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Utilizing a Risk of Crime Measure for Recidivism Research: Moving Environmental Corrections Forward

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Abstract

The current study expands recidivism research by developing a risk of crime (ROC) measure rooted in environmental criminology, reflecting the risk of criminal opportunities, and lending itself to environmental corrections. Data were collected from a city in the Northeast region of the United States. The ROC measure was constructed through risk terrain modeling and reflected a parolee-specific neighborhood ROC. Conjunctive analysis of case configurations was utilized to explore how individual characteristics interacted with the ROC measure. Results indicated a relationship between parolees residing in an elevated ROC neighborhood and the likelihood of recidivism. The results were discussed in relation to how environmental criminology could be further integrated into environmental corrections, accounting for physical and social characteristics of the backcloth.

Keywords

recidivism, environmental corrections, risk terrain modeling, conjunctive analysis

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Introduction

At 2015 year-end, there were about 6.7 million adults under correctional supervision in the United States, with approximately 4.7 million people under supervision in their communities (Kaeble & Glaze, 2016). According to the Bureau of Justice Statistics' most recent data, over 641,000 inmates were released from state and federal prisons in 2015 (Carson & Anderson, 2016). These high numbers of offenders released from prison and back into neighborhoods across the United States becomes important when attempting to understand the rehabilitative and control-oriented needs of former prisoners who are likely to reoffend (recidivate). Research using nationally representative samples of reintegrating former inmates has demonstrated on several occasions that over 50% of those released from prisons are rearrested within 3 years (Durose, Cooper, & Snyder 2014; Langan & Levin, 2002), and recent research has shown that approximately 77% are rearrested within 5 years (Durose et al., 2014). Many of these former prisoners often cluster within only a few neighborhoods, within a small sample of municipalities in a state. Housing, jobs, and social services, among other necessities, are often geographically limited or legislatively restricted for this population, so former prisoners who return to neighborhoods across the United States are often clustered in particular areas. This situational context and churning of released, reintegrated, and rearrested individuals take a toll on these towns and their populations. High crime rates may be one of many symptoms of such areas.

The neighborhood effect on crime has been well established in criminological research (see Morenoff & Sampson, 1997; Sampson, 2012), but empirical studies about neighborhood-level effects and their relationships to recidivism outcomes are limited. S. D. Gottfredson and Taylor's (1988) study was one of the first studies to account for contextual influences beyond individual characteristics; the study included community measures in their models to determine factors related to recidivism beyond individual characteristics. There was a gap in research considering the community context until there was a revitalization by Kubrin and Stewart (2006) when they showed that neighborhood context accounted for approximately 13% of the variance in recidivism in their study of formerly incarcerated individuals returning to Multnomah County, Oregon. The progress of research on recidivism examining environmental factors builds from identifying the "who" and is working toward better understanding the opportunity structure of the "where."

Neighborhood-level factors related to recidivism has garnered some attention since Kubrin and Stewart's (2006) study (e.g., Chamberlain & Wallace, 2016; Grunwald, Lockwood, Harris, & Mennis, 2010; Hipp, Petersilia, & Turner, 2010; Kubrin, Squires, & Stewart, 2007; McNeeley, 2017; Mears, Wang, Hay, & Bales, 2008; Miller, Caplan, & Ostermann, 2016; Onifade, Petersen, Bynum, & Davidson, 2011; Stahler et al., 2013; Tillyer & Vose, 2011; Wang, Hay, Today, & Bales, 2014). Although as a basis for examining recidivism at the neighborhood-level, research has primarily focused on social characteristics (i.e., disadvantage index) of neighborhoods often associated with social disorganization (Shaw & McKay, 1942). Although research continues to expand on the possible neighborhood-level influencers of recidivism, limited studies (e.g., Hipp et al., 2010; Miller et al., 2016) examine the role of criminogenic places, often considered in environmental criminology research. Environmental criminology and specifically, environmental corrections (Cullen, Eck, & Lowenkamp, 2002; Schaefer, Cullen, & Eck, 2015), could further assist in understanding recidivism at the neighborhood-level, beyond previously examined social constructs.

The limited amount of neighborhood-level research on recidivism sets the stage for the current research. We use risk terrain modeling (RTM; see Caplan, Kennedy, & Miller, 2011; Kennedy, Caplan, & Piza, 2011) as an analytical technique to assist in exploring the gaps in the extant literature. RTM examines the dynamic features of a landscape from a risk of crime (ROC) standpoint, and offers environmental corrections an innovative research design that can be leveraged to increase our collective understanding about how neighborhood-level context affects recidivism outcomes for those recently released from prison. We utilize a two-step analytical process. First, we utilize RTM to generate an ROC measure, reflecting a measure of criminal opportunities, followed by conjunctive analysis of case configurations (CACC) to identify the dominant configurations related to the likelihood of recidivism.

Review of Literature

In the past, research has largely focused on individual-level characteristics in examining recidivism (see Gendreau, Little, & Goggin, 1996; Langan & Levin, 2002; Pritchard, 1979), which could, in part, be because recidivism relies on the offenders to commit crime. Some of the strongest predictors for recidivism are age, criminal history, gender, and race (Gendreau et al., 1996). As Kubrin and Stewart (2006) argued, the attention on individual-level recidivism research could be a result of the belief that recidivism is individually determined. As individuals have been the focal point of recidivism, there is limited research considering correlates of recidivism beyond the individual. With much of the scientific community's attention drawn to the study of individual-level factors that are predictive of recidivism, comparatively scant empiricism has focused on the important environmental factors that are correlated with recidivism outcomes, particularly those that can be measured at a neighborhood-level (see T. R. Clear, 2007).

Moving from a discussion on individual characteristics related to recidivism, we provide a review of relevant environmental criminology perspectives and concepts that lead to the development of our current study. To make this argument, elements from crime pattern theory (Brantingham & Brantingham, 1993) and routine activities theory (Cohen & Felson, 1979) are discussed below to provide context for criminal opportunities and how criminal opportunities develop. In addition, concepts from environmental criminology are discussed to further the understanding of geography of criminal opportunities. As Weisburd et al. (2012) discussed, crime patterns present at the micro level could resemble the variation in criminal opportunities. That is, criminal opportunities should share similar spatial patterns given that crimes cluster in certain areas.

Environmental Criminology and the "Where"

Cohen and Felson (1979) developed routine activities theory to examine changes in crime rate trends depending on the type of activities people encounter throughout days/weeks/months. Specifically, both victims and offenders have activities they maintain throughout the day such as work, school, and recreation, taking them away from their home environments and into different spaces. It is within these spaces that victims and offenders can converge at the same time for criminal opportunities to present themselves. In short, for criminal opportunities to exist, there needs to be a suitable target, motivated offender, and a lack of capable guardianship that must converge in time and space.

Brantingham and Brantingham (1993) expanded on RAT by discussing how people develop routine travel patterns based on activities, and even if the routine travel patterns are disrupted by the addition of a new activity or change in home residence, new routines are developed and often influenced by old routines. This approach to routine travel patterns applies to both offenders and nonoffenders. Because of this, "The likely location for a crime is near this normal activity and awareness space" (Brantingham & Brantingham, 1993, p. 84). Activity spaces are locations where people spend a majority of their time and are able to develop an awareness space of criminal opportunities in the surrounding environment when traveling to and from different nodes. Nodes are described as locations where people are able to identify potential criminal opportunities and are common locations in peoples' lives such as home, work, and school areas (Brantingham & Brantingham, 1995). The more often people travel to and from these different locations, the greater awareness space they develop, and it is within these paths and nodes that criminals are likely to commit crimes (Brantingham & Brantingham, 1981).

Brantingham and Brantingham (1981) extended the discussion to address how targets such as businesses attract people during their routine activities because businesses typically fall within activity and awareness spaces. Businesses can act as locations for criminal opportunities that attract both victims and offenders for various reasons. Victims could be attracted to the businesses for the type of products or services at the establishment, and offenders could be attracted to that location because of the type of patrons that frequent that area. These locations that attract and generate crime are known as crime generators and crime attractors (CGAs).

Crime generators refer to locations such as business establishments, institutions, and facilities that draw people to those locations, mostly for noncriminal activities. That is not to say that offenders do not venture to these locations, but both offenders and victims are drawn to those locations for the type of transaction that occurs. Criminal opportunities present themselves in part because of the high volume of people traffic in and around those locations, hence they generate crime. Similarly, crime attractors draw people to locations that have higher potential criminal opportunities. Based on the type of activity/transaction that occurs at crime attractors, they draw a greater quantity of offenders and/or victims, increasing the potential criminal opportunities.

CGAs are often places such as bus stops, bars, liquor stores, pawn shops, and others where the elements of criminal opportunities converge in time and space (i.e., routine activities theory, Cohen & Felson, 1979). The presence of criminal opportunities in space is not uniform as crime has been found to cluster (Sherman, 1995; Sherman & Weisburd, 1995) and because of this, there will be variations in the presence of crime across neighborhoods. Examining the spatial influence of CGAs provides an understanding of how the landscape, or environment, creates risky areas with varying degrees of criminal opportunities.

Miller et al. (2016) examined the presence of CGAs within 1,240 ft of parolees' home addresses to determine if the environmental risk influences parolee failures. Miller et al. (2016) did not find support of environmental risk affecting recidivism, but this could be because of how risk was operationalized. Risk was operationalized as the count of CGAs in close proximity to offenders' residences rather than a quantifiable value of risk based on environmental conditions and spatial interaction effects (not all CGAs are significant risk factors associated with crime). Their study is a step in the right direction, but ROC can be operationalized in an objective and quantifiable way with advancements in analytical tools.

The limited research on CGAs in recidivism research (Hipp et al., 2010; Miller et al., 2016) requires further study to identify how an environmental corrections framework could enhance the understanding of recidivism. Environmental corrections is outlined as (Cullen et al., 2002, p. 31)

> The effectiveness of probation and parole supervision will be increased to the extent that officers systematically work with offenders, family and community members, and the police to reduce the extent to which offenders are tempted by and come into contact with opportunities for crime.

Environmental corrections builds from core concepts of environmental criminology's understanding of criminal opportunities. With advancements in environmental criminology research, greater insights can be applied to the corrections field. Cullen et al. (2002) attributes ineffective supervision to the inability ". . . to impact offenders' access to criminal opportunities" (p. 31). Environmental criminology can provide the means to quantify criminal opportunities and understand the underlying factors of neighborhoods contributing to forming conducive behavioral settings for crime.

Current Study

A concentration on spatial risks that create behavior settings most conducive to recidivism can be seen as a variation of conventional offender-based risk assessment whose principles were established many decades ago as research began to demonstrate that the characteristics of offenders were correlated with their subsequent behavior (Burgess, 1928; Glueck & Glueck, 1950; Miller & Lin, 2007): offender characteristics are scored and combined to form a scale that is indicative of "risk"—such as the risk of rearrest or reconviction, the risk of absconding while on bail, or the risk of violating conditions of parole or probation (T. Clear, Wasson, & Rowland, 1988; M. R. Gottfredson & Gottfredson, 1979, 1984; S. D. Gottfredson & Moriarty, 2006). These methods have substantial margins of error regarding predictions of who will and who will not reoffend (Andrews, 1989; M. R. Gottfredson & Gottfredson, 1984; S. D. Gottfredson, 1987; S. D. Gottfredson & Moriarty, 2006; Klein & Caggiano, 1986; Wiebush, Baird, Krisberg, & Onek, 1995). But that is because they are mostly concerned with the classification of offenders into higher and lower risk groups for the purposes of allocating appropriate criminal justice interventions and resources to the individuals regardless of where they live (Ashford & LeCroy, 1990; Baird, 1984; Juvenile Sanctions Center, 2002; Loeber & Stouthamer-Loeber, 1987; Office of Juvenile Justice and Delinquency Prevention, 1995; Wiebush et al., 1995).

However, specific settings might influence offending behavior and, so, the margins of error in actuarial offender risk assessments may be minimized by considering them in the context of places where former prisoners live, work, and otherwise spend most of their time. Examining the impact of CGAs on recidivism is consistent with environmental corrections as it combines actuarial risk prediction with ecological criminology.

The current study expands recidivism research by developing a ROC measure rooted in environmental criminology, reflecting the risk of criminal opportunities, and lending itself to environmental corrections. Developing an ROC measure can reflect the riskiness for crime based on the neighborhoods offenders reside, and the measure can identify how risk varies across a study area as no two neighborhoods are the same. This differs from prior recidivism research examining neighborhood-level measures primarily based on social characteristics available at the census tract or block group level similar to Kubrin and Stewart (2006). These are two distinctly different types of measures, social and physical, and advancements in analytical techniques allows for a quantifiable measure reflecting the ROC (physical) to be constructed (see Drawve, Thomas, & Walker, 2016; Thomas & Drawve, 2018).

RTM is a spatial analytical technique capable of diagnosing a landscape, such as a city or neighborhood, for underlying risk factors associated with a specific outcome event (i.e., crime; Caplan & Kennedy, 2016; Caplan et al., 2011). RTM quantifies concepts from environmental criminology, such as the environmental backcloth (Brantingham & Brantingham, 1995), to better understand why crime is spatially distributed at the micro level. Furthermore, RTM can measure access to criminal opportunities highlighted by Cullen et al. (2002) as one reason that community supervision has been ineffective. The discussion here is not to delve into the analytical methodology of RTM but to discuss the general purpose of how RTM could be utilized in recidivism research because offenders reside in varying ROC neighborhoods.[1] A detailed discussion of RTM can be found in Risk Terrain Modeling: Crime Prediction and Risk Reduction (Caplan & Kennedy, 2016).

Typically, RTM is used to forecast different criminal events (e.g., Caplan et al., 2011; Drawve, 2016; Dugato, 2013; Kennedy et al., 2011; Moreto, Piza, & Caplan, 2014). Within the framework of forecasting crime, RTM utilizes risk factors—CGAs, from the physical environment to enhance the ability to forecast crime. RTM identifies significant risk factors associated with crime and quantifies the spatial influences the factors have on criminal behavior to create a risk assessment across a study area.[2] With the risk terrain maps, parolee residences, and other nodes of interest, can be joined with local relative risk scores (RRSs) to calculate the neighborhood ROC per parolee. The environmental risk of criminal opportunities quantified through RTM

Table 1. Descriptive Statistics of Variables.

Variables	Coding	*n*	%
Rearrested outcome			
Arrest	1	318	53.9
No arrest	0	272	46.1
Individual characteristics			
Age (in years)			
19-28	0	158	26.8
29-38	1	213	36.1
39-48	2	137	23.2
49+	3	82	13.9
Ethnicity			
Other	0	35	5.9
Black	1	432	73.2
Hispanic	2	123	20.8
Prior arrests			
Below average	0	359	60.8
Above average	1	231	38.2
Environment characteristic			
Risk of crime			
Marginal risk of crime	0	91	15.4
Elevated risk of crime	1	499	84.6

can be utilized to understand which parolees are planning to return to riskier behavior settings for recidivism.

Data and Methodology

The current study examined parolees released in 2011 to an urban city in the Northeast region of the United States. The city is in close proximity to other large metropolitan cities. The data indicate 597 parolees had their most recent postrelease history address located in the study city. Of the 597 residing in the study city, 590 were geocoded for the current study (98.8%). Recidivism was operationalized as a rearrest within 18 months of release. As seen in Table 1, about 54% of parolees were rearrested in the follow-up time period. The three main individual-level predictors of recidivism examined in the current study were as follows: age, ethnicity, and prior arrests.[3] Oftentimes in recidivism research, age is left continuous, but for our analytical technique, categories are required. Reflecting on Hipp et al.'s (2010) figure (p. 965) displaying the hazard ratios of recidivism based on age, we developed our categories for age. In Hipp et al.'s (2010) findings, there was an initial steep decrease in the hazard ratio into the parolees' late 20s of age, with a slowdown in the decrease of the ratio into the 30s of age, and then followed by a steeper decrease in the hazard ratios for older parolees. Drawing from this, age was categorized into four categories for the current study: 19 years to 28 years (n = 158), 29 years to 38 years (n = 213), 39 years to 48 years (n = 137), and 49+years old (n = 82). Ethnicity was separated into three categories: Other (n = 35), Black (n = 432), and Hispanic (n = 123). Prior arrests were dichotomized based on the average number of prior arrests for the parolees (9). Parolees with greater than nine prior arrests were coded as "1" (n = 499).

Neighborhood ROC

Two generalized crime-type RTMs were constructed to develop the neighborhood ROC, violent and property. Violent crime consisted of aggravated assault, sexual assault, robbery, rape, and murder (n = 3,394; 99.5% geocoded). Property crime was comprised of theft, burglary, and auto theft (n = 10,369; 99.8% geocoded). Crime data were collected from the city police department for 2011, and the neighborhood ROC measure was constructed from place feature data collected through a prior federally funded grant (Kennedy, Caplan, & Piza, 2015). These data represent elements of the built, physical environment expected to influence where crime occurs in the city (i.e., crime generators and attractors). A total of 11 potential risk factors of the city were tested to determine their relationship with both violent and property crime: bars, liquor stores, convenience stores, carryout restaurants, gas stations, parking garages, sit-down restaurants, schools, parks, pawn shops, and abandoned properties.

RTMDx software (Caplan & Kennedy, 2013) was utilized to test the relationships between the potential risk factors and two crime categories. RTMDx requires parameters to be set before running the models. The study area was set to the city boundary and the cell size was set to half the average street segment, 226 ft. Risk factors could be operationalized as density, proximity, or testing both. Density refers to the cluster of a specific risk factor For example, clustering of bars in a smaller area could be expected to have higher criminal activity because of the riskiness of that environment. Proximity relates to being within close proximity, RTMDx tests for the "best" distance, being risky for criminal activity. A benefit of RTMDx is the option of choosing both proximity and density. Arguments could be made for CGAs having proximity or density influence, and RTMDx allows for this to be tested.

The factors included were limited in scope based on data availability and to factors known to associate with crime. There are a number of RTM studies that have highlighted factors to consider for both violent (e.g., Drawve et al., 2016; Kennedy, Caplan, Piza, & Buccine-Schraeder, 2016) and property (e.g., Moreto et al., 2014; Piza, Feng, Kennedy, & Caplan, 2017) crimes. Parking garages and parks were tested as only proximity measures. The other nine risk factors were tested for both proximity and density. Last, the maximum spatial influence was set to three blocks, 1,356 ft, and tested at half-block increments (226 ft), allowing for RTMDx to statistically test for the optimal spatial influence. Empirical research by Taylor and Harrell (1996) suggested behavior settings are crime-prone places that typically comprise just a few street blocks (Taylor, 1988). With insights gained from Taylor's (1997) research on behavior settings, we decided not to evaluate spatial influences beyond three blocks with half-block increments. The outcome event the CGAs were tested against was two aggregate crime categories, violent crime and property crime (two separate RTMs).

First Analytical Step

The output from each RTM, located in the "Findings" section, was used to construct a neighborhood ROC for each of the 590 individual parolees who resided in the city. RTMDx provides output with a RRS per cell (226 ft) across the entirety of the defined study area. Once a final risk map is created, the overall risk of the city is determined and discussed in terms of the likelihood for future crime. The lowest likelihood of crime occurring would be one (1). Any cell that has a value greater than one (1) would be interpreted in the following manner: a cell (i.e., place; half-block) with a value of 11.18 has an expected rate of crime that is 11.18 times greater than cells with the value of one (1; see Caplan & Kennedy, 2013). Since the geocoded parolee data were matched relatively high (98.8%), above the 85% threshold set for crime data (see Ratcliffe, 2004) the ROC can be calculated based on where parolees reside and where crime is likely to occur.

To construct the neighborhood ROC, a three-block buffer (1,356 ft) was formed around each parolee residence, similar to the maximum spatial influence CGAs that were tested for in the RTMs, based on Taylor's (e.g., 1988; 1997). The three-block buffer relates to the parolees' home environment, where they have a greater awareness space and potential to identify criminal opportunities in their routine activity spaces. From here, the cells intersecting each individual buffer around the parolees' residences were selected and averaged to the buffer. This resulted in a neighborhood ROC for each parolee. This process was completed for both RTMs, resulting in two neighborhood ROC measures, property and violent crime. Parolees residing in elevated ROC neighborhoods was determined by comparing the neighborhood ROC values to the average RRS for each RTM. If the neighborhood ROC was higher than the average RRS for the corresponding RTM, the neighborhood ROC was coded as "1." Then, if both, property and violent, ROC measures were elevated (i.e., neighborhood ROC property = 1 and neighborhood ROC violent = 1), the parolee was coded as residing in an elevated ROC neighborhood. The expectation is when parolees reside in riskier environments, the likelihood of recidivism would be greater (i.e., greater criminal opportunities).

Second Analytical Step

The current study utilized CACC (see Hart, Rennison, & Miethe, 2017; Miethe, Hart, & Regoeczi, 2008) to explore the situational contexts of recidivism among parolees released from prison to the city considered in this study. As Miethe et al. (2008) discussed, conjunctive analysis is based on exploring categorical data through comparative approaches found in qualitative and quantitative multivariate approaches (see Drawve, Thomas, & Hart, 2017 for CACC and logistic regression comparison). The focus of the study is to explore the context of how ROC interacts with individual-level measures that have been used in traditional actuarial risk assessment instrument in an effort to communicate the likelihood of recidivism. The methods used in the current study allow for a better accounting for both person and place by considering estimates of environmental risks in addition to commonly used static risk factors. Miethe et al. (2008) highlighted that traditional person-centric variable-oriented approaches to risk assessment center on main effects with the assumption of constant influence across all contexts. CACC explores the contextual combination of variables relate to an outcome. In other words, CACC can identify if characteristics are context/situation-specific or constant across contexts. If the variable is not constant (i.e., contextual), the divergence is based on an interaction with another variable.

Situational contexts for recidivism were calculated by multiplying the number of categories per variable by each variable. For instance, age(4) × ethnicity(3) × prior arrests(2) × neighborhood ROC(2) × rearrest(2), resulting in potentially, 96 situational contexts for recidivism. The current study uses combinations with 10 or more observations as an identifier for *dominant* case configurations.[4] These dominant case configurations provide context around recidivism and the interrelationship between the four measures of interest.

Table 2. Violent Crime Risk Terrain Model Output.

Risk factor	OP	SI	Coefficient	RRV
Pawn shops	P	½ block	1.446	4.247
Convenience stores	P	½ block	1.403	4.067
Gas stations	P	½ block	1.289	3.630
Sit down restaurants	P	3 blocks	1.259	3.521
Bars	P	½ block	0.969	2.636
Carryout restaurants	P	½ block	0.895	2.447
Schools	P	3 blocks	0.827	2.287
Abandoned properties	P	3 blocks	0.683	1.980
Liquor stores	P	3 blocks	0.499	1.647
Parks	P	3 blocks	0.164	1.178
Intercept	—	—	−3.821	

Note. OP = operationalization; SI = spatial influence; RRV = relative risk value.

Findings

Before determining the dominant case configurations for recidivism, the violent and property neighborhood ROC measures were calculated. Tables 2 and 3 below, provide the RTMDx output for both crime types. The RTMDx output presented in Table 2 is interpreted as an individual parolee being located within a half-block of a pawn shop (226 ft) has approximately 4 times the risk of being near-violent crime when compared with places beyond a half-block of a pawn shop. The relative risk value (RRV) represents the individual risk of that measure, so when multiple risk factors overlap in spatial influence (i.e., collocate), there is an elevated risk of violent crime occurring (i.e., RRS). The greater the risk, the higher the likelihood for future criminal activity of that individual parolee.

The neighborhood ROC measures were coded based on the individual RTMs. If parolees' neighborhoods (three-block buffer around residence) had an average risk score greater than the average RRS across the city, parolees with higher risk scores were considered to be residing in elevated ROC neighborhoods. For instance, the average RRS for violent crime was 10.698, so if parolees had a neighborhood ROC greater than 10.698, parolees were considered to be residing in an elevated ROC neighborhood for violence. This was also done for property crime, and if parolees were residing in elevated ROC neighborhoods for *both* property and violent crimes, the parolees were residing in an elevated ROC neighborhood. In short, elevated ROC neighborhoods were risky for both property and violent crime, and dichotomized as yes/no (1, 0) for CACC.

Table 3. Property Crime Risk Terrain Model Output.

Risk factor	OP	SI	Coefficient	RRV
Sit down restaurants	P	3 block	1.310	3.706
Gas stations	P	½ block	1.027	2.792
Parking garages	P	½ block	0.948	2.582
Pawn shops	P	½ block	0.892	2.439
Bars	P	½ block	0.860	2.363
Schools	P	3 blocks	0.854	2.348
Carryout restaurants	P	½ block	0.700	2.013
Abandoned properties	P	2 blocks	0.456	1.578
Liquor stores	P	3 blocks	0.429	1.536
Convenience stores	D	3 blocks	0.169	1.184
Parks	P	3 blocks	0.133	1.142
Intercept	—	—	−2.501	—

Note. OP = operationalization; SI = spatial influence; RRV = relative risk value.

Conjunctive analysis was utilized to explore the situational contexts of recidivism among parolees residing in the city. There was a potential for 96 different situational configurations of the measures, but the analysis indicated only 44 configurations. Of the 44, 16 were considered dominant case configurations ($n \geq 10$). The 16 recidivism contexts accounted for 86% of the parolees (509). Table 4 indicates the dominant contexts and was sorted from high to low based on the probability of rearrest (i.e., recidivism). The probability of recidivism, rearrest, ranged from 0% to 92%, offering an array of variation and contextual value surrounding recidivism likelihood.

There are multiple configurations, #6 and #14, #9 and #11, and #10 and #13, where the individual risk factors remain constant but the neighborhood ROC differs. When holding constant the individual level factors, parolees residing in elevated ROC neighborhoods had a higher likelihood of recidivism than parolees residing in marginal ROC neighborhoods. Not surprisingly though, a majority of the dominant case configurations indicated the parolees resided in elevated ROC neighborhoods. In addition, in the dominant case configurations, the higher probability configurations consistently consisted of elevated ROC neighborhoods whereas the lower dominant case configurations (i.e., probability of .00), consisted of marginal ROC neighborhoods. Keep in mind, neighborhood ROC is just one factor, but provides situational context into how the other measures combine to form patterns of recidivism.

Furthermore, when comparing Configurations #1 and #15, the configurations consist of the same age category and ethnicity but opposite prior arrests

Table 4. Conjunctive Analysis Data Matrix.

ID	Age (in years)	Ethnicity	Prior arrests	Neighborhood ROC	Rearrested	Number of cases
1	39-48	Hispanic	Above average	Elevated	0.92	12
2	19-28	Black	Above average	Elevated	0.81	26
3	39-48	Black	Above average	Elevated	0.59	56
4	29-38	Black	Above average	Elevated	0.58	67
5	19-28	Black	Below average	Elevated	0.58	88
6	19-28	Hispanic	Below average	Elevated	0.56	16
7	49+	Black	Above average	Elevated	0.42	38
8	39-48	Black	Below average	Elevated	0.41	37
9	29-38	Black	Below average	Elevated	0.39	69
10	29-38	Hispanic	Below average	Elevated	0.33	21
11	29-38	Black	Below average	Marginal	0.27	11
12	49+	Black	Below average	Elevated	0.16	19
13	29-38	Hispanic	Below average	Marginal	0.06	18
14	19-28	Hispanic	Below average	Marginal	0.00	11
15	39-48	Hispanic	Below average	Marginal	0.00	10
16	49+	Hispanic	Below average	Marginal	0.00	10
					Total = 509	

Note. ROC = risk of crime.

and neighborhood ROC. When Hispanic parolees between 39 and 48 years old had above average number of prior arrests while living in elevated ROC neighborhoods, the probability of recidivism was the highest among dominant case configurations; however, when Hispanic parolees aged 39 years to 48 years had a below average number of prior arrests and lived in marginal ROC neighborhoods, the probability of recidivism was zero. Similar interactions can be seen when comparing numerous configurations and furthers the argument for understanding the situational context surrounding recidivism. View the table as turning on and off a "light-switch," what changes when one of the measures is in the other direction (i.e., category).

Contextual patterns in the data present themselves and indicate differences in the probability of recidivating. For instance, Configurations #1 and #3 are similar on three out of the four measures. The parolees were between 39 years and 48 years old with an above average number of prior arrests while residing in an elevated ROC neighborhood, *but* the difference is the probability of recidivism is lower for Black than Hispanic parolees (.59 and .92, respectively). CACC identifies the greater context of variable interactions as seen when comparing Configurations #11, #9, and #4. Holding constant age, 29 years to 38 years and examining Black parolees, the probability of recidivism increases as prior arrests and neighborhood ROC are “switched-on.” The probability of recidivism is the lowest in the dominant case settings when these parolees reside in marginal ROC neighborhoods and below average number of prior arrests (.27). The probability of recidivism increased from .27 to .39 when the parolees resided in elevated ROC neighborhoods. Furthermore, the probability increased even more when the parolees had an above average number of prior arrests and resided in elevated ROC neighborhoods (to .58).

Discussion

The current study developed an ROC measure and found when parolees resided in elevated risky neighborhoods, the likelihood of recidivism was higher. RTM is a spatial analytical technique that could be employed to quantify the ROC where offenders reside. This is not saying offenders are the ones committing the crimes, however, offenders could be returning to neighborhoods at greater ROC (i.e., criminal opportunities). Offenders could also be protected by neighborhood-level characteristics where there is an absence, or lower value, of ROC. The development of ROC measures in recidivism research has been an untested arena. Recidivism-based research could greatly be advanced from insights gained from an environmental corrections design.

We found general support for offenders residing in elevated ROC neighborhoods having a higher likelihood of recidivism. When holding constant individual-level characteristics, offenders residing in a marginally risky neighborhood had a lower likelihood of recidivating. In addition, evident in the CACC analysis, 11 of the 16 combinations had offenders residing in elevated ROC neighborhoods. This consistency could be the result of limited housing options for parolees.

Environmental corrections is rooted in environmental criminology, and the current study relied on numerous theoretical perspectives and concepts to construct the ROC measure. Specifically, we tested relationships between CGAs and violent and property crime to develop a neighborhood-level ROC measure per parolee. Examining the relationship of CGAs and crime is in line with traditional environmental criminology. At the other end of the spectrum, there are pro social organizations that are argued to have a negative effect on recidivism (Wallace, 2015). That is, when there are more pro social organizations in a neighborhood, their level of recidivism is reduced. This relates to developing neighborhood levels of social control, which assist in developing norms, promoting social organization (see Bursik &

Grasmick, 1993). Wallace (2015) found when a neighborhood suffers a loss of two or more educational organizations, there is an increase in neighborhood-level recidivism, indicating that overtime the influence of pro-social organization could influence levels of recidivism. This assists in understanding that when there is a change in even the pro-social organizations at the neighborhood level, this could potentially influence the level of recidivism in a detrimental manner.

More importantly to the current study, Wallace (2015) expected higher numbers of pro-social organizations to be met with lower levels of neighborhood recidivism, however, Wallace did not find support for the sheer presence of the organizations to influence recidivism. In regard to the current study, we utilized RTM to test the association of suspected risk factors and crime to establish a baseline relationship between CGAs and crime. The presence alone was not expected to influence crime. In addition, we constructed an aggravating model in RTMDx, the association of a risk factor and crime, while there is the option to run a protective model. In a protective model, pro-social organizations could be examined in relation to the absence of crime to determine an overall protective effect at a micro level. This would provide the potential to construct a protective and aggravating model related to crime and better assess criminal opportunities.

Probation/parole officers could use this knowledge to their advantage in assisting offenders desist from criminal activity and lower the likelihood of recidivism. Miller, Copeland, and Sullivan (2015) examined the role of how probation officers can direct offenders away from criminal opportunities through multiple approaches. Translatable to the current discussion is how, "After examining the accounts given by probation officers, we found that officers often paid attention to whether clients had too much unstructured time, spent time at crime-prone places. . . " (Miller et al., 2015, p. 193). For example, in their study, probation officers discussed how parks and rodeos were criminogenic places that were risky for offenders. Probation officers are actively identifying what they consider risky places for criminal activity and trying to deter offenders from going or spending too much time at those locations. RTM provides quantifiable results related to ROC rather than probation officer "gut" feeling that has created issues for police departments (see Koss, 2015). The utilization of RTM to identify crime prone areas can assist probationer officers in developing tactics to limit offender exposure to day-to-day criminal opportunities (see Miller, 2014; Miller et al. 2015), through potentially altering risky places.

This falls in line with environmental corrections and how Cullen et al. (2002) discussed the importance of how environmental criminology has practical insights. There is a line of research on place-based policing (see

Lum & Koper, 2017) and the efforts taken by law enforcement to reduce crime at certain places. With this, law enforcement often target high-crime or high-risk places, through increasing guardianship, place-management, or super-controller presence. The lessons learned through place-based policing could be extending into a place-based supervision model. Cullen et al. (2002) stated how Law Enforcement Information Networks (LEIN) could assist in the reduction of criminal opportunities for supervisees. There is potential for supervisees (i.e., offenders) to be residing in high-crime/risk places, allowing for probation/parole officers (handlers) to be involved crime reduction efforts, while simultaneously potentially reducing the likelihood of recidivism of their supervisees. In essence, there could be a different type of supervision for those offenders residing in high-crime/risk places.

Limitations and Future Research

The current study was limited to one city in the Northeast of the United States. Additional research on the development of an ROC measure and how it relates to recidivism is needed to understand if RTM could be utilized to produce a robust ROC measure. With this, future research should examine other study sites, additional individual-level measures, and potentially additional ways to operationalize ROC based on the built and physical environment surrounding parolee residences.

In recidivism research, the operationalization of recidivism is an important consideration when constructing an ROC measure. For example, if recidivism is operationalized as offenders committing an offense in the same category (drug, property, or violent), separate RTMs could be constructed for property, violent, and drug offenses. This would result in crime category–specific ROC measures. RTM is capable of identifying significant risk factors in relation to a specific crime outcome (i.e., robbery, residential burglary, gun crimes, etc.), allowing for crime-specific ROC measure or aggregate crime categories.

In addition, the current study did not account for traditional social measures. Social measures are often limited based on administrative boundaries, creating MAUP problems (see Bailey & Gatrell, 1995). Neighborhood-level recidivism often operationalizes neighborhood as block groups or tracts, allowing for the social measures to be derived from the Decennial Census or American Community Survey (similar to Kubrin & Stewart, 2006). As RTM is capable of assigning risk values to streets, aggregate risk values can be computed by tract and/or block group (see Drawve et al., 2016; Thomas & Drawve, 2018). Aggregate Neighborhood Risk of Crime (ANROC) could be examined with the more common social measures such as concentrated disadvantage and residential stability. Furthermore, ROC research could utilize an analytical approach similar to how Hipp and Boessen (2013) operationalized Egohoods. This could provide a framework of how to account for both physical and social elements of the environmental backcloth and how they relate to recidivism, extending environmental corrections.

Next, essential to spatial analyses at the micro level is the recording of accurate and reliable addresses. This is often viewed as an issue for police departments as crime analysts utilizes crime data daily, but with a movement in recidivism research to understand "where" offenders reside, corrections agencies will have similar issues pertaining to offenders' reported residential address. If offender home addresses do not represent where they truly reside, the neighborhood argument cannot be reliably tested. Any findings could be spurious and not represent the actual relationship between recidivism and neighborhood characteristics. Furthermore, with reliable and accurate residential data, research could explore the likelihood of recidivism when multiple offenders reside in a similar high-risk areas versus dispersed throughout a study area. In other words, does the clustering of known offenders in high-risk areas lead to a higher likelihood of recidivating, building from prior research on the distribution of offenders across neighborhoods (Chamberlain & Wallace, 2016).

Research should also explore further utilizing CACC and accounting for individual-level and neighborhood-level predictors. This approach to recidivism offers a distinct exploration to identify predictors of recidivism or the more commonly researched "who" characteristics and further advances the "where" understanding. Drawve et al. (2017) discussed how CACC differs from a traditional common statistical approach, binary logistic regression, and how CACC provides greater context. Other methodologies include multilevel approaches to understanding recidivism. This is a design employed by Kubrin and Stewart (2006) who found that offenders returning to disadvantaged neighborhoods are more likely to recidivate when controlling for individual-level predictors. Research could expand ROC and recidivism from both analytical approaches.

Conclusion

The current study provided an analytical approach to develop a measure for the criminal opportunities around parolee residences through RTM. To the researchers' knowledge, this is the first study to utilize RTM to construct a measure related to the risk of future crime and how the ROC relates to the likelihood of recidivism. Community correction agencies can utilize this knowledge to direct policy initiative and identify potential areas where additional resources could be directed with a place-based focus, rather than offender-focused. To continue to extend environmental corrections in research and practice, recidivism research needs to incorporate theoretical underpinnings from environmental criminology that allow for translatable findings to the greater field of practice.

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Notes

1. For a greater discussion on the methodology behind RTM, numerous resources are available at http://Rutgers.weebly.com/rtm.html
2. Koss (2015) discussed how RTM can be used to quantify "“high crime” neighborhoods and inform police where to target rather than relying on gut-instinct/officer intuition.
3. Gender was excluded from the analysis because about 94% of parolees were male. Instant offense was also excluded from the current study because oftentimes parolees had multiple charges for different crime types (violent, sexual, property, drug, and/or technical). To avoid potential shortcomings on offense classification, this was excluded but is discussed in the "Discussion" section.
4. We utilized a more conservative threshold for defining dominant case configurations as outlined by Miethe et al. (2008).

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