (Friday–Sunday) than on weekdays (Monday–Thursday).

The overall spatial patterns of the two types of crime incidences were mapped at the census tract level (Figures 1B, 1C), alongside the three independent variables (Figures 1D, 1E, 1F) derived from 2010 Census data. The spatial distributions of both types of crimes are predominantly similar, exhibiting a higher concentration in the northern section of the study area, particularly over Liberty City, Overtown, and in the southwest in Florida City near Homestead and South Miami Heights (Figures 1B, 1C). The spatial patterns of poverty rates were similar to that observed for the two types of crime (Figure 1D), and higher median populations were mostly concentrated in the western half of the study area (Figure 1E). In general, higher levels of ethnic diversity were located in the south, with limited diversity observed in the northern section of the study area (Figure 1F). More specifically, the northern extreme of the study area in Liberty City, Overtown, and Miami Lakes has a greater proportion of black population, and the central section of the study area near Tamiami Trail has a greater concentration of Hispanics, mostly of Cuban origin. The spatial patterns of poverty rates were again higher (greater than 50 percent) over Liberty City and Overtown in the north and in the extreme south near Homestead (Figure 1D). Finally, the spatial patterns of median age of population revealed a concentration of middle-age and older population (greater than forty years of age) in the central part of the study area, with the younger population concentrated in the northern and southern section of the study area (Figure 1E).

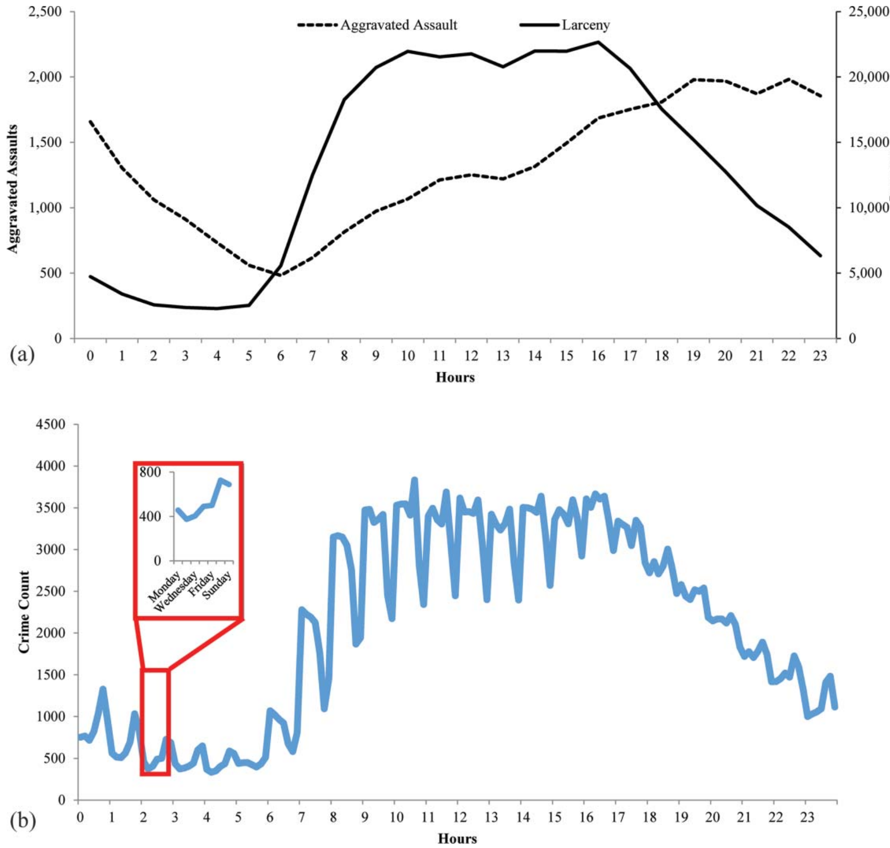

Figure 2 *Distribution of larceny and aggravated assault during the day in Miami–Dade County: (A) time of day for all days and (B) time of day based on day of week. (Color figure available online.)*

We next analyzed the results of EHSA to determine the trends in the spatial patterns of crime. There were significant hot spots in the area just north of Homestead as well as in North Miami for aggravated assaults (Figure 3A). Although most locations were persistent hot spots (i.e., hot spots for the whole study period without a significant trend up or down), some of the areas, in central Miami–Dade County near Homestead, showed up as intensifying hot spots. In other words, those intensifying locations have recently been experiencing more incidences of aggravated assault compared to the beginning of the study period. These areas also overlap with areas of relatively higher poverty rates and the lower median ages (Figure 3A).

In the case of larceny, the results of our EHSA indicated a wider spatial spread of hot spots, ranging from North Miami down to Kendall and Cutler Bay in the southwest (Figure 3B). In addition, the spatial patterns of larceny hot spots revealed more intensifying hot spots than observed in the case of aggravated assaults. Many locations that were identified as persistent hot spots were surrounded by intensifying hot spots. The periphery of the hot spot area is surrounded by consecutive hot spots, hot spots that are uninterrupted for the entirety of the study timeline. There are only a handful of these in the county, with most of them located in the very far west of Kendall near the Hammocks. These areas are more suburban with a higher density of population due to relatively lower property prices. As was seen with larceny, time of day leads to a pattern of crime during the daytime hours when more people are not home, amplified in this case by an area with many homes, a lot of working parents, and children in school. Similarly, areas showing persistent, intensifying, and consecutive hot spots toward the central north Olympia Heights, Westchester, and West Miami are also suburban with a higher population density. The areas with persistent hot spots are northeast and west as well, along the coast toward North Miami Beach and the Miami Lakes and Country Club areas. Although this analysis implies that areas experiencing larceny will experience more crime, there is little indication of areas where there are new hot spots. This caveat indicates that larceny is consistent in areas that are already experiencing higher than normal crime rates. Interestingly, the areas covered in the larceny map all had a wide range of values.

Finally, we conducted a GWR to examine the local-level role of different sociodemographic variables on the spatial patterns of aggravated assaults and larceny.

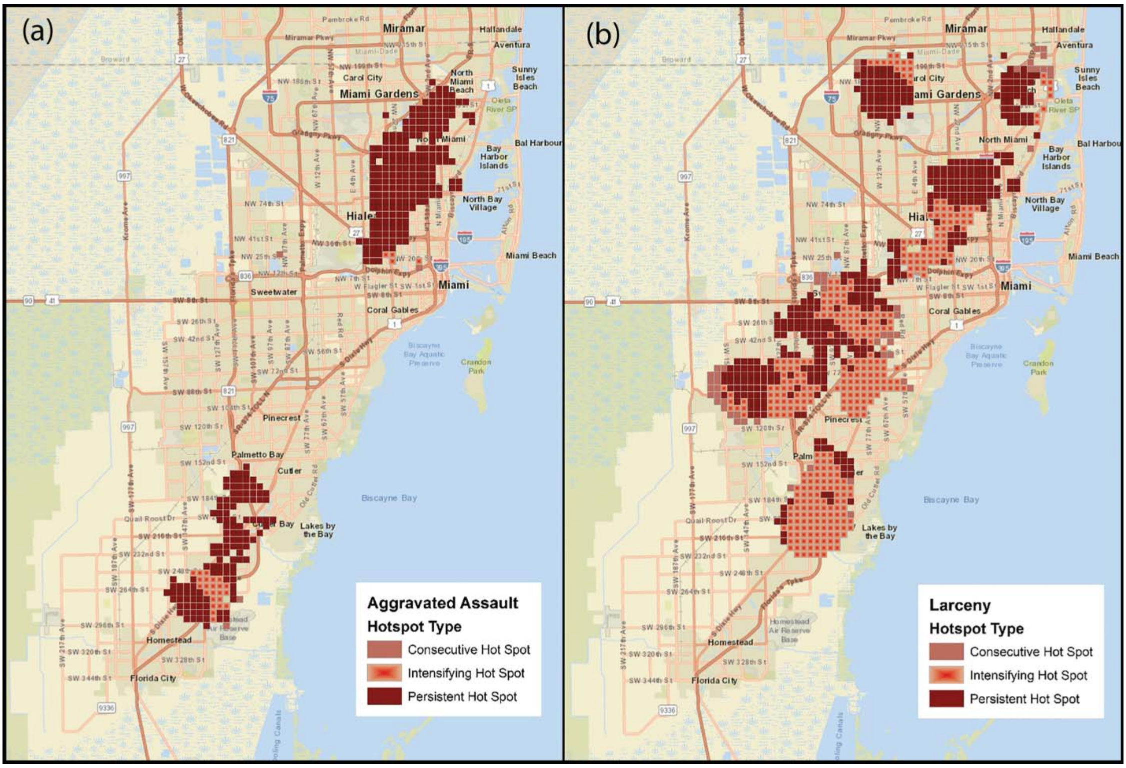

Figure 3 *Results of emerging hot spot analysis for (A) aggravated assault and (B) larceny. (Color figure available online.)*

To determine the suitability of GWR analysis for this study, we conducted an exploratory regression model to assess the role of the three independent variables on the incidence of aggravated assaults and larceny. The exploratory regression model builds the ordinary least square (OLS) models using all possible combinations of the explanatory variables and helps in assessing the best model. The comparative diagnostics between GWR and exploratory regression analysis showed lower AICc values for the GWR model with higher local adjusted R^2 values (Table 1). The results of this analysis indicate that ethnic diversity index has the highest correlation, followed by poverty rates and median age. The local R^2 values for aggravated assault were 0 to 35 percent, and these were located in the south central section, Palmetto Bay, Kendall, Hammocks, and the high-crime areas in the north over Miami Gardens, Miami Lakes, and Liberty City (Figure 4A). The local-level role of poverty on the incidences of aggravated assaults was positive across the entire county, indicating that higher levels of poverty lead to a greater incidence of aggravated assaults (Figure 4B). Thus, lower income areas were more prone to aggravated assaults. The spatial patterns of the beta coefficients for poverty were similar to that observed in the case of the R^2 values for aggravated assaults. The role of the ethnic diversity index was predominantly negative among the three independent variables across the county, except east of US 1 along the coast (Figure 4C). This detail implies higher ethnic diversity leads to higher levels of crime. A similarly negative correlation was observed in the case of median age across most of the county, except in the central part of the western section of the county. Overall, ethnic diversity has a more dominant role on the incidences of aggravated assault in Miami–Dade County, which can be attributed to lower levels of cohesion between ethnically diverse populations.

Local R^2 values, from the GWR model, ranged from 0 to 19 percent for larceny, lower than those observed for aggravated assaults. The spatial patterns for the local R^2 values were the lowest in the high-crime-incidence areas in the northern part of the county, whereas the central western part near the Tamiami Trail showed the highest R^2 values of 10 to 19 percent (Figure 5A). All three independent variables were positively related with larceny incidences in most of the county. In the case of poverty, the highest coefficients were located in the central part of the county, whereas the areas close to the Tamiami Trail in Westchester, West Miami, and Miami Springs exhibited negative correlation with poverty rates (Figure 5B). The coefficients for ethnic diversity index and median age were predominantly positive and relatively higher than those observed in the case of aggravated assaults (Figure 5C and 5D). The spatial patterns for all three variables were similar, with the higher coefficients located in the central part of the county.

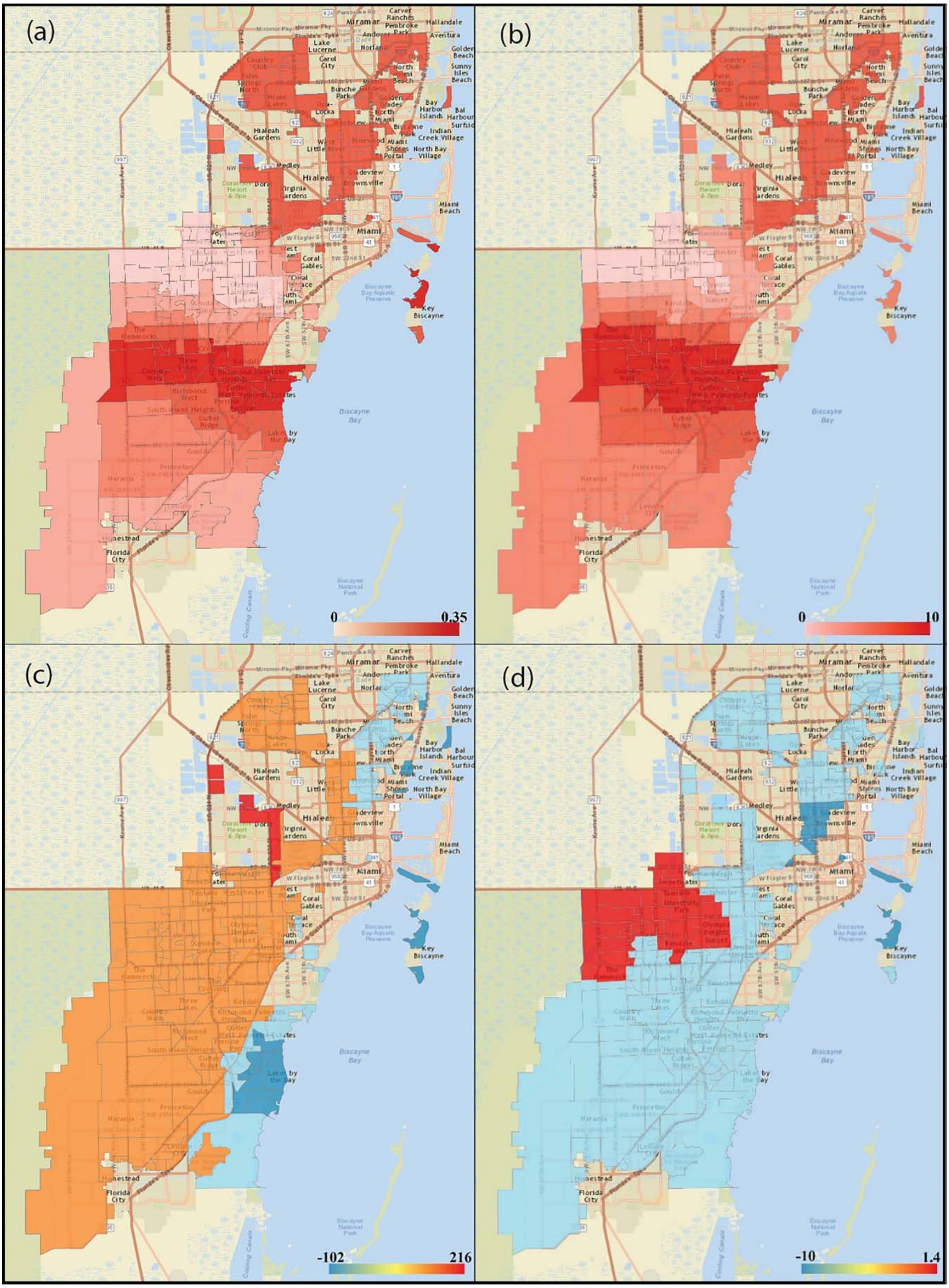

Figure 4 *Results of geographically weighted regression analysis for aggravated assaults: (A) Local R^2 values; (B) beta coefficients for poverty; (C) beta coefficients for ethnic diversity index; (D) beta coefficients for median age. (Color figure available online.)*

Discussion

In general, aggravated assaults peak close to midnight, whereas larceny-based crimes have a broader peak during the day from 6 a.m. to 6 p.m. There is a distinct difference in the temporal patterns of crime between weekdays and weekends. During weekdays, crime peaked during the midday hours, whereas during

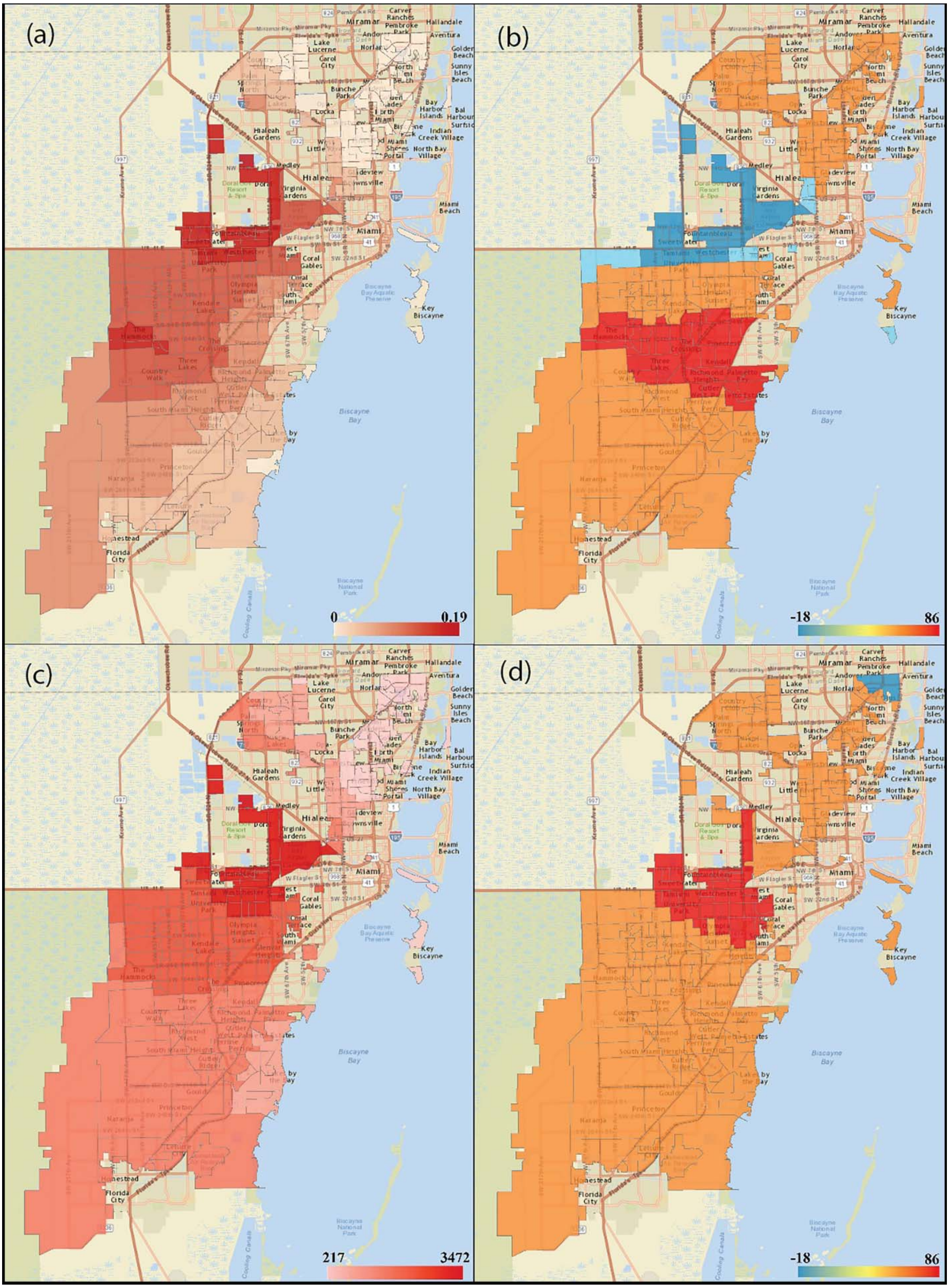

Figure 5 *Results of geographically weighted regression analysis for larceny: (A) Local R^2 values; (B) beta coefficients for poverty; (C) beta coefficients for ethnic diversity index; (D) beta coefficients for median age. (Color figure available online.)*

weekends the peak hours of crimes were close to midnight. This phenomenon can be attributed to the opportunity for crime at midday when most people are at work and at night when most people are at evening recreational activities, often involving alcohol, which can increase aggression. Both types of crimes tended to be higher in inland areas. These findings are consistent with previous studies testing routine activity theory (Felson 1996; Rice and Smith 2002), suggesting that larcenies occur with greater frequency during daytime hours when guardianship (i.e., residents at home supervising their property) is lessened and suitable targets (i.e., homes with valuable property) are plentiful.

The results of EHSA indicate two main areas for intensifying and persistent hot spots: one in the north near Liberty City and Miami Gardens and another in the south, near Homestead and Palmetto Bay. In the case of larceny, however, the intensifying and persistent hot spots were much more spread out across the county. Finally, the use of GWR to analyze the local-level interactions between sociodemographic variables on the incidences of larceny and aggravated assaults revealed that the ethnic diversity index has the strongest impact on increasing crime incidence, followed by poverty and then median age of population[3] at the census tract level. These results replicate findings applying social disorganization theory (Kubrin and Weitzer 2003; Emerick et al. 2014), specifically in that greater ethnic and racial heterogeneity and economic disadvantage (i.e., poverty) are associated with higher rates of neighborhood property and violent crime. The mechanisms by which this empirical relationship operates are as follows. Population heterogeneity, poverty, and population turnover impede the formation of cohesive social bonds among neighbors (i.e., lowered collective efficacy; Sampson 2012), which lessens the chance that they will intervene when witnessing crime and suspicious community activity. Thus, increased levels of social disorganization in such neighborhoods are associated with increased incidences of aggravated assault and larceny.

The overall strong positive correlation between the ethnic diversity index and crime can be explained by distrust of certain ethnic or immigrant groups (Hooghe and de Vroome 2016). Specifically, whites felt threatened by Hispanics and blacks living in close proximity based on interviews of a random sample of 3,000 residents in South Florida (Chiricos, McEntire, and Gertz 2001). The results of the study suggest that Hispanics might be threatened by the presence of blacks. In this context, a study by Putnam (2007) showed evidence of social withdrawal in diverse U.S. communities, which has generated animosity in different aspects of social and political life. This study also suggests that ethnically diverse communities lack public amenities such as community centers, which can cause political inequalities and lead to lower social cohesion and neighborhood trust. The role of ethnic diversity in reducing social cohesion at the neighborhood level has been widely validated (Greif 2009; Laurence and Bentley 2016), which further leads to distrust and higher levels of crime and feelings of animosity (van der Meer and Tolsma 2014). Similarly, the overall positive correlation between aggravated assaults and larceny and poverty is in line with literature examining the relationship between crime and poverty (Warner and Pierce, 1993; Kposowa, Breault, and Harrison 1995; Warner and Rountree, 1997; Hipp 2007). Several recent studies, however, have indicated a diminishing positive relationship between poverty and crime over time (Brush 2007; Hipp and Yates 2011).

Conclusion

In this study, we examined the spatial patterns of two types of crime, aggravated assault and larceny, from 2007 to 2015 in Miami–Dade County. We used a variety of geostatistical techniques to identify the concentrations of crimes in the county. We also examined the role of various sociodemographic variables, including ethnic diversity calculated as ethnic diversity index, poverty, and median age at the census tract level, on the occurrence of aggravated assaults and larceny.

Our analysis reveals substantial spatial and temporal variations in the occurrence of aggravated assault and larceny. The temporal variations in peak times of crime between weekdays and weekends can be useful for crime prevention in terms of partitioning limited police resources across the county. The strong modulating role of ethnic index on the spatial patterns of crime is particularly significant in the context of high levels of inequality and prevalence of ethnic enclaves in the Miami metropolitan area. Additionally, the consistent hot spots of crime over certain sections of the county, such as Liberty City, Miami Gardens, and Kendall, need to be further examined in relation to local neighborhood factors known to be associated with high crime, such as alcohol outlets, measures of gentrification, and drug possession and trafficking arrests. One of the shortcomings of this study is that the crime data only include the neighborhoods that are serviced by the MDPD. They do not include many locations that are popular among visitors and heavily populated like Miami Beach, Brickell, Little Haiti, Little Havana, Coral Gables, Coconut Grove, Hialeah, and Miami Gardens. The results of our study can be applicable for other large metropolitan areas with high levels of ethnic diversity and spatial inequalities. More specifically, based on Sampson's (2012) and Ramey's (2013) findings that social disorganization is applicable across metropolitan and immigrant neighborhoods in cities, because Miami is a densely populated, racially, ethnically, and economically heterogeneous urban area, these results can be generalized beyond the South Florida context. By analyzing a longer time series of crime data, we are able to reveal the long-term trends in aggravated assault and larceny.

The results of the trends in spatial hot spots provide a deeper understanding of effective crime prevention practices in the county, which can be applied in crime prevention in other large metropolitan areas. Additionally, the results of this study might be useful for understanding the role of gentrification on the evolving patterns of crime. ■

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Notes

[1] Introduced in ArcGIS 10.3.2.

[2] Although it is not the primary focus of this article, we investigate and report the temporal results from hourly scale daily analysis to show the differential patterns based on crime type. Our results are consistent with the body of substantive literature on the temporal patterning of crime (e.g., Hipp and Yates 2009; Linning, Andresen, and Brantingham 2016; Pereira, Andresen, and Mota 2016) and support a routine activity framework (Cohen and Felson 1979), which is interpreted in greater detail in the "Discussion" section.

[3] Our findings that crime is higher in areas with a younger population (i.e., ages eighteen to twenty-eight) are consistent with research on criminal involvement across the life course (Laub and Sampson 2003), specifically that participation in crime tends to peak between eighteen and twenty-five among males. Drawing from routine activity theory (Cohen and Felson 1979; Rice and Smith 2002), because these individuals would likely be more motivated offenders, our findings on the spatial patterning of crime show that areas with more motivated offenders also have higher crime incidence.

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