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Abstract

Purpose: To determine if repeat and near repeat analysis is sensitive to the geocoding algorithm used for the underlying crime incident data.

Methods: The Indianapolis Metropolitan Police Department provided 2016 crime incident data for five crime types: (1) shootings, (2) robberies, (3) residential burglaries, (4) theft of automobiles, and (5) theft from automobiles. The incident data were geocoded using a dual ranges algorithm and a composite algorithm. First, descriptive analysis of the distances between the two point patterns were conducted. Second, repeat and near repeat analysis was performed. Third, the resulting repeat and near repeat patterns were compared across geocoding algorithms.

Results: The underlying point patterns and repeat and near repeat analyses were similar across geocoding algorithms.

Conclusions: While detailing geocoding processes increases transparency and future researchers can conduct sensitivity results to ensure their findings are robust, dual ranges geocoding algorithms are likely adequate for repeat and near repeat analysis.

Key Words
Repeat Victimization, Near Repeat Victimization, Geocoding, Spatiotemporal Analysis

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INTRODUCTION

Scholarly interest in spatiotemporal analyses of event data is surging in the social sciences. In the context of criminology, this interest is driven in large part by evidence related to crime concentration at place (Weisburd, 2015), place-based intersections of public health, crime, and disorder (Ratcliffe 2015, White & Weisburd, 2018), effectiveness of place-based crime prevention and hot spots policing at reducing crime (Braga, Papachristos & Hureau, 2019), and the emergence of predictive policing (Caplan *et al*., 2019; Mohler *et al*., 2015). In this vein, repeat and near-repeat (R/NR) spatiotemporal modeling of crime has emerged as an important research area, particularly given its implications for certain crime prevention tactics and predictive policing models (e.g. see Mohler et al., 2011). R/NR analyses seek to identify contagion or diffusion patterns of crime events in space *and* time. Such analyses are reliant upon the positional accuracy of spatial data and appropriateness of the geocoding method employed. Findings from R/NR analyses are in turn used to inform police and crime prevention strategies - thus appropriate geocoding procedures are salient to deploy effective interventions. From an academic perspective, study replication and pursuit of knowledge relies on carefully articulated methodologies. To this end, we examine whether the results of R/NR analyses for various crime types are sensitive to the geocoding algorithm used.

REPEAT & NEAR REPEAT CRIME PATTERNS

To understand the variability of geocoding procedures employed in R/NR analyses, we conducted a comprehensive review of the R/NR literature in criminology and criminal justice. This review yielded 82 unique studies. Several notable themes were evident and pertinent to the current study. First and foremost, only ~21 percent of studies (n = 17) reported the geocoding algorithm used.[1] This is both surprising and concerning for reasons articulated in the discussion below. Second, R/NR studies are frequently published in high-ranking criminology and criminal justice journals that often place an increased emphasis on methodological rigor and clarity. For example, 41 percent (n = 33) of the studies identified in our review were published in *Journal of Quantitative Criminology*; *Justice Quarterly*; *Journal of Research in Crime and Delinquency*; *Journal of Experimental Criminology*; *British Journal of Criminology*; *Crime & Delinquency*, *Criminal Justice and Behavior*; *Police Quarterly*; and *European Journal of Criminology*. Third, 68 percent of the studies identified had been published since 2012, while 42 percent have been published since 2017. This dramatic upward trend is likely to continue as the interest in, and application of, R/NR analyses receive further scholarly attention to help explain a range of crime and place phenomena. Lastly, approximately half of the studies leverage data from the United States, while the other half represent notable international variability across study locations such as United Kingdom, Australia, China, Africa, Austria, Iraq, Netherlands, Turkey, Spain, Germany, Sweden, and New Zealand. This geographic dispersion illustrates the wide-spread interest in R/NR crime patterns, but also the varying geographic, social, and cultural contexts within which these analyses are executed – further demanding the need for refined geocoding processes and reporting.

Nonetheless, R/NR patterns have been identified for multiple crime types, such as:

- Residential burglary (Bernasco, 2008; Bowers & Johnson, 2004, 2005; Chainey *et al*., 2018; Gerstner, 2018; Groff & Taniguchi, 2019a, 2019b; Johnson, 2008, 2013; Johnson *et al*., 2007),
- Aggravated assault (Kennedy *et al*., 2016; Zhang *et al*., 2015),

[1] A table including results of this review is available as online supplemental material.

- Motor vehicle theft (Block & Fujita, 2013; de Melo *et al*., 2018; Lockwood, 2012; Piza & Carter, 2018; Youstin *et al*., 2011),
- Theft from vehicles (Emeno & Bennell, 2018; Johnson *et al*., 2009),
- Arson (Grubb & Nobles, 2016; Turchan *et al*., 2018),
- Shootings (Loeffler & Flaxman, 2018; Mazeika & Uriarte, 2018; Ratcliffe & Rengert, 2008; Renda & Zhang; Sturup *et al*., 2018; Wells *et al*., 2012; Wells & Wu, 2011; Youstin *et al*., 2011),
- Robbery (Garnier *et al*., 2018; Glasner & Leitner, 2017; Grubesic & Mack, 2008; Haberman & Ratcliffe, 2012),
- Terrorism (Behlendorf *et al*., 2012; Braithwaite & Johnson, 2012, 2015; Johnson & Braithwaite, 2009; LaFree *et al*., 2012; Townsley, Johnson, & Ratcliffe, 2008),
- Maritime piracy (Marchione & Johnson, 2013; Townsley & Oliveria, 2015), and
- Economic crimes such as counterfeiting and fraud (Powell, Grubb & Nobles, 2018; Wilson & Fulmer, 2014).

There are two dominant theoretical explanations as to why R/NR crime patterns exist. The risk heterogeneity perspective – also referred to as the "flag hypothesis" – asserts that different geographies have different propensities for crime (Bowers & Johnson, 2005; Pease, 1998; Sparks, 1981). Such places exhibit time-stable environmental characteristics that are conducive to crime and signal to offenders a perceived suitability for crime. Geographic risk heterogeneity is akin to explanations of crime concentration at place (Weisburd, 2015), which are most highly concentrated at micro localized scales (O'Brien, 2019). Alternatively, the state-dependence perspective – also referred to as the "boost hypothesis" - asserts crime has a contagion affect wherein previous offending influences future risk of similar crime events (Bowers & Johnson, 2004; Nobles *et al.*, 2016; Ornstein & Hammond, 2017; Ratcliffe & Rengert, 2008). The boost hypothesis has been evidenced in offender foraging studies of crime (Bernasco, 2008; Johnson, Summers, & Pease, 2009), indicating that offenders develop local, crime-specific knowledge during the course of an original offense that in turn influences the likelihood of future offending in that same location. Moreover, recent research suggests offenders develop time-specific knowledge of their offending environments (van Sleeuwen, Ruiter, & Menting, 2018) and share this learned knowledge among their co-offending networks, thereby increasing the risk that previous victimization will repeat (Lantz & Ruback, 2017).

Finally, R/NR analysis has import for crime prevention and policing strategies. Though hot spots policing has demonstrated crime prevention benefits (Braga et al., 2019), R/NR crime events occur within and outside of places identified by police as stable criminogenic micro-places (Gorr & Lee, 2015; McLaughlin et al., 2007; Mohler et al., 2011). Analogous to near-repeat crime events, Santos and Santos (2015a, 2015b) observed police patrol and enforcement could result in significant crime reductions for burglary and thefts from vehicle in micro-time hot spots, or crime “flare ups” which mirror patterns of near-repeat events. In short, micro-time hot spots are clusters or chains of near-repeat events. Moreover, a recent experiment directed 20-minute patrols to micro-time property crime hot spots and observed significant crime reductions out to 30 days; with greatest treatment effects observed in the immediate 15 days following identification of treatment locations (Santos & Santos, 2020).

Likewise, R/NR patterns underpin other crime prevention tactics, such as cocoon watch (Farrell & Pease, 2017) or citizen notification (Groff & Taniguchi, 2019b), albeit the prevention potential requires careful consideration (Groff & Taniguchi, 2019a). Studies in Europe found significant crime reductions focused on R/NR crime events occurring in multi-family housing complexes and neighborhoods (Anderson, Chenery, & Pease, 1995; Chenery, Holt, & Pease 1997; Johnson et al., 2017). In the United States, Groff and Taniguchi (2019b) conducted a randomized control trial in Redlands, California and Baltimore County, Maryland focused on R/NR residential burglaries. Police employed uniformed volunteers to notify residents in near repeat areas of increased risk, resulting in a slight reduction in burglary events. Similarly, interventions leveraging citizen notification pamphlets in areas where an originating event occurred have demonstrated significant crime reductions (Thompson, Townsley, & Pease, 2008; Stokes & Clare, 2019).

R/NR analysis also underpins some predictive policing models (Johnson et al., 2007, 2009; Johnson & Bowers, 2004; Mohler et al., 2011). As the recent National Academies of Sciences, Engineering, and Medicine (2018, p. 131-132) report on proactive policing noted:

> “Other predictive analytical approaches may be useful, especially the near-repeat techniques that use short-term event patterns to forecast probabilities of future events… These approaches could be more effective at predicting short-term crime hot spots than traditional crime mapping approaches, though the methods to assess predictive accuracy have not yet been generally agreed upon and different approaches often produce different types of crime forecast from different data sources - further confounding comparisons”.

Nonetheless, patrols focused on short-term predicted locations have been effective (Mohler et al., 2011).

However, such crime prevention benefits of R/NR events are contingent upon proper geocoding and police capacity (Goff & Taniguchi, 2019b). From an analytic perspective, recent research suggests near-repeat events vary by geography (Chainey *et al*., 2018) and thus expected crime prevention benefits are dependent upon the frequency of such events in a given place and positional accuracy of such events (Groff & Taniguchi, 2019a). Haberman and Ratcliffe (2012) also note the limited ability of police to translate the empirical reality of R/NR crime events into tangible prevention benefits. They note police agencies must have a robust crime analysis unit that operates in short-term frequencies as well as nimble decision-making processes and tactical resources to respond within the minimal near-repeat temporal window. Overall, R/NR patterns can inform policing and crime prevention strategies, but precise identification of R/NR patterns is paramount.

GEOCODING IN THE CONTEXT OF REPEAT AND NEAR-REPEAT CRIMES

The Technical Details of Geocoding

Geocoding is the process of converting addresses to XY-coordinates (Chainey & Ratcliffe, 2005). In general, geocoding algorithms take (1) a list of addresses and attempt to locate them within (2) references database(s) (Zandbergen, 2009). The optional plural of database(s) in the previous sentence is one important component that distinguishes geocoding algorithms.

Ideally, analysts would have reference data capturing all possible addresses and the addresses' corresponding XY-coordinates (Zandbergen, 2008). The geocoding algorithm would then simply match crime incidents' addresses to the master address list to obtain a set of corresponding XY-coordinates. Master address reference databases might include address points or parcels. While hardware, software, and data collection limitations have meant that digital master address lists have been rarely available and used to geocode crime, they have recently become more common (Zandbergen, 2009).[2] Further, researchers have argued these reference data more accurately capture locations in the physical world (e.g. see Mazeika & Summerton, 2017).

Nonetheless, fully geocoding crime incident addresses with a master address list is typically infeasible due to how crimes occur and incidents' addresses are recorded (Bichler & Balchak, 2007; Brimicombe et al., 2007). First, crimes that occur outdoors do not technically occur at a single, physical address linking to a structure. Second, some crimes occur at a "fuzzy address" where the incident starts at one location and occurs at another (e.g. when a robber follows a victim

[2] In some jurisdictions, parcels may not represent a true master address list as one parcel can contain many addresses that are not official recorded in a parcel dataset (Zandbergen, 2008).

from a bar and commits the act a few blocks away). Third, and related to the previous two points, there are many complexities with how officers record addresses when taking crime reports. One issue is that officers often estimate crime incident addresses. For example, a victim might point to a general area where an assault took place, and the officer will simply select or even interpolate a nearby address (or intersection). Therefore, crime incidents' addresses often do not link to a physical structure or are a rough approximation.

As such, crime incidents are typically geocoded using the "dual ranges" geocoding algorithm based on a street centerline reference dataset (Hart & Zandbergen, 2013; Zandbergen, 2008). In a street centerline GIS layer, a single line digitally represents all lanes of a street segment, hence the term "centerline". Underlying attribute data describe each street segment's characteristics, such as the street name, prefix, suffix, address range, and so on. Using topology, typically odd address ranges are represented on one side the street segment and even addresses on the other side just as they are in the real world.[3] The dual ranges geocoding algorithm then geocodes a crime incident to the correct street segment based on the name attributes and the correct side of the street segment based on the numerical address values and topological principles. The numerical ranges for a street segment, however, present another complexity. The location of each address on a street segment is interpolated. One can imagine each segment as a number line with each side of the street segment having a "from address" or the starting value of the address range and a "to address" or the ending value of the address range. All address values for one side of the street segment are assumed to be equally spaced along the street segment. When geocoding is conducted, the respective location for the corresponding address value is selected and the corresponding XY-coordinates for the location are used for that crime incident. Finally, two more

[3] While extremely rare, we recognize it is not always true that odd and even numbered addresses are on opposite sides of the street.

complexities are introduced into the dual ranges geocoding algorithm. Because the street centerlines are a generalization and there is often physical space between the centerline and structures on that street (i.e., lanes, sidewalks, and maybe yards) an “offset” is applied. The offset is a constant spatial distance in which each geocoded address is moved away from the centerline roughly perpendicularly in order to place points closer to where the actual structure for the address might be on the street. Likewise, it is rare for structures to sit right on a street centerline endpoint due to lanes, sidewalks, and yards on cross streets, so an “endset” is applied. This is a predetermined spatial distance or proportion of the total street segment’s length measured from the intersection where addresses are excluded from geocoding to again provide a more realistic portrayal of where an address might be located in physical space. Thus, it is easy to see how geocoding using the dual ranges algorithm is an estimate of an address’ actual location of in physical space.

Finally, an alternative approach is to use a “composite” geocoding algorithm (e.g. see Brimicombe et al., 2007). Composite geocoding uses multiple geocoding algorithms to assign XY-coordinates to incident addresses. Composite algorithms use a hierarchy system to geocode addresses with multiple algorithms. An obvious combination would be to first attempt to geocode to a master address list (e.g. parcel file), and then move to a dual ranges algorithm. Hypothetically, the algorithm could continue attempting to match addresses to higher-level geographies, such as zip code centroids and ultimately city centroids. While matching to these higher-level spatial units would increase one’s hit-rate (rate at which addresses are successfully matched), it would provide relatively inaccurate XY-coordinates in relation to where a crime incident actually occurred.

Once geocoding is complete, a geocoding algorithm can be evaluated across at least three criteria: (1) positional accuracy, (2) completeness, and (3) repeatability (Hart & Zandbergen, 2013;

Zandbergen, 2009). Positional accuracy is the extent to which a geocoded location matches its actual location. Completeness is the extent to which the geocoding algorithm can identify XY-coordinates for the address list (i.e. match or hit-rate). Repeatability is the extent to which the geocoding results can be replicated across variations on the algorithm parameters.

Most crime and place methodology sections only assess and report completeness (i.e. hit-rate) (Mazeika & Summerton, 2017). In fact, most studies simply state the geocoding hit-rate met or exceeded Ratcliffe's (2004) recommended 85% "acceptable minimum hit-rate" (but see Andresen et al., 2020; Briz-Redón et al., 2019). While typically not discussed, the positional accuracy of crime data geocoding is just as important as completeness (Bichler & Balchak, 2007; Mazeika & Summerton, 2017; Zandbergen, 2008, 2009). Low geocoding hit-rates would call into the question the use of a dataset, but an analyst could also easily achieve a 100% hit-rate by sacrificing positional accuracy. For example, one could simply geocode crime data to city, neighborhood, or police district centroids or allow for less stringent geocoding parameters (Mazeika & Summerton, 2017) to obtain a 100% hit-rate, but the process would result in geocoded incidents too positionally inaccurate to appropriately describe the spatial crime patterns.

To date, the limited research available suggests that geocoding quality impacts spatial crime analysis. First, positional accuracy can be impacted by a number of factors, such as the quality of crime incidents' address input or the underlying reference data (Bichler & Balchak, 2007; Hart & Zandbergen, 2012; Mazeika & Summerton, 2017). Second, the results of some analytical techniques commonly used in crime analysis are sensitive to geocoding results. For example, kernel density estimation appears to be impacted by geocoding quality. Brimicombe and colleagues (2007) suggested unmatched crime incidents might have kernel density intensities that differ from matched incidents (i.e., missing hot spots). Alternatively, Harada and Shimada (2006) demonstrated some differences in two kernel density surfaces produced from the same crime incident dataset geocoded at two levels of precision. In addition, geocoding methods can impact distance calculations. Zandbergen and Hart (2009) showed how the positional inaccuracies from geocoding sex offenders' residences and restricted locations using a dual ranges algorithm (and assuming parcels represent accurate locations) produced errors where sex offenders would be both incorrectly determined in compliance and in violation of residency restriction laws. It follows that crime and place studies should provide geocoding details in their methodology sections as the method employed may influence the studies' results.

Geocoding Crime Incidents for Near Repeat Analysis

Recall, only ~21% studies (n=17) identified in a review of R/NR literature identified the geocoding method. Geocoding methods using street centerline and parcel centroid reference datasets were most commonly reported, followed by an even mixture of grid cell, street segment, and block centroid techniques. The lack of discussion concerning geocoding method and spatial data preparation is especially troubling for R/NR studies given distances among crime incidents is a key parameter in R/NR analysis. Specifically, the assignment of spatial locations of crime incidents are dependent upon geocoding method and this process may skew the premise of a "near" repeat event. For example, if a vehicle is stolen in the parking lot of a large mall, this crime event could be assigned to the parcel centroid (parcel geocoding) or the nearest major road segment (dual ranges geocoding), which are potentially quite distant from each other. This example highlights two issues that would influence the validity of the results of the R/NR analyses. First, the difference in the assignment of spatial location across geocoding methods causes concern for repeatability of the study. Second, in terms of positional accuracy, the assigned location could potentially be several thousand feet from where the crime occurred, drastically misrepresenting the spatial location of the event. Moreover, while this may be less of a cause for concern for one or two thefts, when there are several thousand being considered for any given year, the problem is magnified. This is especially true when the events are proximal to residential areas where the theft event may be closer to capturing residential attributes as opposed to commercial characteristics as would be the case of where the actual crime occurred. Both issues influence the extent to which R/NR analyses can generate reliable results to appropriately inform police strategic operations.

DATA & METHOD

Data

The present study used official crime incident data from the Indianapolis Metropolitan Police Department (IMPD). Indianapolis is the largest city in the state of Indiana, the state capital, and a consolidated city-county municipality. In 2016, Indianapolis had a population of 867,125 persons with a population density of 2,270 persons per square mile. The largest ethnic group in Indianapolis is non-Hispanic White consisting of 55.9% of the total population with much smaller proportions of non-White racial/ethnic groups (28.1% Black, 10.1% Hispanic, and 3.0% Asian). Median household income in 2010 was $44,709 and Indianapolis had 20.1% of residents living below the poverty line (as compared to 13.5% statewide). Additionally, 29.7% of the population had a bachelor's degree or higher as compared to 25.3% statewide.[4] Indianapolis reported a violent crime rate of 1,374 crimes per 100,000 residents compared to 876 per 100,000 for all cities of a similar population in the United States (500,000 - 999,999 residents). In addition, robbery and burglary rates in Indianapolis were similarly high for all cities of a similar population at (458 vs. 282) and (1,178 vs. 768), respectively. The reported motor vehicle theft rate was 576 vs. 525 per 100,000.[5]

[4] All sociodemographic figures based on 2010 ACS estimates
[5] As per FBI *Crime in the United States, 2016.* All crime rates are per 100,000 residents.

IMPD provided 2016 crime incident data for five crime types: (1) homicides or aggravated assaults with a firearm (hereafter shootings), (2) robberies, (3) residential burglaries, (4) theft of automobiles, and (5) theft from automobiles. Incidents for each crime type were identified using UCR classification codes. IMPD's crime incident data are susceptible to all of the well-known limitations of official crime data, such as victim and officer reporting and recoding discretion (Wolfgang, 1963).

Analytic Plan

Two geocoding methods were compared. First, a dual ranges address locator was created using an official street centerline file from IMPD. A dual ranges address locator effectively represents the standard geocoding method used for research and crime analysis. An offset of 20 feet was used. An endset of 3% was used as that is the default value in ESRI's ArcGIS which is commonly used in practice (e.g. see Mazeika & Summerton, 2017: endnote 4). Second, a composite address locator using both parcels and street address ranges was used. The parcel data were procured from the IndyGIS open data portal. The street centerline file from the dual ranges address locator was re-used. All remaining parameters were the same as during the dual ranges geocoding process.[6] The use of composite algorithms made up of separate parcel-based and dual-range algorithms helps to maximize the geocoding hit-rate, as certain common police reporting practices, such as recording incident addresses as street corners (e.g. "Main St. and Central Ave.") rather than precise addresses (e.g. "100 Main St.") (Braga, Papachristos, & Hureau, 2010), generates incident locations that cannot be matched to parcels (Piza & Carter 2018). Table 1

[6] Another option is to use a proprietary geocoding service, such as the Google Geocoding API (Mazeika & Summerton, 2017). This option was not used for the following reasons. First, the proprietary nature of those options sometimes means the exact parameters used are unknown and may not be disclosed due to market competition. Likewise, details about the underlying reference data used in those processes may not be provided for the same reasons. Third, proprietary geocoding services can be costly. Fourth, given the vast amount of geographic data now collected by government agencies, there is no evidence or reason to believe that geocoding algorithms built with freely available local data are inferior to proprietary geocoding services.

displays the original raw incidents counts before geocoding, geocoding hit-rates for both methods, and the percentage of all incidents matched using the composite address locator that were matched to a parcel.[7]

After geocoding was completed, the first set of analyses examined the distances between the incidents' two sets of XY-coordinates to assess how the geocoding method impacted incidents' locations. Distance was computed using Manhattan distance.[8] Descriptive statistics for the distances between crime incidents' locations by geocoding type were computed. Next, because near repeat analyses commonly use street block distances for the spatial bandwidth (discussed in detail below) (e.g. see Haberman & Ratcliffe, 20102; Piza & Carter, 2018), the percentage and frequency of incidents at incremental street blocks distances away from each other were examined. If the two geocoding methods commonly locate the same incidents a street block or more from each other, then it would suggest those incidents would often be counted in different spatial bandwidths during R/NR analyses and knowing that detail would help understand how geocoding methods may impact near repeat analyses. In Indianapolis, the average street block is about 434 feet (Piza & Carter, 2018), so multiples of 434 feet approximated street block distances.

The second set of analyses explored the point-patterns generated by both geocoding methods. A nearest neighbor index (NNI) was computed for both sets of geocoded incidents for each crime type. The NNI is a common measure of spatial concentration, and a component of other spatial statistics, such as nearest neighbor hierarchical clustering (Chainey & Ratcliffe, 2005, pg. 126). All nearest neighbor calculations were computed in ArcGIS 10.3, which defines the NNI as:

[7] The number of incidents matched to a parcel for the composite address locator is equivalent to the number of incidents that would have been matched using a parcel-only address locator. Thus, a hit-rate for a parcel-only address locator could be computed using the number of incidents matched to a parcel and the original incidents counts shown in Table 1.

[8] As a sensitivity check, all analyses were also computed using Euclidean distance. The results using Euclidean distance are presented in the Online Appendix, but they were substantively similar to those reported herein using Manhattan distance.

$$NNI = \frac{\overline{D}_O}{\overline{D}_E} \tag{1}$$

$\overline{D}_O$ is the average nearest neighbor distance ($\overline{D}_O$) for a dataset, computed as:

$$\overline{D}_O = \frac{\sum_i^n d_i}{n} \tag{2}$$

Where:
d_i is the nearest neighbor distance for incident i
n is the number of incidents in the dataset

And $\overline{D}_E$the expected nearest neighbor distance from a point pattern exhibiting complete spatial randomness, which is defined as:

$$\overline{D}_E = \frac{0.5}{\sqrt{n/A}} \tag{3}$$

Where:
A is the geographic area of the study site

A NNI below 1 indicates spatial clustering. A NNI greater than 1 indicate spatial dispersion. Statistical significance can also be determined using a *z*-test:

$$z = \frac{\overline{D}_O - \overline{D}_E}{\left(\frac{0.26136}{\sqrt{\frac{n^2}{A}}}\right)} \tag{4}$$

Third, Ratcliffe's (2020) revised Near Repeat Calculator (NRC) was used to test for near repeat patterns by geocoding method for each crime type. The NRC uses the modified Knox test to identify near repeat patterns (Johnson *et al.*, 2007). The NR analysis starts by specifying the spatial and temporal bandwidth as well as the number of bandwidths to use. The bandwidths are subjective, but can be informed by the literature and police practice (Ratcliffe & Rengert, 2008). For example, common bandwidths include the length of the study city's average street block and 7 days (e.g. see Braithwaite & Johnson, 2012; Haberman & Ratcliffe, 20102; de Melo *et al.*, 2018;

Piza & Carter, 2018). The bandwidths inform the creation of a contingency table where each cell represents a spatial-temporal distance combination extending out to some maximum number of bandwidths. The spatial and temporal distances from each incident to every other incident in the analysis dataset is computed and the number of point-pairs within each cell of the contingency table is counted to create an observed distribution for the contingency table. The observed point-pair counts within each cell are then compared to an expected distribution of point-pair counts generated via permutations. A single permutation is created by randomly reassigning incident dates to a different pair of XY coordinates. Randomizing the incidents' dates rather than XY-coordinates ensures all observed incident locations are realistic. The permutations are repeated, say 999 times, to create pseudo *p*-values using the following formula for the probability equaling the observed cell value's rank relative to the expected values across all simulations (n):

$$p = \frac{n - rank + 1}{n + 1} \tag{5}$$

NR analyses are typically interpreted using Knox ratios – a cell's observed point pair count divided by the mean cell count from the simulated expected distribution of cell counts. After multiplying the difference between a Knox ratio and 1 by 100, the resulting value can be interpreted as the percentage increase in risk of another crime incident within the spatial-temporal distances represented by the cell. For example, a Knox Ratio of 1.20 suggests that the spatiotemporal clustering is at least 20% greater than what would be expected by chance (Ratcliffe, 2009 p. 10).

Finally, three pieces of information are used to assess the sensitivity of NR results to geocoding algorithms in terms of their influence on significance tests results and reported risk. First, we present contingency tables capturing the number of cells that were statistically significant (defined as $p < .05$) in one, both, or neither NR analyses in the dual ranges and composite geocoding algorithms. This contingency table quantifies the extent to which the choice of geocoding method influences the significance testing component of R/NR analyses. Second, the full extent of the NR patterns were compared across geocoding algorithms to determine if different conclusions would be drawn from the individual analyses. The full extent of the NR pattern for each geocoding algorithm is identified by reading the Knox Ratios in the output table from the top-left through the bottom-right on the diagonal and noting which cells achieved statistical significance and how the difference in spatial-temporal risk changes across the table. Generally, it is expected that NR risk will decrease moving along the diagonal, and an analyst will describe the extent of the NR pattern by describing the lower and upper space-time bandwidths that achieved statistical significance (e.g. see Haberman & Ratcliffe, 2012). Third, differences in the magnitudes of the Knox Ratios were computed by dividing the dual ranges method Knox Ratios by the composite method Knox Ratios. A ratio value equal to 1 suggests identical risk levels were identified for a space-time bandwidth between geocoding methods. Ratios greater than 1 suggest the dual-range algorithms resulted in higher reported risk than the composite algorithms for a given space-time bandwidth. A ratio value less than 1 suggests the composite algorithm resulted in higher reported risk than the dual ranges algorithm. The ratios are converted to percentage differences in magnitude by multiplying the difference between the ratios and 1 by 100. The degree to which there is a lack of agreement, in terms of reported risk, has implications for whether that cell is suitable for translation to crime prevention and police operations as it may be overly sensitive to geocoding method.

RESULTS

Table 1 displays the geocoding results. First, for both the dual ranges and composite algorithms and all crime types, the geocoding hit-rate was 90.90% or greater. Thus, it would be reasonable to use the dataset from either geocoding algorithm for spatial analysis according to Ratcliffe's (2004) recommended 85% hit-rate as well as more recent estimates of minimum acceptable geocoding rates (Andresen *et al.*, 2020; Briz-Redón *et al.*, 2019). Second, the differences between the dual ranges and composite algorithms' hit-rates at less than 1% for each crime type are relatively trivial. Third, for the composite address locator, the percentage of incidents geocoded to a parcel was 62.66% (n = 1,054) for shootings, 62.91% (n = 2,295) for robbery, 70.15% (n = 6,121) for residential burglary, 71.21% (n = 3,347) for auto theft, and 74.36% (n = 7,773) for theft from motor vehicles. Therefore, a parcel only address locator would produce inadequate hit-rates (~57 to 71%) for all crime types (see footnote 7). Overall, Table 1 suggests that while more than a majority of incidents of each crime type would be geocoded to a parcel using the composite address locator, the dual ranges and composite algorithms both provide adequate data for spatial analysis (while a parcel only address locator would not).

Table 2 shows descriptive statistics for the distances measured between incidents' geocoded locations from each geocoding method. Table 3 provides frequencies of the distances between incidents' geocoded locations from each geocoding method using incremental street block distances (434 feet). Table 2 shows the mean distance between geocoded incidents range from 146.38 feet (residential burglary) to roughly 277.80 feet (theft from automobiles); both distances are less than an average city block in Indianapolis (434 feet). The relatively short distances between the incident's two geocoded locations is reflected in the fact that anywhere from about 25.75% (Theft from Autos) to 37.4% (Shootings) of incidents of a given crime type were geocoded to the same location by each algorithm (Table 3). Because the composite address locator geocoded incidents to parcels first, another away to think about the incidents geocoded to the same location by both methods is that they are the incidents geocoded using address ranges by both algorithms.

Nonetheless, ~51% to 66% incidents were geocoded within 1 street block (or 434 feet) of each other (Table 3). Finally, the NNI analysis suggested that all datasets, regardless of the address locator, exhibited similar spatial clustering. Overall, the two methods almost always geocoded the incidents to approximately similar locations.

Finally, the relative similarities in the point-patterns across the two geocoding methods was ultimately shown in the consistency of the near repeat analyses. First, Table 4 displays the simple comparisons of how many cells achieved statistical significance ($p < 0.05$) between two geocoding methods by crime type. Divergent results would occur when a cell would have been statistically significant for a NR analysis using one geocoding method but not the other. Second, Table 5 through Table 9 show the NR results for each crime type. Each NR results table displays the Knox Ratios produced for both geocoding algorithms in the top two panels and ratios of the Knox Ratios in the third panel. The ratios of the Knox Ratios show relative differences in the risk levels observed between the two geocoding methods In the bottom panel of each NR results table, grey shading is used to show cells where the spatial-temporal bandwidths were statistically significant ($p < 0.05$) for both geocoding methods, thus capturing the extent of the common NR pattern for both geocoding algorithms. Recall the extent of the NR pattern would have implications for how crime prevention and policing programs would be implemented using the NR results.

For the shootings, the NR results were substantively identical. Only 2 cells showed divergent significance pattern between the dual ranges and composite geocoding methods (Table 4), but those cells that appear to be false-positives as opposed to substantive findings (i.e., errant cells disconnected from the top-left NR pattern). Overall, there was a statistically significant risk of a subsequent shooting on the same day, extending out about one block from the original location regardless of whether a dual ranges or composite address locator was used. The Knox Ratios show roughly the same risk levels for the NR patterns identified for both geocoding methods. The two Knox Ratios making up the statistically significant NR pattern were only about 2% or 9% larger for the dual ranges geocoding results.

The NR robbery patterns were also substantively similar across geocoding methods. First, only two NR result cells had divergent statistical significance patterns between geocoding methods (Table 4). Second, again, when reading along the top-left to bottom-right diagonal, the identified NR patterns were mostly robust to geocoding method. There was one divergence for the NR results for the composite geocoding algorithm data identified; the NR pattern extended out to almost 3 blocks from the originator event on the same day (Table 6). Third, there was also relatively minimal differences in the magnitudes of the Knox Ratios for the analyses using different geocoding algorithms. For the primary NR robbery pattern, grey cells in Table 6, were about 1 to 20% different in magnitude. Overall, the substantive conclusions from NR robbery analyses were mostly robust to geocoding methods.

For the residential burglary NR results, there were 8 cells (14%) showing different significance patterns diverging between the two geocoding methods (Table 4). If one is basing the extent of the NR pattern off of connecting only statistically significant cells along the top-left to bottom-right diagonal (grey cells in the bottom panel of Table 7), a consistent NR pattern was found extending out about two blocks and up to 21 days from an originator residential burglary event. However, discrepancies between the geocoding methods appear in the next spatial bandwidth (3 blocks). In the dual ranges data, the cells for 3 blocks and up to 7 days achieved statistical significance but the cells for 3 blocks and 8 to 21 days were statistically insignificant, whereas all four of those cells were all statistically significant in the composite geocoded data. Additionally, the cells for 4 and 5 blocks away and extending out to 21 days from the originator event also mostly achieved statistical significance for ***both*** geocoding methods but 1 cell did not (5 blocks and >0 to 7 days). The remaining cells with divergent significance patterns were more dispersed across the space-time bandwidths and likely would not impact an analyst's conclusions (Table 7). Albeit it is possible that some analysts would ignore the two statistically insignificant cells when determining the scope of their NR pattern, it is fair to say the residential burglary NR results showed some sensitivity to geocoding method. Nonetheless, in the bottom panel of Table 7, the ratios of Knox Ratios showed only slight differences each across the two geocoding methods. The largest difference in Knox Ratios for the cells capturing the NR pattern specifically was only about 5%.

For auto theft, there were 10 cells with divergent statistical significance (Table 4). Nonetheless, the NR results were consistent across geocoding methods. In short, all analyses suggest that the most consistent risk of subsequent auto theft victimization is at the same location for up to 7 days after an originating event (Table 8). It follows that the divergent significance patterns in the NR results were for cells that were dispersed across the overall results table, and, as such, are likely false positives that would not provide an analyst with any extra actionable information about NR patterns. The bottom panel of Table 8 shows the actual Knox Ratios also only differed in magnitude by about 1 or 2%.

Finally, the theft from autos NR results were also nearly identical across geocoding methods. There were only 3 diverging statistical significance cells (Table 4), and the extent of the theft from auto NR victimization pattern was consistent across all geocoding algorithms (see bottom panel of Table 9). An increased risk of another theft from auto was found at the same location for up to 35 days after an originator event. Additionally, there was an increased risk of theft from auto victimization for up to 6 blocks away and within the first 7 days after an originator event. Nonetheless, the ratios of Knox Ratios show some variability. Most Knox Ratios were only a few percentage points larger or smaller regardless of geocoding method, but the differences between 4 Knox Ratios were 10% or more. Overall, the results were not sensitive enough across geocoding algorithms to impact the design of any crime prevention or policing strategies.

DISCUSSION

This study examined if R/NR analysis results were sensitive to the geocoding algorithm used for the underlying crime incident data. They were not. In short, while there were some differences in significance patterns and Knox Ratios, the differences were relatively trivial and unlikely to impact how an analyst would define the R/NR risk pattern for implementing a crime prevention or policing strategy. In fact, residential burglary was the only crime exhibiting even marginal sensitivity to the geocoding algorithm used, and it is still likely that analysts would have arrived at the same R/NR patterns for operational purposes despite the slight differences.

Spatiotemporal analysis has become commonplace in criminological pursuits to better understand crime. Unfortunately, methodological transparency has not kept pace with this surge in analytic capacity. Specific to the R/NR literature, our literature review revealed a lack of specificity regarding data preparation and geocoding procedures upon which replicable science and effective interventions are developed. Fortunately, our results suggest that the conclusions drawn from the R/NR literature likely have not been impacted by the geocoding algorithms used. Nonetheless, it would be beneficial for the field to provide detailed descriptions of the geocoding algorithms used for crime data used in spatial-temporal analyses given the potential for variation in the reporting and collecting of spatial data as previously discussed. At minimum, researchers should report (1) the geocoding algorithm used, (2) the parameters used by the algorithm, (3) the geocoding hit-rate, and (4) any efforts to assess the positional accuracy of their geocoding process.

This will provide transparency to readers for how the results were generated and is necessary for informing future replication studies or potential comparisons of results across studies.

Additionally, researchers and analysts can conduct sensitivity analyses using different geocoding algorithms to ensure their results are robust. Like many studies, external validity is one limitation of this work, and it is unclear if these results would hold in other cities. If these results would not hold across locations and times, geocoding algorithm sensitivity analyses will be extremely important. If the present results are replicated across other cities and times, however, then the field may gain enough confidence that R/NR are robust to geocoding methods and sensitivity analyses may not be worth the extra effort. Of course, this is an empirical question the present results cannot answer.

Given the consistency of results across geocoding algorithms, and assuming these results will hold in future work, researchers and analysts might begin questioning if more complex geocoding algorithms are worthwhile. Law enforcement agencies with well-designed dual ranges geocoding algorithms may receive little benefit from investing resources in composite algorithms. In effect, they would be investing resources to change their algorithms only to get the same results from their analysis. Alternatively, using proprietary algorithms only for obtaining XY coordinates at the parcel or address level also may be an unnecessary expenditure. While more research is needed before definitive conclusions can be drawn, the street centerline files now commonly maintained by local governments may be plenty adequate for geocoding crime incident data.

With respect to practice and policy, our results in Indianapolis suggest police can leverage R/NR analyses to focus crime prevention efforts as each of the crime types exhibited R/NR patterns. Approaches like micro-time hot spot strategies, cocooning, and citizen notification that have shown promise in the literature (Farrell & Pease, 2017; Groff & Taniguchi, 2019b; Santos &

Santos, 2020) continue to have a place in law enforcement agencies' overall crime reduction strategies.

The present study, however, should be considered in light of its limitations. First, as noted above, the study's substantive conclusions will need to be replicated to ensure its external validity. It is certainly possible that the studies may not hold in other locations, such as those with different street patterns or address recording practices. Second, Knox ratios can change over time, perhaps due to changes in underlying risk, so future work should replicate the present results using longitudinal data (Ornstein & Hammond, 2017; Hatten & Piza, 2020). Third, it is possible that geocoding algorithms impact the results of other analytical methods. For example, geocoding algorithm choice could even impact the near repeat parameters of a Hawkes model. The present results should only be considered for R/NR patterns identified using Knox tables generated via Monte Carle simulation. Fourth, this study only considered two geocoding algorithms – dual ranges and a composite of parcels and dual ranges. Other geocoding algorithms could show more sensitivity (e.g. dual ranges geocoding with random noise added to the XY coordinates). Future research should consider additional geocoding contingencies. Fifth, geocoding algorithms are only as good as the data put into them. The old adage "garbage in, garbage out" remains as relevant as ever. Police departments and researchers should continue to think of ways to improve data collection and entry within law enforcement to overcome any potential data quality limitations.

Nonetheless, the present results are promising for the field. In this study R/NR results were not sensitive to whether a dual ranges or composite geocoding algorithm was used for shootings, robbery, residential burglary, auto theft, and theft from motor vehicles. While researchers and analysts are encouraged to detail their geocoding algorithms and assess sensitivity of their R/NR results in the future, the present results suggest the current R/NR literature is likely robust to past geocoding algorithms used.

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Table 1. Geocoding Results

Crime Type	Original N	Dual Ranges Only Hit-Rate	Composite Hit-Rate	Composite Parcel Hit-Rate
Shootings	1,847	90.90% (n = 1,679)	91.07% (n = 1,682)	62.66% (n = 1,054)
Robbery	3,984	91.32% (n = 3,638)	91.57% (n = 3,648)	62.91% (n = 2,295)
Residential Burglary	8,843	98.28% (n = 8,691)	98.67% (n = 8,725)	70.15% (n = 6,121)
Automobile Theft	4,956	94.35% (n = 4,676)	94.83% (n = 4,700)	71.21% (n = 3,347)
Theft from Automobiles	10,961	95.00% (n = 10,413)	95.37% (n = 10,453)	74.36% (n = 7,773)

Notes: The denominator for geocoding hit-rates are the raw number of incidents for each crime type. The denominator for the percentage of incidents geocoded to parcels for the composite address locator is total number of geocoded incidents by crime type.

Table 2. Distance-Based Statistics by Crime for Manhattan Distance Measurements

	Pairwise Distances Between Geocoded Locations							NNI	
	Min	10th Percentile	Median	Mean	90th Percentile	Max	SD	DR	Composite
Shootings	0.00	0.00	106.32	157.77	324.44	5,993.10	298.91	0.67***	0.68***
Robbery	0.00	0.00	132.81	215.42	470.73	8,358.77	389.71	0.53***	0.55***
Residential Burglary	0.00	0.00	114.85	146.38	295.87	7,808.50	225.81	0.62***	0.65***
Automobile Theft	0.00	0.00	136.77	211.13	450.70	8,121.99	364.01	0.66***	0.70***
Theft from Automobiles	0.00	0.00	165.61	277.80	631.23	7,047.48	472.46	0.61***	0.66***

Notes: ***$p < .001$; **$p < .01$; *$p < .05$. Min = Minimum; Max = Maximum; SD = Standard Deviation; NNI = Nearest Neighbor Index. Incidents were geocoded using dual ranges and composite (parcels & dual ranges) algorithms.

Table 3. Frequencies & Percentages of Pairwise Street Block Distance Increments between Geocoded Locations

	Shootings	Robbery	Residential Burglary	Auto Theft	Theft From Autos
	% (n)	% (n)	% (n)	% (n)	% (n)
Same Location	37.4% (n = 628)	37.22% (n = 1354)	29.97% (n = 2605)	28.93% (n = 1353)	25.75% (n = 2681)
Within 1 Block	56.7% (n = 952)	51.15% (n = 1861)	65.9% (n = 5727)	60.71% (n = 2839)	57.02% (n = 5937)
1-2 Blocks	4.05% (n = 68)	7.92% (n = 288)	3.21% (n = 279)	7.53% (n = 352)	11.45% (n = 1192)
2-3 Blocks	1.07% (n = 18)	1.73% (n = 63)	0.54% (n = 47)	1.11% (n = 52)	3.01% (n = 313)
3-4 Blocks	0.12% (n = 2)	0.85% (n = 31)	0.24% (n = 21)	0.92% (n = 43)	1.12% (n = 117)
4-5 Blocks	0.24% (n = 4)	0.16% (n = 6)	0.00% (n = 0)	0.11% (n = 5)	0.73% (n = 76)
5-6 Blocks	0.12% (n = 2)	0.22% (n = 8)	0.03% (n = 3)	0.24% (n = 11)	0.36% (n = 38)
6-7 Blocks	0.12% (n = 2)	0.60% (n = 22)	0.03% (n = 3)	0.17% (n = 8)	0.30% (n = 31)
7-8 Blocks	0.06% (n = 1)	0.00% (n = 0)	0.01% (n = 1)	0.11% (n = 5)	0.02% (n = 2)
8-9 Blocks	0.00% (n = 0)	0.00% (n = 0)	0.00% (n = 0)	0.04% (n = 2)	0.00% (n = 0)
9-10 Blocks	0.06% (n = 1)	0.03% (n = 1)	0.01% (n = 1)	0.00% (n = 0)	0.02% (n = 2)
More than 10 Blocks	0.06% (n = 1)	0.11% (n = 4)	0.05% (n = 4)	0.13% (n = 6)	0.23% (n = 24)

Notes: Only incidents matched by both the dual ranges and composite algorithms included in statistics. A street block was approximated as 434 feet, the average length of a street block in Indianapolis. The maximum for each row is an open boundary. All distances computed using Manhattan distance.

Table 4. Near Repeat Significance Agreement between Geocoding Methods

Shootings		Composite: Not Significant	Composite: Significant	Composite: Total
Dual Ranges	Not Significant	52	1	53
	Significant	1	2	3
	Total	53	3	56
Robbery		**Not Significant**	**Significant**	**Total**
Dual Ranges	Not Significant	47	1	48
	Significant	1	7	8
	Total	48	8	56
Residential Burglary		**Not Significant**	**Significant**	**Total**
Dual Ranges	Not Significant	21	5	26
	Significant	3	27	30
	Total	24	32	56
Auto Theft		**Not Significant**	**Significant**	**Total**
Dual Ranges	Not Significant	42	6	48
	Significant	4	4	8
	Total	46	10	56
Theft from Autos		**Not Significant**	**Significant**	**Total**
Dual Ranges	Not Significant	28	0	28
	Significant	3	25	28
	Total	31	25	56

Notes: Comparisons are based on near repeat analysis significance tests conducted using Manhattan distance provided in Table 5 - Table 9**.**

Table 5. Shooting Near Repeat Risk – By Method with Knox Ratios and Difference Ratios

Dual-Range Method - Knox Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	8.26**	1.20	1.00	1.03	0.83	0.83	0.98
1 to 434 ft.	7.63***	1.37	0.84	1.27	0.50	0.88	0.98
435 to 868 ft.	1.90	1.08	1.17	0.88	1.23	0.96	0.98
869 to 1302 ft.	1.83	0.95	0.87	0.91	0.72	0.67	1.04**
1303 to 1736 ft.	1.30	1.00	1.08	0.88	1.11	1.02	1.00
1737 to 2170 ft.	1.01	1.00	1.08	1.08	1.21	1.05	0.98
2171 to 2604 ft.	0.80	1.16	0.95	0.95	1.05	1.08	0.99
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Composite Method – Knox Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	7.59**	1.21	1.01	1.02	0.85	0.84	0.98
1 to 434 ft.	7.47***	1.13	0.60	1.44*	0.56	0.79	1.00
435 to 868 ft.	2.15	1.23	1.28	0.97	1.08	0.97	0.97
869 to 1302 ft.	1.81	0.97	0.94	0.84	0.88	0.86	1.02
1303 to 1736 ft.	1.48	1.02	0.95	0.80	1.08	0.89	1.01
1737 to 2170 ft.	0.97	0.97	1.07	0.91	1.19	1.05	0.99
2171 to 2604 ft.	0.80	1.08	0.97	1.01	1.09	1.12	0.99
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Difference Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	1.09	0.99	0.99	1.01	0.98	0.99	1.00
1 to 434 ft.	1.02	1.21	1.40	0.88	0.89	1.11	0.98
435 to 868 ft.	0.88	0.88	0.91	0.91	1.14	0.99	1.01
869 to 1302 ft.	1.01	0.98	0.93	1.08	0.82	0.78	1.02
1303 to 1736 ft.	0.88	0.98	1.14	1.10	1.03	1.15	0.99
1737 to 2170 ft.	1.04	1.03	1.01	1.19	1.02	1.00	0.99
2171 to 2604 ft.	1.00	1.07	0.98	0.94	0.96	0.96	1.00
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Notes: Near repeat analysis conducted using Manhattan distance. Ratio = 1 (Identical level of risk identified), >1 (Dual-Range reported higher risk than Composite), <1 (Composite reported higher risk than Dual-Range). Grey cells represent the common statistically significant NR pattern identified during the analysis.

Table 6. Robbery Near Repeat Risk – By Method with Knox Ratios and Difference Ratios

Dual-Range Method – Knox Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	1.58	1.81***	1.44***	1.13	1.06	0.92	0.94
1 to 434 ft.	1.56	1.30**	0.94	1.15*	1.05	0.98	0.98
435 to 868 ft.	2.03**	1.24**	1.10	1.00	1.10	0.98	0.98
869 to 1302 ft.	1.00	1.01	0.97	1.04	0.89	1.04	1.00
1303 to 1736 ft.	1.16	1.04	1.12*	0.93	0.98	1.06	0.99
1737 to 2170 ft.	0.95	1.02	1.03	0.99	1.04	1.10	0.99
2171 to 2604 ft.	0.78	1.00	1.09	1.02	1.05	0.92	1.00
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00***
Composite Method – Knox Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	1.55	1.80***	1.43**	1.12	1.06	0.96	0.94
1 to 434 ft.	1.27	1.43***	1.09	1.18*	1.05	1.05	0.96
435 to 868 ft.	1.69*	1.11	1.05	1.01	1.07	1.04	0.99
869 to 1302 ft.	1.32	1.20**	0.94	1.03	1.01	0.99	0.99
1303 to 1736 ft.	1.31	0.93	1.16**	0.95	0.91	1.09	1.00
1737 to 2170 ft.	0.78	1.03	1.05	0.96	1.06	1.03	1.00
2171 to 2604 ft.	0.75	1.08	0.97	1.01	1.03	0.97	1.00
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00***
Difference Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	1.02	1.01	1.01	1.01	1.00	0.96	0.96
1 to 434 ft.	1.23	0.91	0.86	0.97	1.00	0.93	0.98
435 to 868 ft.	1.20	1.12	1.05	0.99	1.03	0.94	1.01
869 to 1302 ft.	0.76	0.84	1.03	1.01	0.88	1.05	0.98
1303 to 1736 ft.	0.89	1.12	0.97	0.98	1.08	0.97	0.98
1737 to 2170 ft.	1.22	0.99	0.98	1.03	0.98	1.07	1.00
2171 to 2604 ft.	1.04	0.93	1.12	1.01	1.02	0.95	1.01
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Notes: Near repeat analysis conducted using Manhattan distance. Ratio = 1 (Identical level of risk identified), >1 (Dual-Range reported higher risk than Composite), <1 (Composite reported higher risk than Dual-Range). Grey cells represent the common statistically significant NR pattern identified during the analysis.

Table 7. Residential Burglary Near Repeat Risk – By Method with Knox Ratios and Difference Ratios

Dual-Range Method – Knox Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	8.56***	3.28***	1.77***	1.42**	1.23	1.53***	0.78
1 to 434 ft.	4.58***	1.46***	1.20***	1.16***	1.11*	0.99	0.95
435 to 868 ft.	2.64***	1.27***	1.14***	1.15***	1.05	0.96	0.97
869 to 1302 ft.	1.79***	1.20***	1.05	1.03	1.04	1.03	0.98
1303 to 1736 ft.	1.47***	1.15***	1.13***	1.06*	1.08**	1.04	0.98
1737 to 2170 ft.	1.35***	1.05*	1.08**	1.07**	1.09***	1.05*	0.98
2171 to 2604 ft.	0.94	0.99	1.07**	1.07**	1.02	1.03	0.99
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00***
Composite Method – Knox Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	8.19***	3.20***	1.79***	1.42**	1.26	1.48**	0.78
1 to 434 ft.	4.68***	1.49***	1.18***	1.13*	1.09*	1.00	0.95
435 to 868 ft.	2.67***	1.26***	1.14***	1.12**	1.05	1.00	0.97
869 to 1302 ft.	1.79***	1.21***	1.06*	1.10***	1.060*	1.00	0.98
1303 to 1736 ft.	1.47***	1.14***	1.11***	1.05*	1.06*	1.07*	0.98
1737 to 2170 ft.	1.36***	1.02	1.11***	1.06*	1.09**	1.04	0.98
2171 to 2604 ft.	1.06	1.00	1.06*	1.03	1.05*	1.02	0.99
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00***
Difference Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	1.05	1.03	0.99	1.00	0.98	1.03	1.00
1 to 434 ft.	0.98	0.98	1.02	1.03	1.02	0.99	1.00
435 to 868 ft.	0.99	1.01	1.00	1.03	1.00	0.96	1.00
869 to 1302 ft.	1.00	0.99	0.99	0.94	0.98	1.03	1.00
1303 to 1736 ft.	1.00	1.01	1.02	1.01	1.02	0.97	1.00
1737 to 2170 ft.	0.99	1.03	0.97	1.01	1.00	1.01	1.00
2171 to 2604 ft.	0.89	0.99	1.01	1.04	0.97	1.01	1.00
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Notes: Near repeat analysis conducted using Manhattan distance. Ratio = 1 (Identical level of risk identified), >1 (Dual-Range reported higher risk than Composite), <1 (Composite reported higher risk than Dual-Range). Grey cells represent the common statistically significant NR pattern identified during the analysis.

Table 8. Automobile Theft Near Repeat Risk – By Method with Knox Ratios and Difference Ratios

Dual-Range Method – Knox Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	2.85**	1.75***	1.24	1.02	0.98	1.05	0.95
1 to 434 ft.	1.78	1.02	1.09	0.85	0.96	0.93	1.00
435 to 868 ft.	1.45	1.10	0.95	1.13	1.34**	1.05	0.97
869 to 1302 ft.	0.92	1.22***	1.09	1.09	0.97	0.81	0.99
1303 to 1736 ft.	0.73	1.00	0.99	0.99	0.90	0.91	1.01*
1737 to 2170 ft.	1.27	1.04	1.06	1.00	1.08	1.03	0.99
2171 to 2604 ft.	0.80	1.08*	1.06	1.05	1.04	0.94	0.99
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00*	1.00**
Composite Method – Knox Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	2.82*	1.79***	1.23	1.02	0.98	1.03	0.95
1 to 434 ft.	1.25	1.04	1.23*	0.96	1.17	0.97	0.98
435 to 868 ft.	1.31	1.12	0.87	1.03	1.09	0.94	1.00
869 to 1302 ft.	1.16	1.08	1.13*	1.11*	1.15*	0.83	0.99
1303 to 1736 ft.	0.91	1.12*	0.96	0.94	0.86	0.96	1.01
1737 to 2170 ft.	1.14	1.04	0.97	1.05	1.02	1.01	1.00
2171 to 2604 ft.	0.84	1.06	1.11*	1.04	1.07	0.95	0.99
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00*	1.00**
Difference Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	1.01	0.98	1.01	1.00	1.00	1.02	1.00
1 to 434 ft.	1.42	0.98	0.89	0.89	0.82	0.96	1.02
435 to 868 ft.	1.11	0.98	1.09	1.10	1.23	1.12	0.97
869 to 1302 ft.	0.79	1.13	0.96	0.98	0.84	0.98	1.00
1303 to 1736 ft.	0.80	0.89	1.03	1.05	1.05	0.95	1.00
1737 to 2170 ft.	1.11	1.00	1.09	0.95	1.06	1.02	0.99
2171 to 2604 ft.	0.95	1.02	0.95	1.01	0.97	0.99	1.00
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Notes: Near repeat analysis conducted using Manhattan distance. Ratio = 1 (Identical level of risk identified), >1 (Dual-Range reported higher risk than Composite), <1 (Composite reported higher risk than Dual-Range). Grey cells represent the common statistically significant NR pattern identified during the analysis.

Table 9. Theft from Automobile Near Repeat Risk – By Method with Knox Ratios and Difference Ratios

Dual-Range Method – Knox Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	5.51***	1.36***	1.35***	1.17**	1.21***	1.19***	0.92
1 to 434 ft.	4.72***	1.30***	1.12**	1.00	1.00	1.06	0.96
435 to 868 ft.	4.00***	1.28***	1.12***	1.08*	1.09**	1.06*	0.96
869 to 1302 ft.	3.27***	1.16***	1.05	1.06*	1.02	0.97	0.98
1303 to 1736 ft.	2.21***	1.09***	1.07**	1.05*	1.02	1.02	0.98
1737 to 2170 ft.	2.24***	1.13***	1.08***	1.02	1.03	1.00	0.98
2171 to 2604 ft.	1.66***	1.10***	0.98	1.02	0.98	1.03	0.99
> 2604 ft.	0.99	1.00	1.00	1.00	1.00	1.00	1.00***
Composite Method – Knox Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	5.49***	1.37***	1.34***	1.17***	1.22***	1.19***	0.92
1 to 434 ft.	6.64***	1.39***	1.08	1.04	1.04	1.00	0.95
435 to 868 ft.	4.17***	1.28***	1.12***	1.06*	1.01	1.08*	0.96
869 to 1302 ft.	2.94***	1.18***	1.04	1.04	1.03	0.97	0.98
1303 to 1736 ft.	2.32***	1.12***	1.08**	1.05*	1.04	1.04	0.98
1737 to 2170 ft.	2.16***	1.11***	1.09**	1.00	1.00	1.01	0.99
2171 to 2604 ft.	1.84***	1.07**	1.00	1.02	0.99	0.99	0.99
> 2604 ft.	0.99	1.00	1.00	1.00	1.00	1.00	1.00***
Difference Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	1.00	0.99	1.01	1.00	0.99	1.00	1.00
1 to 434 ft.	0.71	0.94	1.04	0.96	0.96	1.06	1.01
435 to 868 ft.	0.96	1.00	1.00	1.02	1.08	0.98	1.00
869 to 1302 ft.	1.11	0.98	1.01	1.02	0.99	1.00	1.00
1303 to 1736 ft.	0.95	0.97	0.99	1.00	0.98	0.98	1.00
1737 to 2170 ft.	1.04	1.02	0.99	1.02	1.03	0.99	0.99
2171 to 2604 ft.	0.90	1.03	0.98	1.00	0.99	1.04	1.00
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Notes: Near repeat analysis conducted using Manhattan distance. Ratio = 1 (Identical level of risk identified), >1 (Dual-Range reported higher risk than Composite), <1 (Composite reported higher risk than Dual-Range). Grey cells represent the common statistically significant NR pattern identified during the analysis.

The Sensitivity of Repeat and Near Repeat Analysis to Geocoding Algorithms

ONLINE APPENDIX

To save print space, this online appendix contains:

1. A table describing the repeat and near repeat analysis studies reviewed for this manuscript.
2. The results of the sensitivity check using Euclidean distance measures for the near repeat analysis.

Near Repeat Studies and Reported Geocoding Method Summarized in Manuscript

Source	**Study Area**	**Crime Type**	**Geocoding Method**	**Confirmation**
Ajayakumar and Shook (2020)	Simulated data	None	Not reported	NA
Amemiya *et al.* (2020)	Tokyo, Japan	Sex Crimes	City block centroid and parcel centroid	p. 2
Bediroglu *et al.* (2018)	Trabzon, Turkey	Residential burglary	Street centerline	p. 7
Behlendorf *et al.* (2012)	Cities in Spain and El Salvador	Terrorist attacks	City centroid	p. 56
Bernasco (2008)	The Hague metropolitan area, Netherlands	Residential burglary	Unreported	NA
Block and Fujita (2013)	Newark, NJ	Motor vehicle theft	Unreported	NA
Bowers and Johnson (2004)	Merseyside, UK	Residential burglary	Unreported	NA
Bowers and Johnson (2005)	Merseyside, UK	Residential burglary	Unreported	NA
Braithwaite and Johnson (2012)	Baghdad, Iraq	IED attacks	Unreported	NA
Braithwaite and Johnson (2015)	Baghdad, Iraq	IED attacks	Unreported	NA
Briz-Redon et al (2020)	Valencia (Spain)	Residential burglary	Unreported	NA
Caplan *et al.* (2013)	Irvington, NJ	Street violence	Street centerline	p. 248
Chainey *et al.* (2018)	Auckland Central, Manukau Central, Wellington, and Kapiti Mana, New Zealand	Residential burglary	Unreported	NA
Chainey and da Silva (2016)	Belo Horizone, Brazil	Domestic burglary	Unreported	NA
Chen and Kurland (2020)	Beijing, China	Residential burglary	Unreported	NA
Davies and Marchione (2015)	Unknown	Maritime piracy and residential burglary	Unreported	NA
de Melo *et al.* (2018)	Campinas, Brazil	Residential burglary, vehicle theft, commerce robbery, residence robbery, and passerby robbery	Unreported	NA
Emeno and Bennell (2018)	5 Canadian cities	Residential burglary, theft from motor vehicle, and assault	Unreported	NA

Everson and Pease (2001)	Cities in England and Wales	Multiple crime types	Unreported	NA
Farrell and Bouloukos (2001)	Multiple international locations	Multiple crime types	Unreported	NA
Frank *et al*. (2012)	Vancouver, Canada	Residential burglary	Unreported	NA
Garnier *et al*. (2018)	Newark, NJ	Robbery	Grid Cells	p. 2
Gerstner (2018).	Baden-Wurttemberg, Germany	Residential Burglary	Unreported	NA
Glasner *et al.* (2018)	Vienna, Austria	Apartment burglary	Address and street segment	p. 4
Glasner and Leitner (2017)	Vienna, Austria	Robbery	Unreported	NA
Groff and Taniguchi (2019)	10 US cities	Residential burglary	Multiple methods	p. 9
Groff and Taniguchi (2019)	Baltimore County, MD and Redlands, CA	Residential Burglary	Parcel	p.11
Groff and Taniguchi (2018)	Baltimore County, MD and Redlands, CA	Residential Burglary	Unreported	NA
Grubb and Nobles (2016)	Los Angeles, CA	Arson	City block centroid	p. 73
Grubesic and Mack (2008)	Cincinnati, OH	Robbery, burglary, and assault	Unreported	NA
Gu *et al*. (2017)	Cities in China	Residential burglary	Unreported	NA
Haberman and Ratcliffe (2012)	Philadelphia, PA	Street robbery	Unreported	NA
Hatten and Piza (2020)	Newark, NJ	Robbery	Street centerline	p. 7
Hino and Amemiya (2019)	Fukuoka City, Japan	Residential burglary	Parcel	p. 16
Hoppe and Gerell (2018)	Malmo, Sweden	Residential burglary	Unreported	NA
Johnson (2013)	Bournemouth and Poole, UK	Residential burglary	Unreported	NA
Johnson (2008)	Merseyside, UK	Residential burglary	Unreported	NA
Johnson and Braithwaite (2009)	Baghdad, Iraq	IED attacks	Unreported	NA
Johnson *et al.* (2007)	10 different cities	Residential burglary	Unreported	NA
Johnson *et al.* (2009)	Bournemouth, UK	Burglary and theft from motor vehicle	Unreported	NA
Johnson and Bowers (2004)	Meryside, UK	Residential burglary	Unreported	NA

Johnson *et al*. (2017)	West Midlands, UK	Residential burglary	Unreported	NA
Kennedy *et al.* (2016)	Chicago, IL	Aggravated assault	Unreported	NA
Kleemans (2001)	Enschede, Netherlands	Residential burglary	Unreported	NA
LaFree *et al*. (2012)	Multiple international locations	Terrorist attacks	Unreported	NA
Lantz and Ruback (2017)	Centre County, PA	Residential burglary	Unreported	NA
Lockwood (2012)	Lincoln, NE	Motor vehicle theft	Unreported	NA
Loeffler and Flaxman (2018)	Washington, DC	Gun shots	Unreported	NA
Marchione and Johnson (2013)	Multiple international locations	Maritime piracy	Unreported	NA
Matthews *et al*. (2001)	London metropolitan area, UK	Bank robbery	Unreported	NA
Mawbry (2001)	Salford and Plymouth, England; Monchengladbach, Germany; Warsaw and Lublin, Poland; and Miskolc, Hungary	Residential burglary	Unreported	NA
Mazeika and Uriarte (2018)	Trenton, NJ	Firearm incidents	Parcel centroid	p. 6
Moreto *et al.* (2014)	Newark, NJ	Residential burglary	Street centerline	p. 1109
Morgan (2001)	Perth metropolitan area, Australia	Residential burglary	Unknown	NA
Nobles *et al.* (2016)	Jacksonville, FL	Residential burglary	Unknown	NA
Ornstein and Hammond (2017)	Washington, DC	Residential burglary	Unknown	NA
Piza and Carter (2018)	Indianapolis, IN	Residential burglary and motor vehicle theft	Street centerline and parcel centroid	p. 6
Powell et al (2018)	Fort Worth, TX	Counterfeiting, credit card/ATM fraud, false pretense/swindling	Unreported	NA
Rasmusson and Helbich (2020)	Malmo, Sweden	Robbery	Unreported	NA
Ratcliffe and McCullagh (1998)	Nottinghamshire, UK	Residential burglary	Unreported	NA
Ratcliffe and Rengert (2008)	Philadelphia, PA	Shootings	Unreported	NA

Renda and Zhang (2019)	Louisville, KY	Shootings	Grid cells / census blocks	p. 3-4
Sagovsky and Johnson (2007)	Victoria, Australia	Residential burglary	Unreported	NA
Short *et al*. (2009)	Long Beach, CA	Residential burglary	Unreported	NA
Sidebottom (2012)	Malawi, Africa	Residential burglary	Unreported	NA
Stokes and Clare (2018)	Perth Metro Area, Australia	Residential Burglary	Unreported	NA
Sturup *et al*. (2019)	Multiple cities in Sweden	Hand detonated explosives	Unreported	NA
Sturup *et al*. (2018)	Stockholm, Gothenburg, and Malmo, Sweden	Shooting incidents	Unreported	NA
Townsley *et al.* (2000)	Brisbane, AU	Residential burglary	Unreported	NA
Townsley *et al.* (2003)	Brisbane, AU	Residential burglary	Unreported	NA
Townsley *et al.* (2008)	Baghdad, Iraq	IED attacks	Unreported	NA
Townsley and Oliveria (2015)	Northeast region of Africa	Maritime piracy	Unreported	NA
Turchan *et al.* (2018)	Flint, MI	Arson	Address	p. 4
van Sleeuwen *et al*. (2018)	The Hague metropolitan area, Netherlands	Cumulative crime index of violent, property, vandalism, traffic, environmental, drugs, weapons, and other crimes	Postal code centroid	p. 9
Wang *et al*. (2018)	Chicago, IL	Multiple crimes	Unreported	NA
Wang and Liu (2017)	City in the Jiangsu province of China	Residential burglary	Unreported	NA
Wells and Wu (2011)	Houston, TX	Gun assaults	Unreported	NA
Wells *et al.* (2012)	Houston, TX	Gun assaults	Unreported	NA
Whiteacre *et al* (2015)	Indianapolis, IN	Metal theft	Unreported	NA
Wu *et al*. (2015)	Wuhan, China	Residential burglary	Unreported	NA
Youstin *et al.* (2011)	Jacksonville, FL	Shootings, robbery, and auto theft	Mixed method: building, parcel, and street centerline	p. 1049
Zhang *et al.* (2015)	Houston, TX	Residential burglary, street robbery, and aggravated assault	Unknown	NA

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Sensitivity Check Using Euclidean Distance

The results of all analyses in the manuscript were recomputed using Euclidean distance as the distance measurement technique. Overall, the results are not sensitive to the distance measurement technique chosen. In fact, in most instances, the results using Euclidean distance show even fewer divergences than the results obtained using Manhattan distance that were presented in the main body of the manuscript. We present these analyses in this online appendix for the sake of transparency.

Table 1. Distance-Based Statistics by Crime for Euclidean Distance Measurements

	Pairwise Distances Between Geocoded Locations							NNI	
	Min	10th Percentile	Median	Mean	90th Percentile	Max	SD	DR	Composite
Shootings	0.00	0.00	83.60	124.73	260.23	5,917.22	263.53	0.54***	0.55***
Robbery	0.00	0.00	100.62	167.09	365.64	7,981.71	315.37	0.43***	0.45***
Residential Burglary	0.00	0.00	87.95	113.76	229.40	6,025.55	189.31	0.50***	0.52***
Automobile Theft	0.00	0.00	103.30	164.98	348.88	6,272.36	299.58	0.54***	0.56***
Theft from Automobiles	0.00	0.00	124.33	216.71	496.22	6,460.72	379.09	0.50***	0.53***

Notes: ***$p < .001$; **$p < .01$; *$p < .05$. Min = Minimum; Max = Maximum; SD = Standard Deviation; NNI = Nearest Neighbor Index. Incidents were geocoded using dual ranges and composite (parcels & dual ranges) algorithms.

Table 2. Frequencies & Percentages of Pairwise Street Block Euclidean Distance Increments between Geocoded Locations

	Shootings	Robbery	Residential Burglary	Auto Theft	Theft From Autos
	% (n)	% (n)	% (n)	% (n)	% (n)
	Euclidean Distance Measurements				
Same Location	37.4% (n = 628)	37.22% (n = 1354)	29.97% (n = 2605)	28.93% (n = 1353)	25.75% (n = 2681)
Within 1 Block	59.08% (n = 992)	54.67% (n = 1989)	67.41% (n = 5859)	64.31% (n = 3007)	61.67% (n = 6422)
1-2 Blocks	2.2% (n = 37)	5.58% (n = 203)	2.03% (n = 176)	4.58% (n = 214)	8.90% (n = 927)
2-3 Blocks	0.66% (n = 11)	1.26% (n = 46)	0.40% (n = 35)	1.15% (n = 54)	1.91% (n = 199)
3-4 Blocks	0.24% (n = 4)	0.30% (n = 11)	0.05% (n = 4)	0.38% (n = 18)	0.87% (n = 91)
4-5 Blocks	0.06% (n = 1)	0.55% (n = 20)	0.03% (n = 3)	0.24% (n = 11)	0.46% (n = 48)
5-6 Blocks	0.18% (n = 3)	0.27% (n = 10)	0.03% (n = 3)	0.17% (n = 8)	0.14% (n = 15)
6-7 Blocks	0.06% (n = 1)	0.00% (n = 0)	0.01% (n = 1)	0.04% (n = 2)	0.04% (n = 4)
7-8 Blocks	0.00% (n = 0)	0.05% (n = 2)	0.00% (n = 0)	0.06% (n = 3)	0.01% (n = 1)
8-9 Blocks	0.00% (n = 0)	0.03% (n = 1)	0.01% (n = 1)	0.04% (n = 2)	0.05% (n = 5)
9-10 Blocks	0.06% (n = 1)	0.00% (n = 0)	0.00% (n = 0)	0.00% (n = 0)	0.00% (n = 0)
More than 10 Blocks	0.06% (n = 1)	0.05% (n = 2)	0.05% (n = 4)	0.09% (n = 4)	0.19% (n = 20)

Notes: Only incidents matched by both the dual ranges and composite algorithms included in statistics. A street block was approximated as 434 feet, the average length of a street block in Indianapolis. The maximum for each row is an open boundary. All distances computed using Euclidean distance.

Table 3. Near Repeat Significance Agreement between Geocoding Methods

Shootings		Composite		
		Not Significant	Significant	Total
Dual Ranges	Not Significant	49	3	52
	Significant	0	4	4
	Total	49	7	56
Robbery		Composite		
		Not Significant	Significant	Total
Dual Ranges	Not Significant	47	2	49
	Significant	0	7	7
	Total	47	9	56
Residential Burglary		Composite		
		Not Significant	Significant	Total
Dual Ranges	Not Significant	27	1	28
	Significant	1	27	28
	Total	28	28	56
Auto Theft		Composite		
		Not Significant	Significant	Total
Dual Ranges	Not Significant	47	0	47
	Significant	3	6	9
	Total	50	6	56
Theft from Autos		Composite		
		Not Significant	Significant	Total
Dual Ranges	Not Significant	29	0	29
	Significant	4	23	27
	Total	33	23	56

Notes: Comparisons are based on near repeat analysis significance tests provided in Online Appendix Tables A1-A5. All results based on Euclidean distance.

Table 4. Shooting Near Repeat Risk – By Method with Knox Ratios and Difference Ratios

Dual-Range Method - Knox Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	8.59**	1.17	1.01	1.02	0.84	0.84	0.98
1 to 434 ft.	6.28***	1.28	0.88	1.06	0.63	0.83	1.00
435 to 868 ft.	2.27*	1.14	1.03	0.98	0.98	0.80	1.00
869 to 1302 ft.	0.92	0.99	1.06	0.89	0.98	0.93	1.01
1303 to 1736 ft.	1.62	0.90	1.00	0.98	1.30**	0.93	0.99
1737 to 2170 ft.	0.62	1.11	1.09	0.91	0.89	1.15	1.00
2171 to 2604 ft.	0.55	1.00	1.11	1.11	1.08	1.09	0.98
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Composite Method – Knox Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	7.74**	1.21	1.00	1.05	0.82	0.86	0.98
1 to 434 ft.	6.00***	1.39*	0.64	1.27	0.70	0.79	0.99
435 to 868 ft.	2.20**	0.99	1.21	0.99	1.06	0.94	0.99
869 to 1302 ft.	1.70	0.99	0.95	0.76	0.90	0.83	1.02*
1303 to 1736 ft.	0.96	0.91	1.10	0.88	1.22*	0.97	1.00
1737 to 2170 ft.	0.77	1.13	0.88	1.00	1.05	1.17	0.99
2171 to 2604 ft.	0.86	1.03	1.23**	1.06	0.96	1.05	0.99
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Difference Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	1.11	0.97	1.01	0.97	1.02	0.98	1.00
1 to 434 ft.	1.05	0.92	1.38	0.83	0.90	1.05	1.01
435 to 868 ft.	1.03	1.15	0.85	0.99	0.92	0.85	1.01
869 to 1302 ft.	0.54	1.00	1.12	1.17	1.09	1.12	0.99
1303 to 1736 ft.	1.69	0.99	0.91	1.11	1.07	0.96	0.99
1737 to 2170 ft.	0.81	0.98	1.24	0.91	0.85	0.98	1.01
2171 to 2604 ft.	0.64	0.97	0.90	1.05	1.13	1.04	0.99
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Notes: Near repeat analysis conducted using Euclidean distance. Ratio = 1 (Identical level of risk identified), >1 (Dual-Range reported higher risk than Composite), <1 (Composite reported higher risk than Dual-Range). Grey cells represent the common statistically significant NR pattern identified during the analysis.

Table 6. Robbery Near Repeat Risk – By Method with Knox Ratios and Difference Ratios

Dual-Range Method – Knox Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	1.56	1.81***	1.44***	1.13	1.06	0.92	0.94
1 to 434 ft.	1.61*	1.31***	1.00	1.11	1.06	1.02	0.98
435 to 868 ft.	1.82***	1.15*	1.05	1.09	1.03	0.98	0.98
869 to 1302 ft.	0.98	1.03	1.04	0.90	0.98	1.05	1.00
1303 to 1736 ft.	0.93	0.99	1.03	1.03	0.98	1.04	1.00
1737 to 2170 ft.	0.96	1.08	1.05	0.99	1.04	1.04	0.99
2171 to 2604 ft.	0.82	1.07	1.06	0.93	1.05	0.99	1.00
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00***
Composite Method – Knox Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	1.56	1.81***	1.42**	1.13	1.06	0.96	0.94
1 to 434 ft.	1.66*	1.37***	1.07	1.14	1.07	1.02	0.97
435 to 868 ft.	1.52*	1.13*	1.00	0.98	1.02	1.02	0.99
869 to 1302 ft.	1.40*	1.06	1.08	1.03	0.98	1.05	0.99
1303 to 1736 ft.	0.61	1.00	1.03	0.96	0.96	1.02	1.00
1737 to 2170 ft.	1.04	1.06	1.04	0.97	1.00	1.03	1.00
2171 to 2604 ft.	0.99	1.08	0.97	1.06	1.09*	1.02	0.99
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00***
Difference Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	1.00	1.00	1.01	1.00	1.00	0.96	1.00
1 to 434 ft.	0.97	0.96	0.93	0.97	0.99	1.00	1.01
435 to 868 ft.	1.20	1.02	1.05	1.11	1.01	0.96	0.99
869 to 1302 ft.	0.70	0.97	0.96	0.87	1.00	1.00	1.01
1303 to 1736 ft.	1.52	0.99	1.00	1.07	1.02	1.02	1.00
1737 to 2170 ft.	0.92	1.02	1.01	1.02	1.04	1.01	0.99
2171 to 2604 ft.	0.83	0.99	1.09	0.88	0.96	0.97	1.01
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Notes: Near repeat analysis conducted using Euclidean distance. Ratio = 1 (Identical level of risk identified), >1 (Dual-Range reported higher risk than Composite), <1 (Composite reported higher risk than Dual-Range). Grey cells represent the common statistically significant NR pattern identified during the analysis.

Table 7. Residential Burglary Near Repeat Risk – By Method with Knox Ratios and Difference Ratios

Dual-Range Method – Knox Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	8.23***	3.28***	1.77***	1.42**	1.22	1.53***	0.78
1 to 434 ft.	4.21***	1.43***	1.22***	1.14***	1.06	0.98	0.95
435 to 868 ft.	2.30***	1.25***	1.09**	1.09**	1.08*	0.99	0.97
869 to 1302 ft.	1.58***	1.16***	1.08**	1.09***	1.04	1.04	0.98
1303 to 1736 ft.	1.23**	1.05*	1.08**	1.03	1.08**	1.05*	0.99
1737 to 2170 ft.	1.05	0.99	1.06**	1.07**	1.06**	1.00	0.99
2171 to 2604 ft.	1.13	1.04*	1.03	1.01	1.03	1.02	0.99
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00***

Composite Method – Knox Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	7.92***	3.23***	1.80***	1.41**	1.25	1.46**	0.78
1 to 434 ft.	4.08***	1.45***	1.21***	1.14**	1.05	0.99	0.95
435 to 868 ft.	2.39***	1.24***	1.10***	1.08**	1.09**	0.99	0.97
869 to 1302 ft.	1.61***	1.17***	1.08**	1.10***	1.02	1.03	0.98
1303 to 1736 ft.	1.23*	1.02	1.09***	1.03	1.09**	1.05*	0.99
1737 to 2170 ft.	1.12	1.01	1.04*	1.06**	1.06**	1.02	0.99
2171 to 2604 ft.	1.08	1.04*	1.06**	1.02	1.03	1.02	0.99
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00**

Difference Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	1.04	1.02	0.98	1.01	0.98	1.05	1.00
1 to 434 ft.	1.03	0.99	1.01	1.00	1.01	0.99	1.00
435 to 868 ft.	0.96	1.01	0.99	1.01	0.99	1.00	1.00
869 to 1302 ft.	0.98	0.99	1.00	0.99	1.02	1.01	1.00
1303 to 1736 ft.	1.00	1.03	0.99	1.00	0.99	1.00	1.00
1737 to 2170 ft.	0.94	0.98	1.02	1.01	1.00	0.98	1.00
2171 to 2604 ft.	1.05	1.00	0.97	0.99	1.00	1.00	1.00
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Notes: Near repeat analysis conducted using Euclidean distance. Ratio = 1 (Identical level of risk identified), >1 (Dual-Range reported higher risk than Composite), <1 (Composite reported higher risk than Dual-Range). Grey cells represent the common statistically significant NR pattern identified during the analysis.

Table 8. Automobile Theft Near Repeat Risk – By Method with Knox Ratios and Difference Ratios

Dual-Range Method – Knox Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	2.80*	1.76***	1.23	1.02	0.98	1.04	0.95
1 to 434 ft.	1.85*	1.03	1.07	1.01	1.04	0.90	0.99
435 to 868 ft.	1.17	1.15**	0.97	1.03	1.16*	0.95	0.99
869 to 1302 ft.	0.84	1.12**	1.05	1.08	0.96	0.85	1.00
1303 to 1736 ft.	0.84	1.04	1.06	1.02	1.04	1.02	0.99
1737 to 2170 ft.	1.05	1.10*	1.04	0.99	1.00	1.05	0.99
2171 to 2604 ft.	0.95	0.99	1.08*	1.05	0.95	0.98	1.00
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00**
Composite Method – Knox Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	2.83*	1.78***	1.21	1.01	0.97	1.03	0.95
1 to 434 ft.	1.60	1.11	1.07	1.05	1.11	0.88	0.99
435 to 868 ft.	1.02	1.07	1.04	1.05	1.15*	0.91	0.99
869 to 1302 ft.	0.90	1.13**	0.98	1.02	1.02	0.93	1.00
1303 to 1736 ft.	1.01	1.01	1.07	1.05	0.99	0.97	1.00
1737 to 2170 ft.	0.91	1.10*	1.03	0.99	0.98	1.05	0.99
2171 to 2604 ft.	0.97	1.01	1.05	1.07	0.99	1.01	0.99
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00***
Difference Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	0.99	0.99	1.02	1.01	1.01	1.01	1.00
1 to 434 ft.	1.16	0.93	1.00	0.96	0.94	1.02	1.00
435 to 868 ft.	1.15	1.07	0.93	0.98	1.01	1.04	1.00
869 to 1302 ft.	0.93	0.99	1.07	1.06	0.94	0.91	1.00
1303 to 1736 ft.	0.83	1.03	0.99	0.97	1.05	1.05	0.99
1737 to 2170 ft.	1.15	1.00	1.01	1.00	1.02	1.00	1.00
2171 to 2604 ft.	0.98	0.98	1.03	0.98	0.96	0.97	1.01
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Notes: Near repeat analysis conducted using Euclidean distance. Ratio = 1 (Identical level of risk identified), >1 (Dual-Range reported higher risk than Composite), <1 (Composite reported higher risk than Dual-Range). Grey cells represent the common statistically significant NR pattern identified during the analysis.

Table 9. Theft from Automobile Near Repeat Risk – By Method with Knox Ratios and Difference Ratios

Dual-Range Method – Knox Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	5.49***	1.36***	1.34***	1.17**	1.21***	1.19***	0.92
1 to 434 ft.	4.75***	1.30***	1.08*	0.99	1.01	1.08*	0.97
435 to 868 ft.	3.80***	1.26***	1.15***	1.08**	1.05	1.01	0.96
869 to 1302 ft.	2.49***	1.10***	1.02	1.06*	1.00	1.03	0.98
1303 to 1736 ft.	2.15***	1.11***	1.07***	1.02	1.05*	0.97	0.99
1737 to 2170 ft.	1.72***	1.09***	1.00	1.02	1.00	1.05*	0.99
2171 to 2604 ft.	1.67***	1.08***	0.99	1.00	0.99	1.02	0.99
> 2604 ft.	0.99	1.00	1.00	1.00	1.00	1.00	1.00***
Composite Method – Knox Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	5.51***	1.38***	1.34***	1.18***	1.21***	1.19**	0.92
1 to 434 ft.	5.92***	1.37***	1.06	1.04	1.06	1.05	0.95
435 to 868 ft.	3.79***	1.26***	1.13***	1.05*	1.01	1.04	0.97
869 to 1302 ft.	2.51***	1.13***	1.02	1.05*	1.03	0.99	0.98
1303 to 1736 ft.	2.06***	1.08**	1.10***	1.01	0.99	1.01	0.99
1737 to 2170 ft.	1.68***	1.09***	1.01	1.01	1.02	1.04	0.99
2171 to 2604 ft.	1.68***	1.04*	1.00	1.01	1.02	1.02	0.99
> 2604 ft.	0.99	1.00	1.00	1.00	1.00	1.00	1.00***
Difference Ratios	Same Day	>0 to 7 days	8 to 14 days	15 to 21 days	22 to 28 days	29 to 35 days	> 35 days
Same Location	1.00	0.99	1.00	0.99	1.00	1.00	1.00
1 to 434 ft.	0.82	0.95	1.02	0.95	0.95	1.03	1.02
435 to 868 ft.	1.00	1.00	1.02	1.03	1.04	0.97	0.99
869 to 1302 ft.	0.99	0.97	1.00	1.01	0.97	1.04	1.00
1303 to 1736 ft.	1.04	1.03	0.97	1.01	1.06	0.96	1.00
1737 to 2170 ft.	1.02	1.00	0.99	1.01	0.98	1.01	1.00
2171 to 2604 ft.	0.99	1.04	0.99	0.99	0.97	1.00	1.00
> 2604 ft.	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Notes: Near repeat analysis conducted using Euclidean distance. Ratio = 1 (Identical level of risk identified), >1 (Dual-Range reported higher risk than Composite), <1 (Composite reported higher risk than Dual-Range). Grey cells represent the common statistically significant NR pattern identified during the analysis