Are Measures of Patrollability affected by Tessellating Shape: Implications for Grid-Based Crime Hot Spot Maps

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ABSTRACT

A grid-based thematic map is spatial analysis tool that can be used to identify crime patterns, aiding law enforcement agencies in identifying problem areas within their jurisdictions and allocating resources to address them. Grids used to create these maps are comprised of shapes that tessellate (i.e., squares, hexagons, triangles). Square grids are used most often in crime hot spot mapping, but little is known whether the choice of tessellating shape affects performance metrics used to assess prospective hot spot forecasts. Using a purposive sample of known crime locations in St. Petersburg, Florida, the current study investigated whether tessellating shape used in grid-based thematic maps affects one particular performance metric: patrollability. Findings were mixed, showing that the effect tessellating shape has on grid-based thematic maps varies by type of crime and on which patrollability metric is used to assess forecasting performance. Results are discussed in terms of their impact on practitioners' use of crime hot spot mapping in law enforcement and on future research.

Introduction

Thematic maps are special purpose maps used to display information in different ways about a topic or a theme. Different types of thematic maps that can be used in cartography, including graduated symbol maps, dot density maps, and choropleth maps. Choropleth maps are often used to display crime information and involve presenting data aggregated to predefined areal units or administrative boundaries (i.e., census tract, country, or state) and shading or patterning the units in proportion to levels of crime (Berry, 2007). To better understand the spatial distribution of crime and to support the allocation of police resources, choropleth thematic maps can be an effective tool for visually displaying the spatial distribution of crime.

Choropleth thematic maps are well suited for displaying crime data. They can enable general patterns to be easily identified because they offer a good representation of crime risk. However, they are not without certain limitations. The most important challenge to creating a choropleth crime hot spot map is avoiding the modifiable areal unit problem (MAUP). MAUP is defined as a source of statistical bias that is created when point-based measures, such as crime incident locations, are aggregated to arbitrary administrative boundaries, such as census tracts, zip codes, or patrol districts (Nelson & Brewer, 2017). Grid-based thematic maps can be used to overcome this limitation.

Grid-based thematic maps are created by aggregating discrete point data to "regularly" shaped grids, instead of arbitrary administrative boundaries. Uniformly sized grid cells are used to normalize or standardize information presented on a grid-based thematic map. Regularly shaped grids can only be created with equilateral triangles, squares, or hexagons, because these shapes are the only shapes that can tessellate (i.e., repeating the same shape over-and-over again, edge-to-edge, to cover an area without gaps or overlaps) (Birch, Oom, & Beecham, 2007). Grid-based thematic maps are used in crime hot spot mapping because they not only mitigate the MAUP, but because they are visually appealing.

In a recent survey of ecology literature, Birch and colleagues (2007) found that most of the thematic maps published in the ecology literature use square-shaped grid cells. Anecdotally, this also appears to be the preference among analysts and academics who produce grid-based thematic crime maps. Due to a lack of literature on the topic, it is unclear whether the choice of tessellate shape used to create grid-based hot spot maps has an impact on crime pattern analysis beyond simple visual acuity. For example, it is unknown whether tessellating shape could influence hot spot mapping performance metrics, including measures of patrollability. The current study was undertaken in response to this gap in the extant literature.

Literature Review

Crime hot spot mapping is guided by research found in the existing environmental criminology literature (Brantingham & Brantingham, 1991; Brantingham, Brantingham, & Andresen, 2016). Environmental criminology examines crime, criminality, and victimization as they relate to distinct places and how individuals and organizations shape their activities by place-based or environmental factors (Brantingham & Brantingham, 1991, 1998, 2013; Bottoms & Wiles, 1997). Environmental criminologists argue that crime patterns emerge from the opportunity structures in the environment for victimization and offending, which are explained by three well-established lines of empirical inquiry: rational choice theory (Cornish & Clarke, 1987, 2008), routine activities theory (Cohen & Felson, 1979), and the geometry of crime (Brantingham & Brantingham, 1995; Brantingham & Brantingham, 1993). Crime pattern theory has also been widely used to understand the relationship between crime and place, which has been defined as a "meta-theory that integrates these three main theoretical perspectives within environmental criminology" (Brantingham et al., 2016, p. 99). The current study is guided primarily by crime pattern theory.

Rational Choice Theory

In the 1960s and 1970s, Derek Cornish and Ronald Clarke sought to better understand the effects that institutional treatments had on juvenile delinquency (Cornish & Clarke, 1987, 2008). They wanted to know whether various treatments had any long-lasting impact on behavior. When they compared the rates of running away and other forms of misconduct that occurred at treatment centers, Cornish and Clarke found that even though the centers serviced the same types of minors, some of the treatment centers experienced more problematic behavior than others. They began to question whether there were specific environmental factors in treatment centers associated with more misconduct and whether these factors created greater opportunities for delinquency. Today, proponents of rational choice theory argue that crime and delinquency are rooted in a rational decision-making process, but the environment creates some situations that afford greater opportunities for offending than others (Cornish & Clarke, 2008).

Rational choice theory proposes that criminal behavior is subject to considerations of the costs and benefits of engaging in a crime. In other words, people first weigh the costs and benefits of pursuing criminal behavior and come to a rational decision about offending. For example, Townsley and Sidebottom (2010) investigated the distance offenders travel to commit crime and found that criminals tend to commit crimes near where they live. They argued that offenders chose not to engage in criminal activity that required them to travel great distances because the burden of travelling was a "cost" to committing an offense that was not outweighed by the benefit of committing the offense.

Routine Activities Theory

Routine activities theory suggests that for a crime to occur a motivated offender and a suitable target must converge in space and time, without the presence of a "guardian" who is capable and willing to intervene (Cohen & Felson, 1979). The initial focus of routine activities theory explored macro-level factors that influenced human behavior and linked these behaviors to increased crime rates during the post-World War II era. Since then, researchers have focused on how we move through the built environment and how our everyday movements shape the likely convergence of potential victims, offenders, and guardians (Wortley & Townsley, 2017). Researchers continue to build on the routine activity's framework, developing one of the leading theoretical perspectives in environmental criminology.

For example, Olgahere and Lum (2018) recently developed two concepts related to the original routine activities perspective: macroroutines and microroutines. Macroroutines include activities related to work and leisure, while microroutines involve the behaviors, movements, and actions of offenders, victims, and guardians. They argue that the combination of macro- and microroutines produces a criminal event. Microroutines are undertaken immediately before or after a crime event, meaning that they are constrained by space and time, and can produce identifiable crime patterns.

Although the contemporary focus of routine activities theory is still on the three elements necessary for a crime to occur (i.e., a motivated offender, a suitable target, and the absence of a capable guardian), it recognizes the important role the environment plays in influencing how we move through the physical landscape and the subsequent link between that movement and criminal opportunities (Felson & Eckert, 2016). Routine activities theory proposes that the likelihood of criminal activity is dependent on the opportunities for committing an offense; therefore, places with greater opportunities will be associated with greater crime (Jones & Pridemore, 2019). Many criminologists have investigated the specific types of places that generate the greatest opportunities for crime and the resulting crime patterns produced by them, using the geometry of crime perspective.

The Geometry of Crime

The geometry of crime emerged from the work of Paul and Patricia Brantingham (1993) and their efforts to understand and explain spatio-temporal crime patterns. The Brantinghams' approach to understanding crime incorporated elements of environmental psychology, transportation research, and research from the field of criminology. New concepts emerged from the geometry of crime theory that not only help us better understand how we move through the physical world and the relationship between our movements and criminal opportunities, but how crime patterns emerge from our spatial behavior. These concepts include activity nodes, pathways, activity space, awareness space, and the environmental backcloth that defines the physical landscape (Brantingham & Brantingham, 1993).

Activity nodes represent the places that we spend most of our time (e.g., home, work, or school) and pathways are the routes we take from one activity node to the next (Song et al., 2017). Going to and from specific activity nodes and taking pathways that connect them become routine to people's daily lives. They are also shared by other people engaged in their daily routine activities. People's overlapping activity nodes and pathways bring them together, allowing for greater criminal opportunities. Awareness space refers to the areas in which we are comfortable and aware of our surroundings. We get to know the environment in which we spend most of our time, which inevitably provides us a certain level of awareness of those areas. This awareness reduces uncertainty, which influences the way in which we interact with our environment and those in it (Brantingham & Brantingham, 1991; Bruinsma & Johnson, 2018).

Crime generators (i.e., activity nodes that create criminal opportunities due to high flows of people) and crime attractors (i.e., activity nodes where individuals who have a greater willingness to commit crimes congregate) are also important concepts related to the geometry of crime perspective (Brantingham & Brantingham, 1995; Brantingam et al, 2016; Song et al., 2017). Crime generators create crime because motivated offenders and suitable targets are brought together in large numbers, like a shopping mall. Crime attractors are activity nodes that attract motivated offenders because they are places that are known for providing opportunity for crime. Finally, edges represent boundaries—physical or perceived—that define the transition from one area of the environment to another. Concepts that have emerged from the geometry of crime literature have been applied to understand and explain patterns commonly observed in crime data.

For example, Hart and Miethe (2014) conducted a study on activity nodes in relation to robbery incidents. They found that the majority of robberies that occurred in their study took place in environments that were characterized by only nine dominant situational profiles (i.e., activity nodes with a history of 10 or more robbery incidents) out of the 76 profiles they observed, suggesting that most crime clusters within a few areas (e.g., hot spots; Hart & Miethe, 2014). This study also examined the prevalence of robberies at specific activity nodes (i.e., bus stops). Hart and Miethe found that robberies occurring at a bus stop varied depending on the inclusion of other activity nodes, such as ATMs or fast food restaurants. In addition, Birks and colleagues (2012) found support for their hypothesis that the greatest increases in spatial clustering will occur when the routine activity approach, rational choice perspective, and crime pattern theory are applied. Spatial analytic tools that were used to identify crime hot spots in these and other studies have played a key role in advancing this line of academic inquiry.

Spatial Analysis Tools for Identifying Crime Hot Spots

Many tools are applied to a grid cell output, such as an interpolated surface area produced from kernel density estimation (KDE), where local associations are compared against the global average. For this technique, the user is required to define several parameters that can affect whether hot spots are identified as significant clusters of crimes or not (Hart & Zandbergen, , 2014).

One category of spatial analysis tools that are not based on formal statistical tests can be used to identify crime hot spots. Thematic mapping of geographic boundaries, KDE, and grid-based thematic maps are examples of these techniques (Eck et al., 2005). Thematic mapping of geographic boundaries involves aggregating crime incidents to pre-defined administrative boundaries, such as zip codes, census tracts, or patrol beats, and creating a choropleth map from these results. Color intensity on the map will correspond to the intensity of crime across the areal units. However, as discussed previously, areal units that reflect artificial boundaries often vary considerably in shape and size, which can introduce spatial bias and lead to misinterpretation of findings due to the MAUP.

KDE is a density estimation method that involves creating a continuous crime risk surface from discrete crime incident locations and is considered by some to be the most suitable method for visualizing crime data as a continuous surface (Eck et al., 2005). KDE crime risk surfaces are created by placing a grid network of equal-size cells over a distribution of crime event point locations. Next, a three-dimensional kernel function (e.g., quartic function) with a pre-defined search radius moves over each cell of the grid network and calculates weights for each cell based on the number of points within the kernel's radius and the distance from the center of the cell. Points closer to the center receive more weight, whereas points farther away receive less weight. Values for each grid cell are calculated by adding the values of all search results for each grid cell location. Some research suggests that quartic KDE maps are the best method for mapping crime data (Chainey et al., 2008; Eck et al., 2005).

Grid-based thematic maps represent another popular spatial analytic tool for identifying crime hot spots. Along with thematic mapping of geographic areas and KDE, grid-based thematic maps are not based on formal statistical tests. They are thematic maps that combine some elements of KDE with some elements of choropleth maps. As with KDE, grid-based thematic maps are constructed using a grid network instead of administrative boundaries; and like choropleth maps, crime counts are aggregated to each grid cell of a grid-based thematic map. The primary advantage of using grid-based thematic maps over others is that they avoid the MAUP. Nevertheless, they have been criticized for being visually unappealing due to the "blocky" appearance of output created by the grids when square-shaped grids are used (Eck et al., 2005).

Patrollability Metrics for Assessing Prospective Hot Spot Maps

Our ability to visualize crime on digitized maps has not always been easy. However, as the tools for spatial analysis of crime patterns have evolved, so have the metrics for assessing them, including metrics specifically designed to measure the performance of prospective crime hot spot maps presented as grid-based thematic maps. Some of these performance metrics include area-to-perimeter ratio (APR; Bender, 1962), clumpiness index (CI; Turner, 1989), and dynamic variability index (DVI; Adepeju et al., 2014; Hart, 2021) and are designed specifically to assess crime risk estimation in terms of the "patrollability" of a prospective hot spot map. Each of these measures provides unique information about crime forecasts that can help explain patterns of victimization and offending and support law enforcement strategies aimed at reducing and preventing crime.

The APR is used to measure the patrollability of crime hot spots by examining the compactness of a 2-dimensional shape (Bender, 1962). The APR is easily calculated by dividing the area of a crime hot spot by its perimeter. Hot spots with large APRs are more compact than hot spots with small APRs, which are considered more easily patrolled. The area of all hot spots is determined, which is then divided by their perimeter. For example, if the area of all hot spots is 40 and the perimeter is 64, the APR is 0.625. Bowers et al.'s (2004) study on crime mapping demonstrated how law enforcement agencies could use the APR to draw conclusions about allocating police patrol resources to hot spots. Adepeju, Rosser, and Cheng (2016) also examined the utility of the APR, showing how its value can vary significantly by the forecasting method used to predict crime. However, a limitation of the APR is that it is strongly influenced by the size of the grid cells used in the analysis and the overall size of the study area.

The CI is another performance metric used in prospective hot spot mapping to quantify patrollabillity of forecasted crime hot spots (Adepeju et al., 2014, 2016). The CI measures the compactness based on the size of an area classified as a hot spot and the number of grid cells contained in a hot spot that share edges with adjoining cells (Turner, 1989). Hot spots that are very compact will have a relatively small area and a relatively large number of adjoining grid cell edges. In contrast, hot spots that are less compact will be much larger in area and have relatively fewer adjacent grid cells that share sides. CI values range between -1 and 1, where -1 represents the least amount of compactness and 1 represents the most.

The CI considers the overall size of a study area and whether the edges of a cell depicting a hot spot are adjacent to another hot spot cell or not. As illustrated in Figure 1, the shaded grid cells are hot spots, grid cell edges adjoining another hot spot cell are blue and those that adjoin a non-hot spot cell are shown in red. The total area of the jurisdiction is .40 (.40 = 40 / 100). There are 42 grid cell edges that join an edge of a hot spot cell to a non-hot spot cell (i.e., red lines), whereas there are a total of 19 grid cell edges that adjoin hot spot cells (i.e., blue lines). In this example, the CI is .52, or the ratio of grid cell edges that adjoin hot spot cells to all edges, relative to one minus the proportion of the entire study area defined as a hot spot (.52 = [19/61]/[1-.40]).

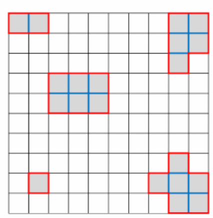

Figure 1. Illustration of How the CI is Calculated

A DVI can also be used to evaluate the patrollability of grid-based thematic maps used to forecast crime hot spots. It is designed to measure the stability of crime patterns over time, which can support a more efficient allocation of police patrol resources. DVI scores area calculated based on the number of grid cells classified as newly *emerging* or *disappearing* hot spots at a second point in time, relative to the total number of grid cells classified as hot spots during the same time interval. The higher the DVI value, the less stability there is in crime hot spots, which could make patrolling them more challenging. Empty cells outlined in blue at Time 2 indicate the hot spot "disappeared" since Time 1, whereas grey cells outlined in red are "emerging" hot spots. As shown in Figure 2, the DVI is the proportion of all hot spot area that are emerging or disappearing.

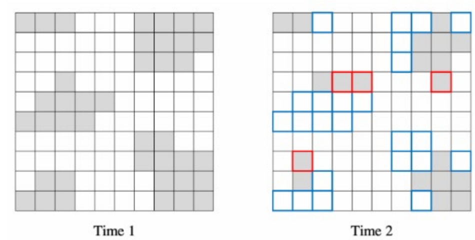

Figure 2. Illustration of How the DVI is Calculated

The utility of the DVI as a hot spot forecasting metric has been demonstrated recently in the literature. For example, Adepeju and colleagues (2016) tested different prospective forecasting techniques and predictive policing algorithms and found that KDE produces the most stable crime location forecasts at micro-temporal intervals. Hart (2021) also used DVI scores to assess the stability of crime hot spots produced from KDE at micro-temporal intervals and found that they were influenced significantly by both crime type and geographic locations. Although measures of hot spot compactness are useful, they are used relatively less often compared to other hot spotting metrics designed to measure patrollability.

Hypotheses

This study seeks to determine whether the type of tessellate shape used in grid-based thematic crime hot spot mapping affects forecasting metrics designed to assess forecasting patrollability. Stated formally, the current study tests the following research hypotheses:

H_0: Measures of patrollability are not affected by the tessellating shape used in grid-based thematic hot spot maps.
H_1: Area-to-perimeter ratio (APR) will be affected by the tessellating shape used in grid-based thematic hot spot maps.
H_2: Clumpiness intex (CI) will be affected by the tessellating shape used in grid-based thematic hot spot maps.
H_3: Dynamic variability index (DVI) will be affected by tessellating shape used in grid-based thematic hot spot maps.

Methods

The current study uses different tessellate shapes to construct a series of grid-based thematic maps that depict crime hot spots in St. Petersburg, Florida. Crime patterns are assessed using the metrics designed to measure the patrollability of crime forecasts. This section begins by describing the research design that was followed in the current study. Next, details about the sample and the primary data analysis approach that were used in the study are presented. This is followed by information about how key concepts in the study were conceptualized and operationalized.

Research Design

A growing number of law enforcement agencies make their crime data available to the public online, including the St. Petersburg Police Department (SPPD). These administrative data are available for free and contain information about the type of crime recorded by police, when the incident occurred, and its geographic location. Secondary administrative data were obtained for the current study, and exploratory research was conducted to answer the research hypotheses.

Sampling Procedure

A non-probability purposive sample was used for this research. In purposive sampling, the sampled elements are chosen for a certain purpose. In this study, only those incidents known to and recorded by SPPD as aggravated assaults, residential burglaries, and motor vehicle thefts that reportedly occurred between January 1, 2020 to December 31, 2021 were used in the current study.[1] These data were organized into 12 groups of data for each crime type, based on 2-month intervals.[2]

According to the FBI's Uniform Crime Reporting (UCR) Program definition, an aggravated assault is "an unlawful attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury"; a burglary is "the unlawful entry of a structure to commit a felony or a theft"; and a motor vehicle theft is "the theft or attempted theft of a motor vehicle" (FBI, 2004). Aggravated assaults also involve the use of a weapon or something likely to produce death or great bodily harm. Attempted aggravated assaults that involve displaying or making threats with a gun, knife, or other weapon were also included in this study. Motor vehicle thefts consist of vehicles that run on land, such as trucks, buses, and automobiles.

A purposive sample of aggravated assaults, residential burglaries, and motor vehicle thefts were used for several reasons. First, aggravated assaults are one of the most frequently occurring violent crime recorded by police. Therefore, the sample was large enough to detect hot spot patterns and to make forecasts. Second, analyzing three crime types gives the current study greater scope, which creates more meaningful findings for researchers and practitioners. Finally, because this sample is of publically-available crime location data and not human subjects, the study was exempt from Institutional Review Board (IRB) review. Purposive sampling has an important drawback, however. Findings from studies that use purposive samples may not produce results that are generalizable. This means that findings from the current study might be unique only to SPPD's jurisdiction. The time and money saved using a purposive sample outweighed the abovementioned drawbacks.

Patrollability Metrics

The quality of the maps created in the current study was assessed using the patrollability metrics described above. A total of three metrics were used, including the APR, CI, and DVI. The way in which each of these measures were calculated in the current study is described below in greater detail.

Area-to-perimeter Ratio

The APR was one of the three "patrollability" measures used in the current study to assess forecasts from grid-based thematic hot spot maps. The APR measures the compactness of a 2-dimensional shape, which gauges how easily hot spots can be patrolled. As the name suggests, the APR is a simple ratio that compares the area of hot spots to their corresponding parameter (Bender, 1962) and is presented in Equation 4:

$$APR = \frac{Hot\ spots_a}{Hot\ spots_p} \tag{4}$$

where $Hot\ spots_a$ is the area of hot spots, and
$Hot\ spots_p$ is the parameter of hot spots.

Larger APR values represent hot spots that are more compact, which could be more easily patrolled.

Clumpiness Index

The CI was used in the current study to measure the performance of prospective hot spot maps (Turner, 1989). Like the APR, the CI is designed to measure the compactness of hot spots. It is defined as the proportion of grid cell edges that share an edge with an adjoining cell edge of the same hot spot class (i.e., a within-class edge) to the proportion of grid cells in the total study area. If a hot spot lacks compactness, then there will be fewer adjoining grid cells because the hot spot is more sporadic around the displayed map.

The formula for calculating the CI is presented in Equation 5:

$$CI = \frac{G_i - P_i}{1 - P_i} \tag{5}$$

where G_i is the proportion of all hot spot cell edges that are within-class (i) edges, and P_i is the proportion of grid cells in the total study area that are classified as a class (i) of hotspot cells.[3]

The value of CI is bounded between -1 (i.e., maximally disaggregated hot spots) and 1 (maximally aggregated hot spots). A CI value of 0 indicates a random distribution of hot spots (Adepeju et al., 2014, 2016).

Dynamic Variability Index

The final performance measure that was used in the current study is the DVI. The DVI measures the stability of crime patterns over time (Adepeju et al., 2016; Hart, 2021). The DVI is defined as the number of grid cells classified as newly emerging or disappearing hot spots, relative to the total number of grid cells classified as hot spots during that time that were either emerging or reoccurring (Equation 6):

$$DVI = \frac{E + D}{(E + D + R)} \tag{6}$$

where E is the number of newly emerging hot spot cells at Time 2,
D is the number of hot spot cells that disappeared at Time 2, and
R is the total number of hot spot cells reoccurring at Time 2.

Larger DVI values represent hot spots that are less stable (i.e., they have greater variability), compared to smaller DVI values (i.e., hot spots that are more stable). This measure can be used to help police patrols identify the most stable hot spots within their jurisdiction and focus their intervention strategies on them.

Data Analysis

The primary approach to analyzing results produced from this study consisted of exploratory data analysis (EDA) methods described by Tukey (1977), including measures of central tendency, measures of dispersion, and visual summaries (e.g., maps). In addition, average patrollability metric scores were used to test the current study's hypotheses, using a series of grid-based thematic maps: one series created with tessellating square grids and one with hexagonal grids. This analysis involved testing whether average scores for each patrollability measure evaluated (i.e., APR, CI, and DVI) differed significantly, based on a two-tailed Wilcoxson's sign-ranked test. All tests were assessed at the 95% confidence level. A Wilcoxson's test was conducted because the assumption of normality was violated for each patrollability measure.

As discussed previously, this study involved analyzing crime data obtained from the St. Petersburg Police Department and was made up of calls for service (CFS) data for assaults (N = 2,249), residential burglaries (N = 2,195), and motor vehicle thefts (N = 2201). These incidents were aggregated into 12 groups for each crime type, based on 60-day intervals.[4] These data were used to create a series of square grid-based maps and hexagonal grid-based maps, using equal size tessellating shapes (i.e., areas equalling 40,000ft^2). All maps were produced in ArcGIS for each crime type and grid-shape map, which were then analyzed based on three patrollability metrics.

Results

The current study tested whether the shape of grid cells used in grid-based thematic crime hot spot maps affected crime forecasts. The research hypotheses were assessed by conducting a series of two-tailed Wilcoxon's test at the

95% confidence level. Three tests (i.e., one for each performance metric) were conducted for each of the three crime types (i.e., aggravated assault, residential burglary, and motor vehicle theft). This section presents descriptive statistics for each performance metric and results of the hypotheses tests.

Descriptive Statistics

Descriptive statistics for the three patrollability measures evaluated in the current study are presented in Table 1 for all three crime types and for both types of grid-based thematic maps. For example, the DVI values for assault were similar across both types of maps (DVI = 0.21). For burglary, the median APR score was 312.89 on the square grid-based map, compared to 353.32 on the hexagonal grid-based map. Finally, the clumpiness index for motor vehicle thefts displayed on square grid-based maps was 0.67, compared to 0.70 on hexagon maps.

Table 1. Descriptive Statistics for Patrollability Metric Calculated, by Crime Type

Patrollability Metrics	Type of Grid					
	Square			Hexagon		
	Min	Max	*Mdn*	Min	Max	*Mdn*
	Assault ($N = 12$)					
APR	339.63	455.75	376.54	396.02	500.86	436.66
CI	0.72	0.78	0.75	0.74	0.79	0.76
DVI	0.21	0.30	0.26	0.21	0.30	0.26
	Burglary ($N = 12$)					
APR	248.77	363.66	312.89	275.52	413.59	353.32
CI	0.63	0.72	0.69	0.64	0.75	0.70
DVI	0.27	0.39	0.30	0.38	0.21	0.32
	Motor Vehicle Theft ($N = 12$)					
APR	255.27	476.48	287.89	295.42	699.34	359.66
CI	0.31	0.72	0.67	0.66	0.75	0.70
DVI	0.26	0.36	0.30	0.23	0.38	0.31

Note: APR = Area-to-perimeter ratio; CI = Clumpiness index; DVI = Dynamic variability index.
[a] Base line data consisting of the 60 days prior to the first interval of data were used.

Hypothesis Test Results

A Wilcoxon's signed-rank test was conducted 9 times (i.e., three performance metrics for three crime types) to investigate whether the shape (i.e., square or hexagon) of grid cells used in grid-based thematic hot spot maps affects crime forecasts. Results are reported in Table 2 and provide mixed support for the research hypotheses. Specifically, findings show that the performance of grid-based thematic maps varies based on tessallating shape, but only for certain metrics. However, some differences in rank-ordered patrollability metrics were observed. This pattern was most consistent for the APR. The APR was significantly higher for grid-based thematic maps using hexagons instead of squares for assault ($W_+ = 78.00$, $z = 3.06$, $p = .002$, $r = .88$), burglary ($W_+ = 71.00$, $z = 2.51$, $p = .012$, $r = .72$), and motor vehicle theft ($W_+ = 73.00$, $z = 2.67$, $p = .008$, $r = .77$). Similar patterns were observed for the CI, but only for assault ($W_+ = 68.50$, $z = 2.32$, $p = .021$, $r = .67$) and motor vehicle theft ($W_+ = 76.00$, $z = 2.90$, $p = .004$, $r = .84$). Differences in the rank-ordered CI scores for burglary were not significantly different across the two types of grid-based maps examined ($W_+ = 55.50$, $z = 1.30$, $p = .195$). Collectively, these results indicate that, in terms of forecasting, the shape of a grid-based thematic map matters, but only for some types of crime and for some types of patrollability metrics. These findings will be discussed in further detail in the following sections.

Table 2. Results of Wilcoxon Sign-Ranked Tests

Patrollability Metrics	W_+	Z	p	r
	Assault			
APR	78.00	3.06	0.002	0.88
CI	68.50	2.32	0.021	0.67
DVI	23.50	0.120	0.905	n.s.
	Burglary			
APR	71.00	2.51	0.012	0.72
CI	55.50	1.30	0.195	n.s.
DVI	35.50	-0.28	0.782	n.s.
	Motor Vehicle Theft			
APR	73.00	2.67	0.008	0.77
CI	76.00	2.90	0.004	0.84
DVI	37.50	-0.12	0.905	n.s.

Discussion

Hot spot maps are created to identify where crime clusters and to better allocate law enforcement agency resources. Within law enforcement agencies, crime analysts create hot spot maps using different methods, including methods that utilize grid-based thematic maps that aggregate crime counts to grids comprised of tessellating shapes. The most standard shape used in grid-based maps created to identify crime hot spots are squares. Although grid-based thematic maps used in crime hot spot mapping may produce maps that differ in terms of their visual appeal, prior to the current study, it was unknown whether the type of tessellating shape affected the performance of grid-based thematic maps, based on hot spot patrollability metrics.

In response to this gap in the crime mapping literature, the current study investigated the influence that tessellating shapes (i.e., squares versus hexagons) had on crime forecasts, produced from grid-based thematic maps. Three metrics not commonly used in hot spot mapping (i.e., APR, CI, and DVI) were calculated to assess the patrollability of maps created for aggravated assault, burglary, and motor vehicle theft crime patterns. Results indicated that the DVI was not significantly influenced by the type of tessellating shape. However, findings showed significant differences in APR for all three crime types examined. Furthermore, the CI for two types of crimes (i.e., aggravated assaults and motor vehicle thefts) was also significantly affected by the type of tessellating shape used to create a grid-based thematic hot spot map. Collectively, the current study showed that the type of tessellating shape used to create a grid-based thematic map may influence crime forecasts in terms of patrollability.

Findings related to patrollability that were observed in the current study were not surprising, given how the two patrollability measures are derived and the type of tessellating shapes examined. The APR and CI measure a hotspot's compactness and results of the current study indicated that the hexagon maps produce more concentrated patterns in some instances. The APR and CI performance metrics use area, perimeter, and edges that are classified into different types (i.e., within class and cross class) of the grid shapes in their calculations, respectively.

Figure 3 illustrates how the APR and CI could be impacted by the two tessellating shapes, based on how those performance metrics are calculated. Although the area of both shapes was held constant in the current study (i.e., 40,000ft^2), squares have a slightly larger perimeter than hexagons, resulting in a downwardly biased APR. Similarly, with two fewer sides, the CI could be downwardly biased for the thematic maps using square grids because of the likelihood those hot spots would have fewer within- and cross-class edges. In other words, the type of shared edge (i.e., within- or cross-class) could be influenced by the number of *possible* shared edges that would be found in the grid overlay, which would be greater for the hexagon than the square grid maps.

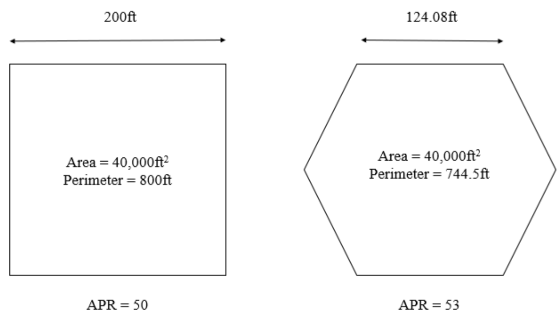

Figure 3. How Tessellate Shape Could Affect APR Shape

The different characteristics of the two shapes used in the current study may have affected results by creating different hot spot patterns, particularly the size of a hotspot's area. Consider Figure 4, which illustrates how the two shapes used in the current study could create hot spots that differ in area, given how the aggregated and calculation process works[5]. This has important implications on the theoretical perspectives that informed the current study. For example, according to the geometry of crime and crime pattern theory, crime attractors and crime generators create different opportunities for criminal activity. A square grid-based map may have created hot spot patterns that were significantly different than those created with hexagon grids, which may have resulted in the inclusion/exclusion of important environmental factors that are known to influence crime. In other words, grid-based thematic maps that use different tessellating shapes may produce hot spots that vary based on area and these different areas may include/exclude various crime attractors and/or generators[6] and these differences may influence how we think about crime patterns. For example, as Hart and Miethe (2014) concluded, robberies that occurred at bus stops varied depending on the inclusion of other activity nodes (e.g., ATMs). In the current study, a hot spot created with one type of shape may have generated a hot spot that did not include an ATM, while a hot spot created with the other type of shape may have created a slightly different hot spot at same map location, but that did include an ATM. This disparity could affect the way we think about how ATMs—as crime attractors—could influence crime patterns.

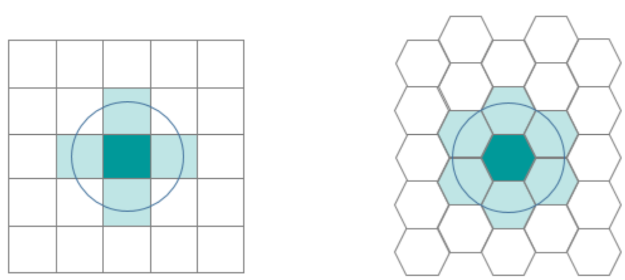

Figure 4. Hot Spot Comparison between Two Grids: One Composed with Squares and One Composed with Hexagons. Source: [https://pro.arcgis.com/en/pro-app/2.9/tool-reference/spatial-statistics/h-whyhexagons.htm. Acquired 10/19/2022](https://pro.arcgis.com/en/pro-app/2.9/tool-reference/spatial-statistics/h-whyhexagons.htm).

Conclusion

In conclusion, the current study was conducted to investigate whether the type of shape used to create grid-based thematic crime hot spot maps influenced forecasting performance. Results revealed that the tessellate shape affects patrollability measures like APR and CI, but not DVI. Given the limitations of the current study, results must be viewed with caution, however. Despite these limitations, the current study adds to the growing body of crime mapping and analysis knowledge and suggests that practitioners and researchers consider the influence that their choice of tessellating shape may have on hot spot mapping results and conclusions based on them.

Limitations

The current study adds to what we know about how tessellating shapes can impact the crime forecasting performance of grid-based thematic hot spot maps. Nevertheless, important limitations of this study should be identified. First, the current study used a purposive sampling method. Therefore, findings from this investigation are only applicable to the St. Petersburg Police Department's jurisdiction. Future research should replicate this study in different jurisdictions to determine whether findings observed in the present study are unique to St. Petersburg or are observed in other locations.

A second limitation is that this study used one time interval. Though 60 days of data was enough time to identify crime patterns for the three crime types examined, future research should consider examining different time intervals to investigate whether findings observed in the current study were unique to the time interval (i.e., 60 days) or event time period (i.e., January 1, 2020, to December 31, 2021) considered. It should be noted that most of the period used in the current study spans the time in which COVID-19 emerged in the United States. Pandemic restrictions change human behavior, which could have impacted crime patterns in unique ways. It is unclear whether or to what degree current findings were influenced by the effects of COVID-19, particularly on the crime patterns identified by grid-based thematic maps. Future research in this area that considers a post-COVID time period would be worthwhile.

A third limitation is that this study only considered three types of crimes. These three crimes represent both personal and property crimes; however, other crimes could produce different patterns and outcomes related to the use of certain tessellating shapes to create grid-based thematic maps. Future research should investigate other crimes, such as robberies and larcenies to determine whether findings observed in the current study apply to other types of incidents.

[1] Seventeen crimes were in the original data, but removed for falling outside SPPD's jurisdiction.

[2] More details about how the data were organized is presented in the Data Analysis section.

[3] If $P_i \geq .50$, or $G_i \geq P_i$, then the denominator is P_i instead of $1 - P_i$.

[4] For the DVI patrollability metric, incidents that occurred 60 days prior to the inclusive dates were used as baseline data.

[5] The light teal squares and hexagons represent an entire hot spot area. The dark teal area represents the grid cell whose density value is being calculated.

[6] This concept was not measured in the current study.

References

Adepeju, M., Cheng, T., Shawe-Taylor, J., & Bowers, K. (2014). *A new metric of crime hotspots for operational policing*. A paper presented at the 19th Geographical Information Science Research UK Conference, Leeds, UK.

Adepeju, M., Rosser, G., & Cheng, T. (2016). Novel evaluation metrics for sparse spatio-temporal point process hotspot predictions: A crime case study. International *Journal of Geographical Information Science, 30*(11), 2133–2154. DOI: 10.1080/ 13658816.2016.1159684.

Bender, E. (1962). Area-perimeter relations for two dimensional lattices. *The American Mathematical Monthly, 69*, 742–774.

Berry, J. K. (2007). *Map analysis: Understanding spatial patterns and relationships*. GeoTech Media: San Francisco, CA.

Birch, C. P. D., Oom, S. P., & Beecham, J. A. (2007). Rectangular and hexagonal grids used for observation, experiment, and simulation in ecology. *Ecological Modelling, 206*(3–4), 347–359.

Birks, D., Townsley, M., & Stewart, A. (2012). Generative explanations of crime: Using simulation to test criminological theory. *Criminology*, *50*(1), 221–254.

Bottoms, A. E., & Wiles, P. (1997). Environmental Criminology. In M. Maguire, R. Moran, & R. Reiner (Eds.), *The Oxford handbook of Criminology* (pp. 620–656). Oxford: Clarendon Press.

Bowers, K. J., Johnson, S. D., & Pease, K. (2004). Prospective hot-spotting: The future of crime mapping? *British Journal of Criminology, 44*(5), 641–658. DOI: 10.1093/bjc/azh036.

Brantingham, P. J. & Brantingham, P. L. (1991). *Environmental Criminology*. Prospect Heights, IL: Waveland Press.

Brantingham, P. J. & Brantingham, P. L. (1995). Criminality of place: Crime generators and crime attractors. *European Journal on Criminal Policy and Research, 3*(3), 5–26. https://doi.org/10.1007/bf02242925.

Brantingham, P. J., Brantingham, P. L. (1998). *Environmental criminology: From theory to urban planning practice*. Studies on Crime and Crime Prevention.

Brantingham, P. J., & Brantingham, P. L. (2013). *Environmental criminology and crime analysis*. https://doi.org/10.4324/9780203118214.

Brantingham, P. L., & Brantingham, P. J. (1993). Nodes, paths and edges: Considerations on the complexity of crime and the physical environment. *Journal of Environmental Psychology, 13*(1), 3–28.

Brantingham, P. J., Brantingham, P. L., & Andresen, M. A. (2016). *The geometry of crime and crime pattern theory*.

Bruinsma, G. N., & Johnson, S. D. (2018). *The oxford handbook of environmental criminology*. New York, NY: Oxford University Press.

Chainey, S., Tompson, L., & Uhlig, S. (2008). The utility of hotspot mapping for predicting patterns of crime. *Security Journal, 21*, 4–28.

Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: A routine activity approach. *American Sociological Review, 44*, 588–608.

Cornish, D. B., & Clarke, R.V. (1987). Understanding crime displacement: An application of rational choice theory. *Criminology*, *25*(4), 933–948.

Cornish D.B., & Clarke R.V. (2008) The rational choice perspective. In: Wortley R, Mazerolle L (eds) *Environmental criminology and crime analyses.* Willian, Cullompton

Eck, J. E., Chainey, S., Cameron, J. G., Leitner, M., & Wilson, R. E. (2005). *Mapping crime: Understanding hotspots*. National Institute of Justice Special Report.

Federal Bureau of Investigation (FBI). (2004). *Uniform crime reporting handbook: UCR*. Retrieved from www.fbi.gov/ucr/ucr.htm.

Felson, M. & Eckert, M. (2016). *Crime and everyday life* (5th ed.). Sage: New York, NY.

Hart, T. C. (2021). Investigating crime pattern stability at micro-temporal intervals: Implications for crime analysis and hotspot policing strategies. *Criminal Justice Review, 46*(2), 173–189. https://doi.org/10.1177/0734016821996785.

Hart, T. C., & Miethe, D. (2014). Street robbery and public bus stops: A case study of activity nodes and situational risk. *Security Journal*, *27*, 180–193. DOI: 10.1057/sj.2014.5

Hart, T. C., & Zandbergen, P. A. (2014). Kernel density estimation and hotspot mapping: examining the influence of interpolation method, grid cell size, and bandwidth on crime forecasting. *Policing: An International Journal of Police Strategies & Management, 37*(2), 305–323. doi.org/ 10.1108/PIJPSM-04-2013-0039.

Jones, R. W., & Pridemore, W. A. (2019). Toward an integrated multilevel theory of crime at place: Routine activities, social disorganization, and the law of crime concentration. *Journal of Quantitative Criminology*, *35*, 543–572. doi.org/10.1007/s10940-018-9397-6.

Nelson, J. K., & Brewer, C. A. (2017). Evaluating data stability in aggregation structures across spatial scales: revisiting the modifiable areal unit problem. *Cartography and Geographic Information Science, 44*(1), 35–50. https://doi.org/10.1080/15230406.2015.1093431.

Olgahere, A., & Lum, C. (2018). Classifying "micro" routine activities of street-level drug transactions. *Journal of Research in Crime and Delinquency*, *55*(4), 466–492. doi.org/10.1177%2F0022427818760103.

Song, J., Andresen, M. A., Brantingham, P. L., & Spicer, V. (2017). Crime on the edges: Patterns of crime and land use change. *Cartography and Geographic Information Science*, *44*(1), 51–61. https://doi.org/10.1080/15230406.2015.1089188.

Townsley, M., & Sidebottom, A. (2010). All offenders are equal, but some are more equal than others: variation in journeys to crime between offenders. *American Society of Criminology*, *48*(3).

Tukey, J. W. (1977). *Exploratory data analysis*. Reading, Massachusetts: Addison-Wesley.

Turner, M. G. (1989). Landscape ecology: The effect of pattern on process. *Annual Review of Ecology and Systematics, 20*(1), 171–197. doi:10.1146/annurev.es.20.110189.001131.

Wortley, R., & Townsley, M. (2017). *Environmental criminology and crime analysis*. New York: Routledge.