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Locating Offenders: Introducing the Reverse Spatial Patterning Approach

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Locating Offenders: Introducing the Reverse Spatial Patterning Approach

Abstract

Objectives: Current strategies for locating where offenders live either focus exclusively on individual suspects or generalize to entire neighborhoods. However, better estimates of where offenders are located may improve models of the ecological distribution of crime, and forecasts of the locations of future crime incidents.

Methods: We propose a novel *reverse spatial patterning* (RSP) strategy that estimates where offenders may live based on the spatial locations of crime events. We rely on a distance decay function – based on the consistent finding that offenders do not travel far to commit crime – and Hipp's (2016) general theory of spatial crime patterns, to work backwards from the locations of actual crime events to make predictions about where offenders may live in subsequent years. We then use these estimates in models predicting crime locations. We create two versions of the RSP: one which assumes everyone is equally likely to offend, and another that creates an estimate assuming disproportionate offending across persons.

Results: We test the effectiveness of our proposed strategy for these two measures using offense and arrest data from St. Petersburg, FL, and assess how well they predict the location of offenders (proxied by arrestees) and future crime events. We find consistent evidence that our RSP strategy provides better predictions of the locations of where offenders are located and also future crime incidents across a variety of crime types compared to existing strategies.

Conclusion: The RSP approach is useful for creating estimates of where offenders live, which allow for better predictions of the locations of future crime incidents. These better forecasts will allow for more efficient allocation of police resources and targeted crime suppression efforts.

Keywords: crime; offenders; micro-crime

Bio

John R. Hipp is a Professor in the departments of Criminology, Law and Society, and Sociology, at the University of California Irvine. His research interests focus on how neighborhoods change over time, how that change both affects and is affected by neighborhood crime, and the role networks and institutions play in that change. He approaches these questions using quantitative methods as well as social network analysis. He has published substantive work in such journals as *American Sociological Review, Criminology, Social Forces*, *Social Problems*, *Mobilization, City & Community, Urban Studies* and *Journal of Urban Affairs*. He has published methodological work in such journals as *Sociological Methodology*, *Psychological Methods*, and *Structural Equation Modeling*.

Lyndsay N. Boggess is an Associate Professor in the Department of Criminology at the University of South Florida. Her research focuses on communities and crime, primarily how crime affects and is affected by neighborhood change, racial/ethnic composition, and gentrification and economic investment. Her work has appeared in *Criminology*, the *Journal of Quantitative Criminology*, and *the Journal of Research in Crime and Delinquency*.

Alyssa W. Chamberlain is an Associate Professor in the School of Criminology and Criminal Justice at Arizona State University. She received her Ph.D. from the University of California, Irvine in 2012. Her research focuses on neighborhood dynamics related to changes in social and demographic structure, housing, and inequality and the spatial distribution of crime. She also examines issues related to prisoner reentry and recidivism, and how incarceration and reentry both affect and are affected by community structure.

Locating Offenders: Introducing the Reverse Spatial Patterning Approach

INTRODUCTION

Crime and offender locations are unevenly distributed across the neighborhoods of a city. Knowing where offenders are located is useful for forecasting where future crimes may occur. Current offender location strategies, however, are either narrowly focused on singular offenders (i.e., geographic profiling) or broadly assume that offenders live in socially disorganized neighborhoods (e.g., social disorganization theory). We propose an alternative approach that extends the offender-specific strategy used in geographic profiling, and refines the more general assumptions of social disorganization theory: The *reverse spatial patterning* (RSP) strategy uses the spatial distribution of known crime events to create estimates of where offenders live, which can allow for better models of the ecological distribution of crime, as well as more effective forecasts of where future crimes may occur.

The RSP strategy is built on insights from the journey to crime literature and Hipp's (2016) general theory of spatial crime patterns. Both journey to crime and spatial patterning are based on the contention that the spatial interactions of individuals are constrained by distance, with contact more likely to occur when individuals are in closer proximity to one another. Journey to crime research has found consistent evidence that offenders commit crimes close to their own homes with a distance decay function (Barker 2000; Bernasco and Block 2009; Chamberlain and Boggess 2016); and is the basis for geographic profiling. The general theory of spatial crime patterns suggests that we can potentially predict where crimes may occur based on where offenders live and the constrained movements of offenders and targets. RSP uses the spatial distribution of known crime in a city and works backwards using principles of distance decay to compute estimates of where the offenders might live who commit those crimes. This approach calculates estimates of "offender intensity" for blocks surrounding the incident. Offender intensity measures the probabilities of offenders residing on each block, which can be used to create estimates of the location of offenders to allow better prediction of where future crimes will occur.

We introduce two versions of the RSP strategy. The first version of the RSP strategy assumes that all persons have an equal likelihood of being offenders. The second version builds on existing research that members of certain demographic groups are more likely to be offenders, or that certain neighborhood characteristics increase the likelihood of becoming an offender. This implies that certain characteristics might explain why some neighborhoods have more offenders, and incorporating this information may improve the predictions of where offenders may live. Therefore, we test a second RSP strategy that weights the distance decay estimates by the presence of characteristics associated with a disproportionate likelihood to offend (e.g., young age or low income (Gottfredson and Hirschi 1990)); we refer to this second strategy as the reverse spatial patterning – disproportionate offending (RSP-DO) strategy.

To further examine the effectiveness of our proposed RSP approaches, we compare our two RSP strategies (RSP and RSP-DO) with three other strategies. First, certain neighborhood characteristics among the general population of residents are associated with more crime generally, and neighborhoods with disproportionately more of these characteristics would be expected to have more offenders; Hipp (2016) referred to this as a social demography (SD) strategy. This is distinct from the RSP-DO strategy because the SD approach does not incorporate information on the location of potential offenders like we do in our RSP-DO equations. We assess two neighborhood characteristics associated with increased rates of offending: the age structure of the neighborhood (SD-AGE) and levels of poverty (SD-POV). This is based on prior research which has found that individuals who are younger tend to have a higher likelihood of offending relative to older individuals (Laub and Sampson, 1993; Sampson and Groves, 1989), and neighborhoods with higher rates of poverty are associated with more crime (Sampson and Morenoff, 2006). Third, we incorporate a disproportionate offending (SD-DO) model, which accounts for the characteristics of residents in a neighborhood that may increase the likelihood of offending, but in doing so, we do not incorporate the location of potential offenders. This enables us to compare the RSP strategies, which account for the potential spatial movement of offenders, to the overall distribution of residents in neighborhood that may be at increased risk to engage in crime. To this end, we compare the utility of our two RSP strategies (RSP; RSP-DO) relative to the utility of the three different SD approaches (SD-AGE; SD-POV; SD-DO). We use data with known address information for suspects' residences and crime locations from St. Petersburg, FL between 2010 and 2012 and assess the utility of the RSP and RSP-DO approaches to determine which strategy most accurately predicts the locations of offenders (using arrestees as a proxy) and which best predicts future crime incidents based on one particular crime forecasting strategy.

LITERATURE REVIEW

The RSP approach is based on insights from the journey to crime literature that offenders do not travel far from their homes (i.e., a distance decay) and Hipp's (2016) general theory of spatial crime patterns. The voluminous journey to crime literature has consistently demonstrated a strong distance decay effect in which offenders are more likely to commit crimes closer to their home, and much less likely to target locations that are further from where they reside. This holds true across crime types, including burglary (Barker 2000; Rengert, Piquero, and Jones 1999), robbery (Pettiway 1982), sex offenses (Beauregard et al. 2005), and homicide (Groff and McEwen 2005). Offenders typically only travel within a few miles of their homes (Ackerman and Rossmo 2014; Rossmo 2000; Santtila et al. 2008). For example, examining journey patterns for 10 different types of crime, Phillips (1980) found a mean distance to crime of 1.43 miles. However, offenders may be more inclined to travel further distances to engage in property than violent crimes (Rossmo 2000) or to areas with particularly attractive targets (Bernasco and Luykx 2003; Snook 2004; Vandeviver and Bernasco 2017). Prior research has found a mean distance to violent offenses was 0.83 miles compared to 1.73 miles for property offenses (White 1932). There is also evidence that offenders are more likely to select a location if the persons there are of a similar background as themselves (Bernasco and Block 2009) or to their home neighborhood (Chamberlain and Boggess 2016). Importantly, these studies consistently show that there is a strong distance decay effect in which offenders are most likely to commit crimes closer to their home, and much less likely to commit crimes at locations further from their home. Adults may also travel slightly further distances from home to engage in crime relative to juveniles, but whether they offend alone or as part of a group has a negligible effect on distance (Chamberlain, Boggess, and Fisher 2022). This also suggests that crimes attributed to a single offender or group of offenders will spatially cluster (i.e., the basis for geographic profiling) and that a concentration of crime events potentially signals the locations of nearby offenders.

Offenders are more likely to engage in criminal behavior close to home, in part, because they are the most familiar with these areas (Brantingham and Brantingham 1993). Through the course of their routine activities, individuals develop activity spaces comprised of the nodes and paths through which they travel (Brantingham 2010). In doing so, potential offenders become aware of situational characteristics that may help or hinder criminal activity and the levels of guardianship that are associated with the risk of being caught (Beavon, Brantingham, and Brantingham 1994). These activity spaces are constrained to the typical movement patterns of persons. Consequently, many would-be offenders commit crime in their own neighborhood and nearby neighborhoods (Ratcliffe 2006). Offenders may not even be aware of criminal opportunities that exist outside of their typical activity space (Brantingham and Brantingham 1993). Although crime pattern theory considers additional nodes beyond an offender's residence, the majority of the journey to crime work has measured the distance from residence to crime location.[1]

Hipp's (2016) general theory of spatial crime patterns estimates probabilities of where, when, and how much crime may occur across locations based on the spatial distribution of potential offenders, targets, and guardians. More specifically, the general theory of spatial crime patterns combines information on where individuals are located along with the expected spatial movement patterns of individuals (based on a distance decay function), and the characteristics of locations (schools, retail, parks, entertainment) to estimate the potential for crime at certain locations during certain times of day. Hipp's theory starts with an estimate of where offenders might live and assumes offending based on a distance decay function—important insights for the RSP strategy proposed here. Hipp's (2016) theory is built on the insight that people (including offenders) exhibit the least effort principle (Zipf 1949). Under this basic principle, persons are more likely to travel to destinations that are closer to home rather than farther away when they are traveling to various amenity destinations including retail, restaurants, parks, and entertainment establishments. Similarly, offenders will tend to commit crimes closer to their own

[1] It is worth pointing out that these additional nodes themselves will tend to exhibit a distance decay function from the home, given evidence on spatial patterns of typical activity spaces (Golledge and Stimson 1997; Palmer et al. 2013), as well as evidence of a distance decay effect in how far residents tend to travel to work (Wang 2001).

residence rather than further away, all else equal, which is what the journey to crime literature consistently finds. As a consequence, patterns of offense locations display a distance decay effect in which the likelihood of an offender targeting a location decreases as the distance from the offender's home increases. The implication is that we can work backward from known crime locations to generalize the locations of all potential offenders, rather than that of a single known offender, as we demonstrate shortly.

Recent crime forecasting strategies: Whither offenders

Other crime modeling strategies largely focus on the spatio-temporal distribution of past crimes to predict the locations of future crimes more generally. For example, hot spot policing identifies areas with high frequencies of crime, and uses those to estimate where future crime is likely to occur. Within hot spot strategies, there are several mapping techniques (such as point pattern or kernel density), but all are based on the geographic concentration of past crime events (Groff and La Vigne 2002; Sorg et al. 2013; Weisburd, Groff, and Morris 2011). Similarly, Risk Terrain Modeling (RTM) is a crime forecasting model based on a grid system that uses physical and structural characteristics to identify areas most at risk for crime. RTM differs from hot spot techniques in that RTM incorporates environmental features such as restaurants and bars, convenience stores, and other retail outlets to predict areas most at risk. In 2016, Drawve (2016) compared the predictive capabilities of six hot spot strategies and RTM and found that kernel density estimation most accurately predicted the general locations of future crimes while RTM had better precision. Recent research has applied more complicated deep learning techniques (Solomon et al. 2022)(Wang et al. 2019) and neural network modeling (Rummens, Hardyns, and Pauwels 2017) to predict crime. Hwang and colleagues (2017) used simulation models to get more granularity in order to predict which buildings would be burglarized. These techniques all focus on the general prediction of crime locations, and are primarily based on the locations of prior criminal events.

Our proposed RSP strategy also relies on the locations of past crime, but rather than forecasting generally where crime might occur next, focuses on finding where the people who committed those crimes live. While the distinction may be nuanced, our RSP strategy may be more effective in reducing crime in the long run by solving open cases and incarcerating offenders. However, Drawve (2016) and others (e.g., Caplan et al., (2011) argue the best approach would be to use multiple predictive strategies, and our proposed RSP is a novel addition to the crime mapping toolkit. Furthermore, these existing modeling strategies may be enhanced in the future by incorporating information on the possible presence of offenders into their model, an issue to which we return in the Discussion section. We next turn to describing how our approach generates an estimate of the locations of offenders across the spatial landscape.

REVERSE SPATIAL PATTERNING STRATEGY

Given the above insights derived from research on geographic profiling and the general theory of spatial crime patterns, we propose a model to better estimate where offenders may live based on the concentration of crime at particular locations. In doing so, we rely on the location of crime events relative to the potential number of offenders residing nearby, with the initial assumption that all residents are potentially offenders. Taken together, we can construct geographic buffers around crime events to determine where offenders are expected to live given the distribution of crime in the proximal areas. We next further detail this approach.

Modeling where offenders go

Before we can generalize where offenders might live with the RSP approach, we first need to know the probability that a location would be targeted. Journey to crime research often uses discrete choice models (McFadden 1978) based on offenders' home addresses and the spatial distribution of criminal opportunities in relation to offender residence (Bernasco 2010; Bernasco and Block 2009; Clare, Fernandez, and Morgan 2009) to estimate the likelihood that an offender will select a particular target location. Knowing that offenders exhibit patterns of distance decay, we can model the probability that any potential offender selects any particular target location using a combination of nearby opportunities and an assumed preference for committing crimes nearby. This strategy accounts for the observed distance decay effect by including a measure of distance to any particular location from the offender's home address. Hipp (2016) noted that this implies the equation:

$$\text{(1)} \qquad \mathrm{Prob}(\mathrm{C}_{iqbt}) = \mathrm{f}(\mathrm{O\_I}_{i}, \mathit{dist\_O}_{ibt}, \mathrm{T}_{bt}, \mathrm{G}_{bt}, \mathrm{SIT}_{bt}, \mathrm{SOCDIST}_{ibt})$$

where C is a crime incident of type *q* at location *b* at time *t* committed by person *i*, O_I is a latent measure of offender intensity of individual *i* (the frequency and willingness to commit an offense),[2] *dist_O* is the distance from offender *i* to a particular location *b* (distance decay), T is the number of targets at location *b* at time *t*, G is the number of guardians at location *b* at time *t* that may affect the probability of being caught if committing the offense, SIT are a set of situational characteristics that characterize the environment at a particular point in time (e.g., the lighting, features that obstruct visibility, etc.), and SOCDIST measures social distance, or a set of neighborhood characteristics that assess the similarity of persons in the environment (*b*) to a particular offender (*i*) at a particular point in time (*t*).

Computing reverse spatial patterning (RSP)

[2] If this is estimated on a sample of known offenders, then this would either be constrained to a value of 1 (given that everyone in the sample was an offender) or else could be weighted by the number of known offenses.

Reverse spatial patterning approach

We now describe our proposed reverse spatial patterning (RSP) approach for estimating the general locations of offenders, which uses the just-described spatial information on how offenders travel about the environment and distance decay information on offender travel, along with the location of actual crime events, to estimate where offenders live. We slightly modify equation (1) from Hipp (2016) predicting the expected count of crimes of type *q* in block *b* at time *t* as follows:

$$\text{(2)} \qquad \mathrm{Exp}(C_{qbt}) = f(O\_I_h, \, dist\_O_{hbt}, \, T_{bt}, \, G_{bt}, \, SIT_{bt})$$

The above equation predicts the expected count of crime events in a block, but focuses on potential offenders in a home block *(h)* rather than the location of a specific offender *(i)*. In this equation, O_I_h is the number of potential offenders on a home block (*h*), or a measure of block level offender intensity, and the value of $dist\_O_{hbt}$ is the distance of location *b* from *h* at time *t*, or the distance decay function of the journey to crime. SOCDIST is dropped because it is a race/ethnicity-specific measure that would require us to create race-specific groups, which is outside the scope of the current study; all other terms remain the same as Eq. 1.

One question is how to assess how many potential offenders live in a home block (O_I_h) given that we do not know which persons have offending propensity. Our baseline RSP assumption is that it is the population of the block: that is, everyone is equally likely to be an offender. An alternative approach would presume that some types of people have a greater propensity to be offenders, and incorporate this information; we will return to this idea later. Also, as a first estimate of this equation we likely would not have time-specific information on the journey to crime and therefore we would not subscript *dist_O* by time (*t*). Indeed, if we are getting a count of potential offenders at locations, the time subscript is only important in that it allows us to capture the differential presence of targets, guardians, and situational characteristics at the location. In this equation the presence of targets, guardians, or situational characteristics would affect the number of crimes in the location but would not affect the functional form of $dist\_O_{ibt}$.

For computing offender intensity, we want to compute the number of crimes on the block as a ratio to the number expected based on the assumption that all persons have an equal probability of being offenders (C_{qbt} / Exp(C_{qbt})). This potentially tells us that offenders may be living nearby who would be disproportionately likely to offend on this block given the distance decay function. If all persons living on or near the block were equally likely to be an offender, we can calculate the expected number of crimes on the destination block using Eq. 2. However, if the actual number of crimes exceeds the expected number of crimes, this indicates either that there are more offenders on or near the block or that some offenders offend particularly often, and therefore is an estimate of offender intensity. Note that if we only wish to predict the location of *offenders*, and not the *offender intensity* of a location (which is a latent variable), we do not need to divide by this baseline estimate (Exp(C_{qbt})) that all persons are equally like to be offenders. Instead, we can use the spatial distribution of the locations of known crimes (C_{qbt}) to create an estimate of the locations of offenders in blocks in the city (O_h).

To understand the distinction between offenders and offender intensity, consider two extreme examples. In one case, there is a block with several persons with high-offender intensity (they are likely to engage in offending), but there are very few crime opportunities in the surrounding area. For instance, if their neighborhood is located far from retail amenities, such as restaurants, bars, grocery stores or parks, they will have fewer target opportunities nearby. In this case, we would expect them to engage in very little crime activity given the limited number of nearby opportunities. In a second case, there is a block with several persons with moderate offender intensity, but there are many crime opportunities in the surrounding area as there are many nearby commercial districts. In this case, we would expect them to engage in a fair amount of crime activity despite the lower propensity to offend. If we simply use the existence of crime incidents in our equations, we will detect the likelihood of nearby offenders, and we would identify the second block as having more offenders than the first block. However, if we divide by the expected crime opportunities in the nearby area, we would determine that the first block has more high-offender intensity individuals. It is simply a matter of which measure the researcher is interested in. In what follows we will describe the approach for detecting the latent measure of offender intensity in blocks, but in our analyses we validate the ability of RSP to predict where offenders might live. We compare the ability of RSP to accurately predict future crime incidents based on these estimates of offender locations.

Given our knowledge of the distance decay function, we can use this information to estimate a decay-based area around each crime incident to capture offender intensity (or offenders). Later we will refer to this decay-based area as a "buffer". In order to do this, we rearrange Eq. 2: we multiply this estimate of excess crimes on the block (*b*) by the same distance decay function to get an estimate of offender intensity on all the blocks (*h*) surrounding the block:

$$(3) \qquad \text{Exp}(\text{O\_I}_{h}) = \text{f}([\text{C}_{qbt} / \text{Exp}(\text{C}_{qbt})], \textit{dist\_O}_{hbt})$$

Note that this is an average of offender intensity on the block: it is the sum of offender intensities of the persons in the block divided by the number of persons. As such, this is a distribution of offender intensity among the individuals in the block.

Computing offender intensity (Eq. 3) is done through a series of four steps, using data on actual crime event locations. First, for a specific block *b*, the number of excess crime events on block b (C_{qbt} / Exp(C_{qbt})) is multiplied by the distance decay function to each block (h) surrounding it. Multiplying this by the number of persons in the home block (h) yields the overall offender intensity in each home block:

(4) $(O\_I_h) = f(([C_{qbt} / Exp(C_{qbt})], dist\_O_{ibt})*pop_h)$

Second, we need to account for the number of other potential offenders in the buffer of these crime events; this is accomplished by summing the number of potential offenders in the buffer:

(5) $(O\_I_{buff\_b}) = f(\Sigma\ O\_I_h)$

This summation occurs for all blocks in a buffer of block b. Third, we divide the value of O_I_h for a block h by the total number of potential offenders in the buffer ($O\_I_{buff\_b}$) to get the expected count of the number of offenders residing in each block of the buffer:

(6) $Exp[(O\_I_{h\_b})] = f(O\_I_h / O\_I_{buff\_b})$

This gives the expected count of offenders residing in block h based on the crime events for block b. We would similarly compute the offender intensity around all other blocks with crime events. Finally, we would then sum these expected counts of offenders for each block in the city:

(7) $Exp(O\_I_h) = \sum_{b=1}^{B} Exp[O\_I_{h\_b}]$

Thus, each block (h) would have a computed estimate of the number of persons weighted by their offender intensity based on the estimates obtained from all the buffers (b) with crime incidents overlapping this home block. This $Exp(O\_I_h)$ is our estimate of the offender intensity in each block.

Computing disproportionate offending – RSP-DO strategy

A recurring question in the field of criminology is the extent to which certain types of people are more likely to be offenders than others (Gottfredson and Hirschi 1990). Up to now, we have assumed that all persons are equally likely to be offenders and explicitly built this into the RSP strategy. However, studies have found that members of certain demographic groups are disproportionately more likely to be offenders compared to others (Farrington 1990; Gottfredson and Taylor 1986; Nagin and Land 1993), and that certain neighborhood characteristics may increase the likelihood of offenders in those neighborhoods (Braga and Clarke 2014; Brantingham and Brantingham 1995; Shaw and McKay 1942; Weisburd 2015). This information can be used to proxy for the greater presence of offenders on some blocks compared to others and may improve estimates of where offenders are located. This suggests modifying RSP with information on characteristics of persons within blocks who are more likely to offend. For example, neighborhoods with a greater proportion of renters, more youth, or a higher poverty rate might be expected to have a greater number of offenders (Boggess and Hipp 2010; Krivo and Peterson 1996; Sampson and Groves 1989). The most direct way to accomplish this is by weighting the number of persons in the block based on their demographic characteristics that might increase the likelihood of offenders residing in the block. We modify Eq. 4 above using these weighted estimates instead of the total population (which assumes that all persons are equally likely to be offenders). We refer to this modified RSP approach as reverse spatial patterning-disproportionate offending (RSP-DO).

Social demography – SD strategy

Hipp (2016) proposed accounting for differential tendencies to offend by using block-level information of demographic characteristics and/or the structural characteristics as proxies for the possible presence of more potential offenders; he referred to this as a *social demography*

(SD) strategy. The SD approach accounts for individual traits (e.g., low self-control Gottfredson and Hirschi 1990) that might increase the likelihood of being an offender (see pages 658-659 in Hipp 2016). This strategy looks at individuals with certain characteristics, such as age, prior number of arrests, or low income that are associated with a higher likelihood of offending (Blumstein and Cohen 1979; Crutchfield 1989; Nagin and Land 1993). Neighborhoods with a greater concentration of these individuals have higher offender intensity and this disproportionality should be taken into account when predicting the location of offenders. We test the SD approach directly and compare it to our proposed RSP and RSP-DO strategies in two ways. First, we compute an estimate of where offenders are located based on each of the described strategies, and compare these to where arrestees are located (our imperfect proxy for the actual location of offenders given that many crime incidents are not "solved" by identifying an offender). Second, we use the estimates of where offenders are located from each of the techniques to construct estimates of where crime incidents will occur in the subsequent year, as another method of comparing the techniques.

DATA AND METHODS

We test the proposed RSP and RSP-DO strategies using data on crimes and arrestees in St. Petersburg, FL. We have data on the locations of crime incidents in 4,872 blocks and the home locations of arrestees from 2010 to 2012. We geocoded these addresses, with a geocoding match rate of 98.5%, which is extremely good. We use arrestees as a proxy for offenders: for our crimes of interest, there were 1,023 arrests in 2010 1,009 in 2011, and 864 in 2012. The crime data from 2010-12 is presented in Table 1.

<<<Table 1 about here>>>

Reverse spatial patterning approach

In our approach, we use data from 2010 to estimate a discrete choice model to get an approximation of the distance decay parameter in order to predict how far potential offenders might reside from crime locations (McFadden 1978). We computed the straight line distance between the centroids of each set of blocks, log transformed this value, and then computed quadratic and cubic versions of this measure to flexibly capture nonlinearity in the distance decay effect. The log transformation allows us to estimate an exponential distance decay function, which has been frequently detected in prior research. The discrete choice model includes as the choice set the block where the crime occurred (and therefore has a value of 1 for the logistic regression model) and all other blocks (the choice set, and have values of zero since the crime did not occur there). Given the large number of blocks, we follow the standard strategy in discrete choice models in such instances of pulling a random sample of blocks from the choice set for estimating the models, given the favorable statistical properties of such a strategy (Bernasco and Block 2009). We used a sample of 50 blocks to pair with the block where the crime occurred. The obtained parameter estimates from the 2010 data were then used to capture the distance decay between crime incidents and potential offender locations using the 2011 data. This is accomplished by including these distance decay estimates into the equations we described earlier in the manuscript (equations 2, 3 and 4). Based on these computations, we get estimates of offenders in each block. Given prior evidence that distance decay functions can differ across crime types (e.g., Phillips 1980), we obtained parameter estimates from discrete choice models on four types of crime: aggravated assault; robbery; motor vehicle theft; burglary. This allows us to assess the efficacy of the RSP strategy for several different types of crime that vary in their tendency to spatially cluster. We then used these estimates of offender locations from the 2011 data to create estimates of the locations of crime incidents in 2012, as described below.

We display the estimated distance decay functions from the discrete choice models for each of the four crime types in Figure 1, which display the probability that a block at this distance would experience a crime incident. As seen there, the curves show that aggravated assaults and burglaries both experience the highest probability of very nearby offenses (the left side of the graph). Robbery has the next highest probability of experiencing a very nearby offense, with a flatter slope compared to aggravated assaults and burglaries. Finally, motor vehicle theft has the lowest probability of experiencing a very nearby offense, and is more likely to occur further away. Note that these discrete choice models only included distance in the model, as this estimated distance function is key for our RSP approach. We also estimated ancillary models in which we included measures of business locations in the blocks, and the estimated decay functions were extremely similar. This result implies that nearby opportunities do not appear to drive these distance decay functions in this sample.

<<<Figure 1 about here>>>

We modify the assumption that all individuals on a block are equally likely to offend in our RSP-DO strategy. We do this by replacing the total population (which assumed that all persons are equally likely to be offenders) in Eq. 4 with an estimate of the persons in the block being potential offenders based on socio-demographic variables that may be associated with a disproportionate likelihood of offending. To capture this, we averaged the number of residents in a block that are: 1) aged 15-29; 2) unemployed; 3) not immigrants; 4) without a bachelor's degree; 5) renters; 6) single parent households; and 7) below the poverty line.[3] These factors

[3] There are more complicated ways to combine these measures. These alternative strategies could be explored in future research, but are outside the scope of the current study.

capture persons in the high offending part of the age/crime curve (#1), who may be more likely to turn to crime (#2), who may have lower social control (Gottfredson and Hirschi 1990) (#3-5), and those persons who may be more likely to be offenders based on social disorganization theory and a lack of neighborhood informal social control (#6-7) (Shaw and McKay 1942).

Our third, fourth and fifth approaches use the SD strategy. One combines the measures involved in the RSP-DO approach, but does not account for information on locations of crime in prior years. This is the disproportionate offender (SD-DO) approach. We use two single social dimensions when constructing the other two measures: the age of arrestees (SD-AGE) and the level of poverty in the neighborhoods of arrestees (SD-POV). Both of these factors have been shown to be strong correlates for offending and crime concentration (Farrington 1986; Krivo and Peterson 1996). For the 2010 data we: 1) estimated a negative binomial regression model of the number of offenders in a block regressed on the neighborhood socio-demographic characteristics in 2010 (age categories; or the number below 125% of the poverty line; or the combined measure)[4]; 2) multiplied the coefficients from that model by the neighborhood composition in 2011, and exponentiate the value to get an estimated count of offenders. This estimate of offenders is then used to create crime forecasts in 2012.

Methods

Each of these five approaches makes predictions of the number of offenders expected in each block. We used the approach of Hipp (2016) to compute estimates of the number of potential targets in the city based on the locations of various businesses. The business data are based on the Reference USA Historical Business data providing the exact addresses of businesses in each year from 2010-12 (Infogroup 2015). After geocoding the businesses to

[4] These categories are the number of residents in the following age bins: 10-14, 15-17, 18-19, 20, 21, 22-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-61, 62-62, 65-66, 67-69, 70-74, 75-79, 80-84, 85 and up.

census blocks, we used the NAICS 6-digit codes to classify the businesses into the following categories: retail; food and accommodation; bars; liquor stores; convenience stores; grocery stores; sporting goods stores; restaurants; fruit and vegetable stands; religious locations.

Each of the strategies we describe predicts the number of offenders expected in each block. We test how similar these different predictions are compared to the number of arrestees in some geographic unit. Note that arrestees are by no means a perfect proxy for actual offenders, given that between just 9% and 32% of the crimes in our study area are cleared, but we use this measure as one way of comparing these strategies. Looking at specific blocks is arguably too narrow, whereas aggregating blocks to tracts may be too large and spatially diffuse to be useful. We therefore aggregate predictions of the number of offenders for all blocks within some buffer of the block, but weight them based on inverse distance decay. This provides a gravity estimate of the likelihood of offenders being located in a block or the surrounding area, as the distance decay implies that the center block has the highest probability of containing the offenders, whereas more distant blocks have a lower probability. We tested ¼ and ½ mile buffers (beyond which the probability goes to zero). We use the ¼ mile buffer given that it is more spatially precise and yields results essentially as good as the ½ mile buffer (assessed in ancillary models). We then assess how well these predictions are correlated with the number of arrestees in those blocks in 2011-12.

In our second set of analyses, we assess how well these different estimations of offender locations help in predicting the location of crime the following year. We estimated negative binomial regression models with crime incidents in 2012 as the outcome variables for the four crime types (aggravated assault, robbery, burglary, motor vehicle theft). These models include three variables: the number of targets; the number of offenders within an exponential distance decay of the block (based on one of the five strategies for computing offenders), and an interaction of these two measures.[5] For each model we assessed model fit based on the pseudo R-square, and then compare across these different strategies for estimating the location of offenders and the subsequent prediction of crime in the following year. There are, of course, other possible crime forecasting models, but our goal here is simply to use one model consistently to better compare these different offender location estimation strategies.

RESULTS

Where are offenders located?

We begin by describing the results assessing the degree to which the various approaches yield results that are similar to the location of arrestees in 2011-12 in ¼ mile buffers, shown in Table 2. Regarding robbery offenders, the predicted number of robbery offenders based on our RSP strategy is correlated .55 with the number of arrestees, and the RSP-DSP approach that combines our RSP approach with disproportionate likelihood of offending is nearly as good, with a correlation with arrestees of .53. We display these results visually in the maps shown in Figure 2, which demonstrate the spatial similarity between where robbery arrestees are located, and where the RSP-DO strategy predicted they would be located. We see for robbery that the poverty composition is also a relatively good predictor of the presence of arrestees, correlated at .54. The SD-DO approach does not perform as well (.35 correlation), and the age distribution does not at all predict the location of robbery offenders.

<<<Table 2 about here>>>

For the results predicting the other violent crime of aggravated assaults, we again see that our RSP approach is the best strategy. Our RSP strategy performs the best of all approaches as a

[5] This distance decay captures the likely spatial movement of these offenders (Hipp 2020).

predictor of the number of arrestees between 2011 and 2012. The correlation between the predicted number of offenders based on our RSP strategy and the actual number of arrestees is .7. The RSP-DSP strategy yields very similar results to the RSP approach (a correlation of .67 with arrestees). The SD strategy using the poverty composition of the block is only correlated .5 with the number of arrestees, and using the age distribution performs even worse with a correlation of only .32. The SD-DSP strategy also does not perform nearly as well (.32 correlation). In sum, we find that our RSP and RSP-DSP strategies are strong approaches to predicting the locations of violent offenders.

<<<Figure 2 about here>>>

Turning to the property crimes, for burglaries, our RSP approach is again the best, with a correlation of .46 with arrestees. The RSP-DO strategy is close behind with a correlation of.43. The SD approaches do not perform as well. For motor vehicle thefts, the SD-POV strategy does the best, with a correlation of .33. However, our RSP approach is nearly as good at.26, and the RSP-DSP strategy has a correlation of .3. The SD-DO is correlated just .14, and the age distribution does a poor job predicting the location of motor vehicle theft arrestees.

Predicting crime

Table 3 presents the relative results of the models predicting the four different crime types. In this Table, each cell presents the results from a separate model. In each column, we defined the model using offenders based on the age structure as the reference model, we show the pseudo R-square value, and the percentages represent how much the pseudo R-square is improved for the model using the particular alternative measure of offenders compared to the one based on the age structure. For the robbery and motor vehicle theft models, measuring offenders simply based on the age structure does the weakest job predicting the locations of future crimes, given that the other four offender definitions have positive values, indicating that they all have improved pseudo R-square values. In the aggravated assault model and the burglary model the SD-DO and poverty (SD-POV) strategies, respectively, are even worse than using the age structure.

<<<Table 3 about here>>>

Importantly, we find that the RSP-DO approach yields the best predictions for all crime types except motor vehicle thefts. The RSP-DO strategy improves the robbery prediction 11.7% compared to the age strategy, 16.4% better for aggravated assault, 14.6% better for burglary, and 6.4% better for motor vehicle theft. Furthermore, by taking into account the spatial patterns of earlier crime, the RSP-DO approach does a better job than the SD-DO approach, as it improves predictions of robbery, aggravated assault, and burglary 6%, 20%, and 15%, respectively. Only for motor vehicle thefts does the SD-DO approach do a better job predicting this crime type than the RSP-DO approach. In sum, we find that the RSP-DO strategy does the best job predicting the locations of future crime incidents.

The second-best prediction of future crimes comes from the RSP strategy. This strategy assumes that everybody is equally likely to be an offender, and only accounts for the potential spatial patterns of where offenders go in predicting the locations of offenders. The strategy does the second-best job of predicting aggravated assaults, robberies and burglaries, and is only slightly less effective than the RSP-DO approach. The SD-DO approach does quite well for predicting motor vehicle thefts, but is not nearly as effective at predicting the other three crime types. Thus, it appears that the multi-faceted assessment of potential offenders is best for predicting motor vehicle thefts. In contrast, the two SD strategies do not do nearly as well as our two RSP strategies. It does appear that measuring potential offenders simply based on the level of poverty provides better predictions of robberies, but not nearly as well for the other crime types.[6]

DISCUSSION

We have proposed a new approach for estimating the locations of offenders in a city. This strategy builds on the insights of geographic profiling, which attempts to determine the location of a single offender (Rossmo 2000). Our proposed strategy, however, attempts to identify the likely locations of offenders in general and not one committing specific crime incidents. This strategy has useful theoretical and policy implications, as it can help forecast the location of crime events based on the approximate locations of offenders and various opportunities in the environment (Hipp 2016). These potentially improved crime forecasts also have useful policy implications, as they can help police target their limited resources into locations that are more likely to experience future crime incidents. Indeed, there is evidence that targeted police activity after crime spurts, such as direct patrol and contacting victims and known offenders, can suppress short-term clusters of crime (Santos and Santos 2015). This suggests that using the insights of the RSP and RSP-DO strategies may provide law enforcement with a more circumscribed location to direct such efforts.[7]

[6] While the pseudo R-squares are not large, it is well known that they are not an appropriate measure of variance explained. We therefore also estimated OLS models to obtain R-squares for the comparisons, and the relative comparisons were similar. The values were nonetheless larger, with R-squares of about .13 for the robbery models, .05 for aggravated assault, and .02 and .03 for burglary and motor vehicle theft. Nonetheless, we highlight that our goal is in comparing these strategies for predicting the location of offenders, and our focus is not on the specific crime forecasting models.

[7] As a general point, we highlight that our focus was on estimating the presence of offenders. This is certainly of interest to police agencies. For theoretical reasons, researchers are also interested in offender intensity, which is a latent measure (Hipp 2016). Nonetheless, it is relatively straightforward to extract the offender intensity by simply employing a useful baseline measure of offenders (such as a model that all persons are equally likely to be offenders) to create estimates of this latent measure. This could then be used in other cities to predict the location of crime. Nonetheless, we leave this to future work.

The RSP strategy helped predicting the location of arrestees as well as future crime incidents and sometimes did an even better job when taking into account the disproportionate likelihood of offending. The RSP strategies generally provided the best predictions for arrestees of all crime types. This suggests that we can use the locations of crime events to work backwards to predict where offenders may be located, and that these predictions may be even more useful when we account for the demographic composition of neighborhoods or neighborhoods with more residents prone to offending. These strategies enable us to simultaneously capture populations of individuals at greatest risk to engage in crime while also accounting for place-based characteristics that create greater opportunities for crime. These insights may be particularly helpful for examinations of the spatial patterning of crime (e.g., Cohen, Gorr, and Olligschlaeger 2007; Hipp, Wo, and Kim 2017) by providing an additional layer of risk associated with a particular location, or for locating place-based initiatives, such as the development of low-income housing (Freedman and Owens 2011).

The RSP and RSP-DO strategies were stronger predictors of the general locations of offenders for certain types of crime. Notably, RSP or RSP-DO more strongly improved the future crime forecasts of burglaries and the two violent crimes. The general ability of the RSP approach to better predict violent crime offender locations over property crime offender locations aligns with the journey to crime findings that offenders may be more willing to travel further for property crimes (Ackerman and Rossmo 2014; Rossmo 2000). In this sample, motor vehicle thefts were the crime type least likely to occur nearby, which may reduce the effectiveness of the RSP strategy for this crime type; future research will need to assess this. Indeed, the risks associated with committing a violent crime, such as assault or robbery, may be greater and thus align more closely with the least effort principle (Ratcliffe 2006). In contrast, the home locations of burglars and motor vehicle thieves may be further away given the lower risk associated with these crimes (Chamberlain and Boggess 2016). Further, car thefts may be concentrated in commercial or industrial locations (Copes 1999; Weisel et al. 2006) with few residences nearby. Given that vehicles move about, there is reason to expect this crime type to be more spatially dispersed (Markley 2018). This suggests that car thieves are specifically traveling to target areas that are further away from their residence.

We highlight that the primary goal of the RSP strategy is to identify potential locations of offenders. Indeed, we saw evidence that this strategy seems successful at this task when showing how the predictions were correlated with the locations of arrestees (acknowledging that arrestees are a quite imperfect measure of offenders). Furthermore, we also showed that these estimated offender locations based on the RSP strategy improved the crime forecasts of one particular forecasting strategy compared to other methods for predicting the locations of offenders. We used one forecasting strategy to allow direct comparisons between the different methods of predicting offender locations. Nonetheless, we emphasize that the predictions of offender locations based on our RSP strategy can be incorporated into any forecasting model. We pointed out earlier that most existing forecasting models do not account for the possible locations of offenders. We suggest that such forecasting models may be improved in the future by incorporating the locations of potential offenders into them, an area of needed future research. Thus, we highlight that our RSP approach is potentially complimentary to existing forecasting models, which may be improved in the future by including information on possible offenders.

While we have proposed a novel strategy to predicting the locations of offenders, we note some limitations to our study and directions for future research. First, it is worth noting that there is undoubtedly some additional bias in the study given that we are trying to predict the locations of *arrestees* rather than *offenders*. A potential consequence is that this may result in a *downward* bias to our RSP approach. That is, if our approach accurately predicts the location of offenders, but these offenders are not detected and arrested because of a systematic bias for an agency to focus on specific blocks when making arrests, this will reduce the correlation between our RSP measures and arrestees, and may impact our distance decay estimates. Unfortunately, we cannot be certain on this conjecture, but it is certainly worth considering.

Second, our study did not take into account the time of day of crime events, or whether the journey to crime distance decay differs over the hours of the day. Indeed, few studies have accounted for the temporality of crime events (Hipp and Kim 2019; Song et al. 2019), and fewer yet as to whether it impacts the distance decay pattern for offenders. Nonetheless, exploring this question would be useful to assess whether it improves the predictions from our strategy.

It is also worth emphasizing that our models of disproportionate offending used here were simply a first step, and quite rudimentary. There is considerable room for extensions and more sophisticated improvements on this approach, which should be the focus of future research. A better enumeration of characteristics of importance, as well as more sophisticated ways of combining such measures, would be useful (we simply equally combined the dimensions we measured). Furthermore, it may be that certain characteristics are more likely to increase offender intensity for specific crime types, so incorporating this crime-specific information could improve our estimates of the location of offenders. These results imply that a useful direction for future research would be to create better estimates of the likelihood of offender intensity based on demographic, or other, characteristics.

In conclusion, we have demonstrated that the RSP approach is a potentially useful technique for determining the possible location of offenders. Our proposed strategy uses the distance decay parameter of how offenders typically travel to locations for various types of crime to work backwards from the locations of actual crime events to make predictions about where offenders may live. This approach builds on the insights of the geographic profiling literature, the journey to crime literature, and Hipp's (2016) general spatial crime pattern theory. In general, our RSP approach to locating offenders appeared to do a relatively good job predicting the location of arrestees, and was better at predicting future crime incidents than other strategies for predicting offender locations. When the strategy made the simplifying assumption that all persons are equally likely to be offenders it did a relatively good job predicting the location of offenders. However, when we relaxed this assumption of equal offending propensity and allowed for the possible disproportionate likelihood of offending by certain types of persons we obtained the strongest prediction results of future crime incidents. Further research on understanding offender intensity should help improve the novel RSP strategy.

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Tables and Figures

Table 1. Summary statistics of crime incidents and arrests in St. Petersburg, FL from 2010-12

	Crime incidents			Arrests		
	2010	2011	2012	2010	2011	2012
Aggravated assaults	1342	1294	1291	461	413	391
Robberies	753	704	578	128	115	76
Motor vehicle thefts	1339	953	934	118	99	84
Burglaries	4168	4116	3390	316	382	313

Table 2. Correlation of arrestees in ¼ mile inverse distance buffers with predicted offenders based on RSP, RSP-SDP, and SD approaches, 2011-2012

	Robbery	Aggravated assault	Burglary	Motor vehicle theft
	R	R	R	R
RSP by offenders (RSP-DO)	0.532	0.665	0.429	0.248
RSP by population (RSP)	0.554	0.697	0.459	0.298
Offenders based on 7 categories (SD-DO)	0.353	0.317	0.236	0.138
Offenders by poverty level (SD-POV)	0.542	0.495	0.315	0.329
Offenders by age structure (SD-AGE)	-0.008	0.322	0.220	-0.017

Table 3. Models using different estimates of offender location to predict crime in blocks in St. Petersburg, 2012

	Robbery		Aggravated assault		Burglary		Motor vehicle theft	
	Pseudo rsq	% chnge	Pseudo rsq	% chnge	Pseudo rsq	% chnge	Pseudo rsq	% chnge
RSP by offenders (RSP-DO)	0.052	11.7%	0.015	16.4%	0.005	14.6%	0.010	6.4%
RSP by population (RSP)	0.052	11.1%	0.015	14.5%	0.005	11.3%	0.010	7.5%
Offenders based on 7 categories (SD-DO)	0.049	5.8%	0.013	-3.1%	0.005	-0.4%	0.011	12.4%
Offenders by poverty level (SD-POV)	0.051	10.1%	0.014	4.5%	0.005	-2.3%	0.010	6.7%
Offenders by age structure (SD-AGE)	0.046	0.0%	0.013	0.0%	0.005	0.0%	0.010	0.0%

Note: showing pseudo R-square for model and percentage improvement in pseudo R-square for model compared to model measuring offenders based on the age structure.

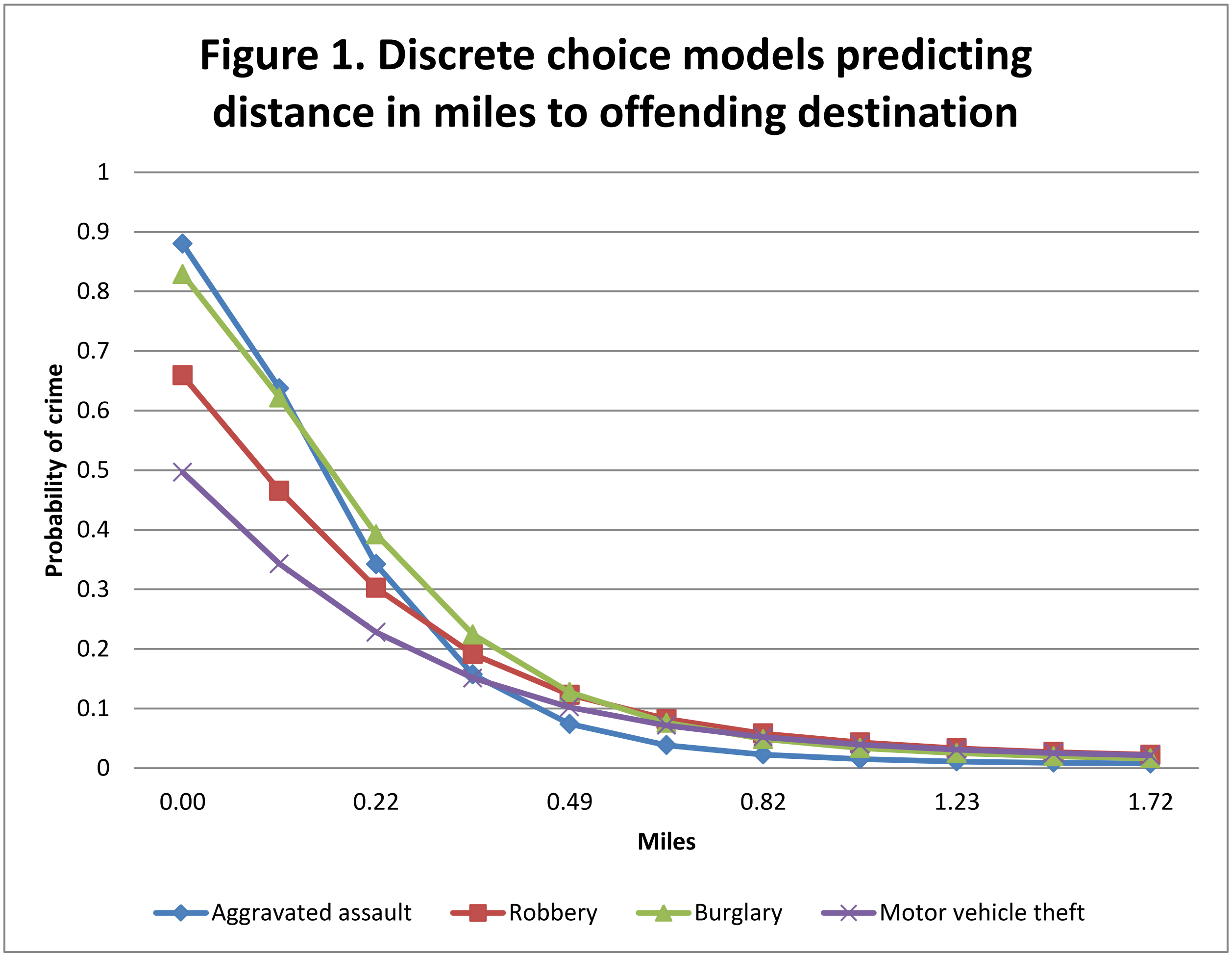
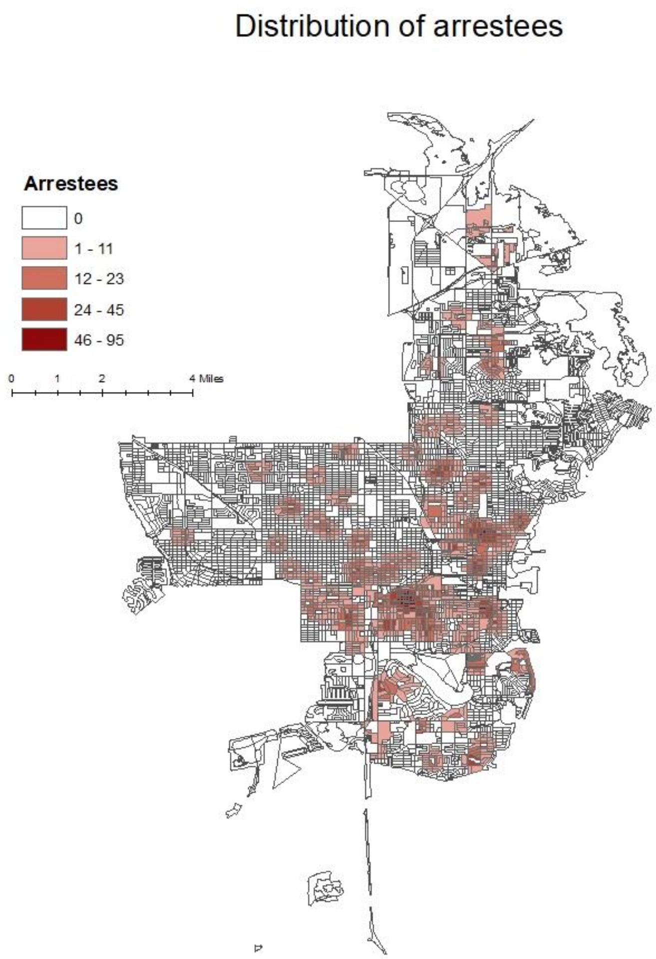


Figure 1. Discrete choice models predicting distance in miles to offending destination
Probability of crime
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0.00
0.22
0.49
0.82
1.23
1.72
Miles
Aggravated assault
Robbery
Burglary
Motor vehicle theft

Reverse spatial patterning approach

Figure 2: Geographic distribution of the number of arrestees and the predicted locations of arrestees for robberies using the RSP-DO method[8]



[8] Comparison of the geographic distribution of the number of arrestees and the predicted locations of arrestees for robberies using the RSP-DO method, with a ¼ mile inverse distance decay buffer. Categorizations are based on minimizing variations between groups.