USING SPATIAL AND SPATIAL-TEMPORAL PREDICTIVE ACCURACY MEASURES TO ACCESS THE PERFORMANCE OF THE CRIME HOTSPOT MAPPING METHODS

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TABLE OF CONTENTS

ABSTRACT

A series of hotspot mapping theories and methods have been proposed to predict where and when a crime will happen. Each method has its strengths and weaknesses. In addition, the predictive accuracy of each hotspot method varies depending on the study area, crime type, parameter settings of each method, etc. The spatial predictive accuracy of hotspot methods can be quantified by three measures, which include the hit rate, the predictive accuracy index (PAI), and the recapture rate index (RRI). This research applied eight hotspot mapping techniques from the crime analysis field to predict crime hotspot patterns. In addition, these hotspot methods were compared and evaluated in order to possibly find a single best method that outperforms all other methods based on the three spatial predictive accuracy measures. In addition to the spatial analysis, a spatial–temporal analysis of the same crime dataset using space-time scan statistic was also conducted. To evaluate the performance of this spatial-temporal hotspot mapping method, I designed several spatial-temporal predictive accuracy measures. The reported crime data analyzed in this study are from the city of Houston, TX, from January 2011 to December 2012. The results show that the predictive accuracy is affected by both the hotspot mapping method and the crime type, although the crime type has a more moderate effect. Considering the use of the three predictive accuracy measures, the kernel density estimation could be identified as the method which could most accurately predict the overall Part1 Crimes for the city of Houston. The nearest neighbor hierarchical clustering and kernel density estimation could be identified as the methods which are best at predicting each of the five crime types examined based on PAI and RRI, respectively. Also, the various newly-designed spatial-temporal predictive accuracy measures do provide a promising way to assess the space-time crime hotspot prediction method, though their validity still remain verified.

CHAPTER 1 INTRODUCTION

When crime analysts in law enforcement agencies conduct crime analysis, including crime prediction, a key element centers on where crimes tend to occur. Like some other human involved activities (traffic accidents, disease outbreaks, gentrification, etc.), crime incidents are not distributed randomly throughout space. Their distribution is dense at some locations while sparse at others. This feature of crime events distribution was described as an 'inherent geographical quality' by Chainey and Ratcliffe (2005) and was explained by theories such as the ecology of crime (Brantingham and Brantingham, 1984) or routine activities (Cohen and Felson, 1979), and others. The places where crime events are relatively densely distributed are called hotspots. Crime hotspots are referred to as areas where crimes concentrate spatially (McLafferty et al., 2000; Eck et al., 2005).

The concept of a hotspot is widely used in our daily life. Being aware of which places are safer and which places are with a higher risk of being a victim of crime, people visit or live in some locations while they avoid others. Based on the knowledge of risks of victimization, people make choices of the communities they live in, the schools they send their children to, or the recreation area they spend their weekend in, etc. In some western countries, people living in some neighborhoods need to install a closed-circuit television (CCTV) to secure their house and deter potential offenders. In other neighborhoods they do not have to worry about their properties even if they forgot to lock their door during the day. The hotspot concept is also of critical importance to policing and patrolling actions. Provided with information about the specific spread of hotspots, police commanders could then make more appropriate decisions about where and when to allocate limited manpower resources to the places where patrolling demands are at the highest.

Hotspot analysis is at the center of the analysis of crime, and hotspot mapping is paid most attention among crime mapping.

Hotspot mapping is an effective and widely used analytical technique which uses retrospective crime data to identify crime hotspots. Hitherto a number of hotspot mapping techniques have been proposed and applied to identify crime clusters. These include spatial ellipse, thematic mapping of geographic boundaries, quadrat thematic mapping, interpolation and continuous surface smoothing methods, and local indicators of spatial association (LISA) statistics mapping, among others.

When we extend our study from spatial to spatial-temporal hotspot mapping analysis, there are also quite a number of spatial-temporal hotspot mapping techniques. One of the most commonly used spatial-temporal hotspot mapping method is the space-time scan statistic. It is derived from the space scan statistic which is aimed to identify spatial clusters by imposing circular windows with various radii to scan across the study area (Kulldorff, 1997). Each circular window with a particular radius assigned to it will cover sets of neighboring areas and a likely candidate of including a hotspot or cluster. The other visualization method is the hotspot spot which aims to present spatial analysis with consideration of the distribution of events in time within hotspots (Townsley, 2008). Different from other spatial-temporal hotpot analysis and mapping methods such as Kulldorff's scan statistic, hotspot plots focus more on visualizing data and communicating information to users efficiently. Intuitively, the hotspot plot comprises three parts that include the long term trend in crime, the intra-day trend in crime, and the spatial crime clusters map (Townsley, 2008).

As we already know, a lot of mapping methods exist for the researchers to detect clustering patterns (hotspots) of crimes. These clustering patterns may spread in the dimension of space or in the dimension of both space and time. How could we decide which method is better than the other in order to obtain a deterministic choice among various methods for the law enforcement agencies or the crime analysts? Measures based on which different hotspot mapping methods for crime prediction could be evaluated are needed. A series of spatial predictive accuracy measures have been designed and applied by previous researchers, among which include the hit rate, the Predictive Accuracy Index (PAI), and the Recapture Rate Index (RRI). Based on these measures, we can calculate the values of the specific measure for various spatial hotspot mapping methods and then compare their values. The method with a higher predictive accuracy measure value performs better at predicting future crimes than the method with a lower value. However, little research has been done for the spatial-temporal predictive accuracy measure. This research also designed some new measures for the evaluation of spatial-temporal hotspot mapping in crime prediction.

CHAPTER 2 LITERATURE REVIEW

The use of hotspot mapping has gained its popularity both from crime prevention practitioners and academics. In some western countries such as England, the U.S., and Australia, hotspot mapping techniques have been increasingly adopted by law enforcement agencies and police officers (Gottlieb et al., 1994; Maguire, 2000; Ratcliffe, 2002c; Seddon and Napper, 1999). The reason for the increasing trend to apply hotspot mapping can be partly explained to the limited fiscal budget provided to law enforcement agencies. This method offers the agencies a way to assist with allocating their limited resources or manpower to the areas where a crime is more likely to happen.

In the academic area, hotspot mapping has been increasingly drawn attention by the advance of both hotspot mapping theories and techniques. Different theories have been developed by a variety of researchers to help find theoretical explanations for the definition and cause of hotspots. These theories range from the social ecology of crime to theories on routine activities and repeat victimization (Anselin et al., 2000). In addition, the advance of Geographic Information Systems (GIS) has prompted the further development of hotspot mapping techniques. A variety of crime analysis tools available in GIS make it easier and attract more researchers both in more practical and theoretical academic fields to focus on the research of hotspot mapping. A detailed literature review of these hotspot mapping techniques, including spatial and spatial-temporal hotspot mapping, will be discussed next.

Spatial crime hotspot mapping techniques have witnessed their development alongside huge innovations in information technology (IT). Some of these spatial techniques are associated with the spatial arrangement and the size of the subdivisions inside the study area (e.g. districts, blocks, census tracts, etc.). Thematic mapping is the simplest method regardless of what spatial arrangement and size of subdivision is. One problem occurs when this method is applied to statistical or administrative areas such as census blocks. The individual units of these different spatial subdivisions (census blocks versus census tracts) have different shapes and boundaries, i.e. a different spatial arrangement. The main problem is that different spatial arrangements of such statistical / administrative areas result in hotspot maps that differ from each other. This problem is referred to as the Modifiable Areal Unit Problem (MAUP). The effect of MAUP cannot be neglected when methods associated with administrative / statistical areas are applied (Chainey et al., 2008; Openshaw, 1983; Ratcliffe, 2004).

A simple solution to the MAUP would be the use of a regular grid imposed onto the study area. Grid thematic mapping is among one of the commonly used methods that produce grid maps. Each grid cell has a uniform size and shape. In addition, each grid cell has a value, usually crime counts, assigned to it. The value could also be a density value such as crime rates (Eck et al., 2005). Kernel density estimation (KDE) also imposes a regular grid onto the study area and uses a three-dimensional kernel function to visit each grid cell and to calculate a density value assigned to each grid cell (Eck et al, 2005). This method has been viewed by several researchers as the most suitable method for the purpose of visualization (Chainey and Ratcliffe, 2005) and as the most accurate method for predicting future crime incidents (Chainey et al., 2008).

The improvement of computing power has also spurred the development of some computer programs in crime analysis. One of earliest software packages used was the Spatial and Temporal Analysis of Crimes (STAC) to identify crime hotspots (Illinois Criminal Justice Information Authority, 1996). The output of a crime hotspot is displayed as ellipses. Though STAC has been used by many crime prevention practitioners and crime analysts, weaknesses exist in this method. One such weakness is that the distribution of crime clusters does not necessarily form an ellipse. This may create misleading results to the police decision makers who may use these results to allocate limited patrol manpower (Bowers and Hirschfield, 1999; Chainey et al., 2008; Ratcliffe, 2002b).

As for now, STAC has been integrated to the widely used crime analysis program CrimeStat 4.0 (Levine, 2013). CrimeStat 4.0 is usually used by crime analysts and practitioners to investigate the distribution of point patterns data (crime event locations), which means, the input data should be point data, or centroids when polygon data were used (where a centroid represents the geometric center of the corresponding area). This program contains a series of functionalities to examine crime point patterns data, including hotspot mapping techniques. Nine hotspot mapping techniques are provided by the program. These are mode, fuzzy mode, nearest neighbor hierarchical clustering, risk-adjusted nearest neighbor hierarchical clustering, STAC, K-means clustering, local Moran's I, Getis Ord local "G", and kernel density estimation. Each technique requires the user to enter suitable parameters.

Another problem in crime mapping is related to the heterogeneity of the study area. In some urban geographic spaces (e.g. the city of Houston as explored in this thesis research), some areas may have a number of crimes which is small compared to the entire study area, but relatively large compared to its local neighbors. This area which has a local cluster pattern is referred to as a local hotspot. Measures designed to detect these local hotspots are called Local Indicator of Spatial Association (LISA) statistics (Anselin, 1995; Ord and Getis, 1995; Getis and Ord, 1996; Ratcliffe and McCullagh, 1999). They include the local Moran's I, the Local Geary's C, Gi and the Gi* statistics. Among these LISA statistics, the local Moran's I and the Gi* received the most attention (Chainey and Ratcliffe, 2005). The difference between these two statistics is that the local Moran's I is based on covariance and identifies Moran's I value for each zonal area so that the area can be examined as being different or similar to its neighborhoods. The Gi* compares local averages to global averages. Some other techniques are also available to produce spatial crime hotspots. These include, but are not limited to the Nearest Neighbor Hierarchical Clustering (Levine, 2004), K-Means clustering, spatial scan statistic, etc.

These visualization techniques possess both strengths and weaknesses. To better assess the quality of these techniques to forecast the occurrence of future crime events, three different standard measures which are commonly referred to as predictive accuracy measures have been proposed. The hit rate is one of the earliest and most used measures. It is calculated as the percentage of crime events that falls within hotspot areas produced from retrospective crime data. Another measure is the Predictive Accuracy Index (PAI) which takes both the effect of the hit rate and the size of the study area and the crime hotspots into consideration. In addition, Levine (2008) provided the Recapture Rate Index (RRI) as an adjustment to the PAI. To compare how accurately these techniques work to predict where and when crimes may occur in the future, each predictive accuracy measure (hit rate, PAI, RRI) is calculated in this thesis research to represent the relative accuracy level of each technique. Also, the literature indicates that crime types have an effect on the predictive accuracy (Chainey et al, 2008; Hart and Zandbergen, 2012). For this reason, the three predictive accuracy measures (hit rate, PAI, RRI) will be computed and examined for five different crime types, including aggravated assault, auto theft, burglary, larceny-theft, and robbery.

Much effort has been devoted to studying the relevance of space in identifying patterns of crime or crime clusters. The eight hotspot mapping techniques discussed in this thesis research may just represent the “tip of the iceberg” of the large volume of work that has been contributed to this topic. By contrast, temporal analysis has received much less attention. In fact, if crime analysts or crime prevention practitioners do not consider the temporal factor of crime analysis, at all, they may provide incomplete, biased, or even misleading results to police officers or law enforcement agencies. According to the routine activity theory (Cohen and Felson, 1979), a motivated crime offender is more likely to commit a crime when he/she encounters a suitable target (or victim) under the circumstance of the absence a guardian. The factors which result in the occurrence of crime have to meet both in the dimension of space and time. Many activities like traffic rush hours or the difference between workload during weekdays and weekends present changes in the temporal pattern. Felson and Paulson (1979) thus reasoned that certain types of crime tend to concentrate at certain times of day/weak/year. Several but not too many studies have been carried out to address differences in crime concentrations across different temporal scales (Johnson et al., 2008; Felson and Paulson, 2002; Paulson and Robinson, 2004). One simple idea is to use to compare a pair of timestamps to detect changes of crime clusters in the temporal dimension. For example, in a research conducted by Leitner and Helbich (2011) to investigate the impact of Hurricane Rita and Hurricane Katrina on crime, the Kulldorff’s scan statistics was used to detect spatio-temporal crime clusters over two periods, namely before and after the landfall of both hurricanes. Another example is given by Bowers and Johnson (2003), who developed statistical testing structures to access crime prevention before and after some specific measures have been implemented.

Choosing a pair of timestamps could produce problems of underestimating the importance of time in the distribution of crime clusters, particularly for distinguishing stable and fluid clusters (Nakaya and Yano, 2010). Consequently, larger time periods have been chosen by some researchers. A time interval of an hour, day, week, month, season, or year are most commonly used by researchers. For example, Rengert's study (1997) concluded that crime cluster patterns varied based on different periods of time within one day. Nakaya and Yano (2010) chose one month as the time interval in their study to explore a 3-D hotspot mapping method for visualizing crime clusters.

Some work has examined crime changes over periods of time, either to look at long-trend changes such as years or seasons (Block, 1984; Lebeau, 1992) or to look at short-trend changes such as weeks, days or intra-days (Bowers et al., 1998; Johnson et al., 1997; Ratcliffe and McCullagh, 1998). There exist a series of techniques to detect spatial-temporal patterns of crime clusters. According to a comparative study of spatial-temporal hotspot analysis techniques used in the area of security informatics conducted by Zeng et al. (2004), two types of spatial-temporal hotspot analysis and mapping techniques have gained more popularity among researchers and practitioners. One was developed by the advance of different scan statistics which are primarily applied to the realms of public health and epidemic prevention (Kulldorff, 2001). The other one was built upon the growing of data clustering analysis and its variations. Among these two types of spatial-temporal hotspot techniques, scan statistics and nearest neighbor hierarchical clustering received most attention (Leitner and Helbich, 2011).

To evaluate the performance of the spatial-temporal hotspot mapping methods in predicting crimes in the future, measures similar to the hit rate, the PAI or the RRI are also needed. However, contemporary literature seems to neglect this topic due to some reason. Little research was conducted in the study of the spatial-temporal predictive accuracy measures. To complement this, I designed several spatial-temporal predictive accuracy measures, on the base of the existed spatial predictive accuracy measures. While the validity and appropriateness of these newly designed measures remain unseen, it at least provides future researchers with some likely standards they can refer to in assessing how the spatial-temporal hotspot mapping technique performs.

CHAPTER 3 DATA AND GEOCODING

3. 1 The Study Area and the Spatial Data

The study area of this research consists of the jurisdiction of the Houston Police Department (HPD), which is the primary law enforcement agency serving the City of Houston and which overlaps with several other law enforcement agencies such as the Harris County Sheriff's Office and the Harris County Constable Precincts. On a geographic scale, the boundary of the HPD districts extends from -95.784602°W to -95.000783°E and from 30.126094°N to 29.519338°S (see Figure 3.1 below).

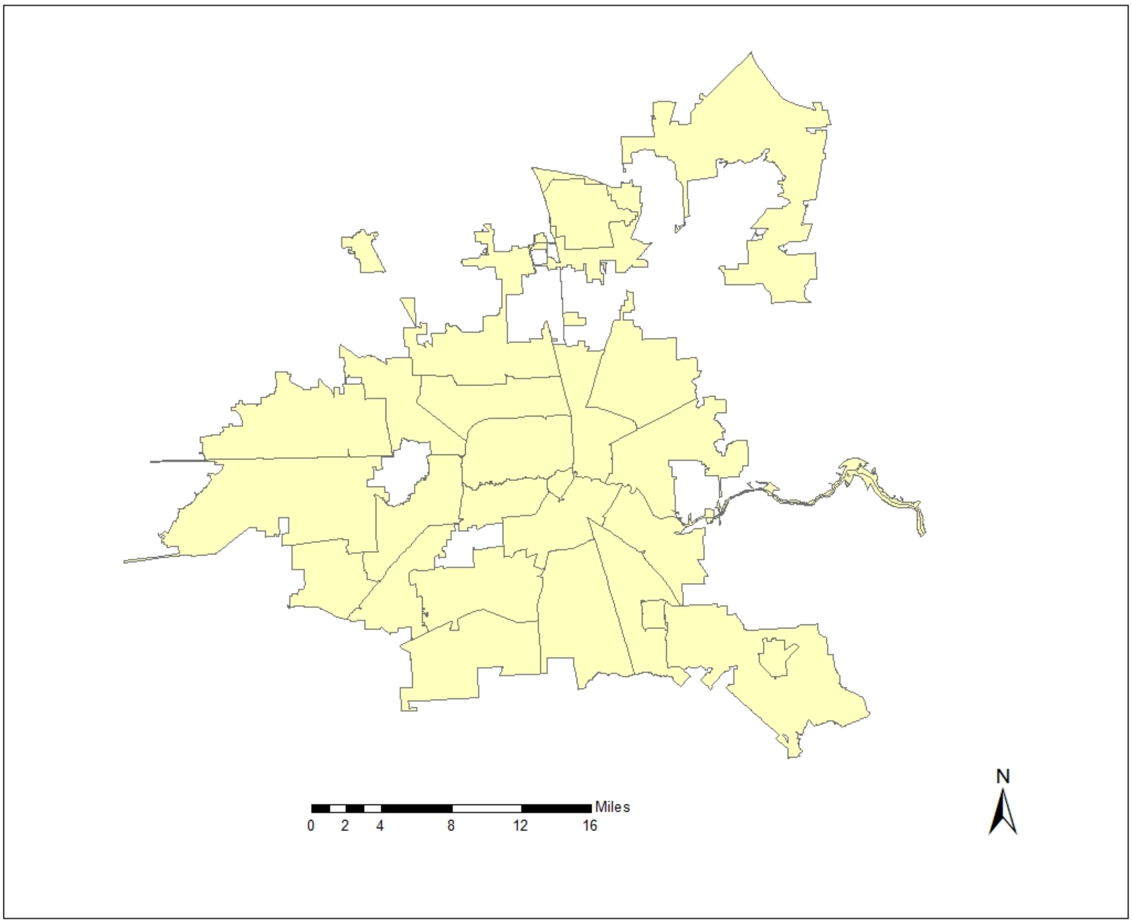

Figure 3. 1 Geographic boundary of the study area, the City of Houston

In order to geocode crime incidents onto a street network map, the census tract shapefiles for 2010 were downloaded for free online as part of the products of the City of Houston GIS Release, which is also known as COHGIS (http://gisdata.houstontx.gov/cohgis). The COHGIS data release contains administrative places, roads, boundaries, blocks, and census tracts datasets, etc. Compared to the commonly used TIGER/Line shapefiles, which can be downloaded through the U.S. Census Bureau website (http://www.census.gov/geo/maps-data/data/tiger-line.html), the COHGIS not only includes geographic data, but also include some demographic data such as population, race, house unit, etc. For the purpose of this research, the population information of 2010 is required to conduct risk-based hotspot methods that include the risk-based thematic mapping and risk-adjusted nearest neighbor hierarchical clustering method. Also, the boundaries of the COHGIS data correspond to the spatial extend of the crime data which is to be discussed in the next section. The boundary of the TIGER/Line shapefile includes the entire Harries County, where the city of Houston is located. There would have been a need to do “clip” to narrow the study area down to the city extent when using the TIGER shapefile.

3. 2 The Crime Data

The crime data used in this research could have been obtained from the Houston Police Department (HPD) website (http://www.houstontx.gov/police/cs/stats2.htm). However, crime data were collected free of charge from the HPD through the Texas Public Information Act by submitting an open record request. Acquiring the crime data through an open record request results in a more complete and accurate dataset, than the one available at the HPD website. The crime data set includes all reported crimes classified according to the Federal Bureau of Investigation’s (FBI) Uniform Crime Reporting (UCR) program. This research will investigate nine Part 1 Crimes which include murder and non-negligent manslaughter, manslaughter by negligence, forcible rape, robbery, aggravated assault, burglary, larceny-theft, auto theft, and arson. Only Part 1 Crimes are included in this thesis research because these crimes are taken as more serious than others in crime analysis and the data sources are more reliable. The police are usually on the scene to record these types of crimes. Table 3.1 shows the UCR codes for the nine Part 1 Crimes.

Table 3. 1 UCR classification offenses codes for Part 1 Crimes

UCR Classification Offenses for Houston Police Department	
Part 1 Crimes	(Part 1 crimes, except for 01 & 09, are included in the Crime Index.)
	Violent Crimes
00	Murder And Non-negligent Manslaughter
01	Manslaughter By Negligence (Usually not included with other Part 1 Crimes)
02	Forcible Rape
03	Robbery
04	Aggravated Assault (Class I)
	Non-Violent Crimes
05	Burglary
06	Larceny – Theft (Includes Burglary of Motor Vehicles)
07	Auto Theft
09	Arson (This includes only those Arsons which also have other offenses. The Houston Fire Department Arson. Arson is included with Crime-Index Crimes in the Modified Crime Index)

In addition to the almost 50 offense types (Part 1 and Part 2 Crimes, and Other Offenses), the data set includes the offense date and time, police beat, and the actual street address, where the offense took place. A complete set of crime data for the selected nine Part 1 Crimes from January 2011 to December 2012 will be used in this research.

The original crime data are provided in either a Microsoft Office Access Database format or a Microsoft Excel format and are limited to those crime events which are known to the police. The 2011 crime dataset includes a total of 131,707 recorded crime incidents and the 2012 dataset 130,218 recorded incidents. Table 3.2 lists the number of crime incidents by crime type and by year.

Table 3. 2 Number and percentage of crimes for nine Part 1 Crime types for the year 2011 and 2012

UCR Code	Type of Crime	Number of Crimes and Percentage 2011		2012	
00	Murder and Non-negligent Manslaughter	226	(0.17%)	245	(0.19%)
01	Manslaughter By Negligence	17	(0.01%)	44	(0.03%)
02	Forcible Rape	820	(0.62%)	640	(0.49%)
03	Robbery	8435	(6.4%)	9394	(7.21%)
04	Aggravated Assault	12484	(9.48%)	11310	(8.69%)
05	Burglary	27783	(21.09%)	26579	(20.41%)
06	Larceny-Theft	68978	(52.37%)	67893	(52.14%)
07	Auto Theft	12826	(9.74%)	13948	(10.71%)
09	Arson	138	(0.1%)	165	(0.13%)
	All Part I Crimes	131707		130218	

Table 3.2 shows that larceny-theft takes up more than 50% of all Part 1 Crimes. Robbery, aggravated assault, burglary and auto theft make up almost 50% of all Part 1 Crimes, while the proportion of murder and non-negligent manslaughter, manslaughter by negligence, forcible rape and arson total less than 1%. This may be explained by the fact that the four crime types whose proportion of crimes of all Part 1 Crimes is less than 1% are all violent crimes. The occurrence of a violent crime is less likely to take place than a non-violent crime. A law enforcement agency branch may receive a couple of burglary reports during a single day, but may receive only one murder report every other day or days.

3. 3 Geocoding

Geocoding is a process to transfer indirect geocodes (e.g. place names, zip codes, census tracts, etc.) to direct geocodes (e.g. x and y coordinates, latitude and longitude). In my thesis research, the indirect geocodes are the names of addresses where crime incidents occurred. The direct geocodes are the X and Y coordinates of the crime locations. The crime incidents must be geocoded onto the street map for the purpose of hotspot mapping.

After the acquisition of the crime data set and the street network data (the TIGER/Line shapefile), geocoding can then be accomplished using ArcGIS 10.2. The street network data contain all roads information (e.g. names, addresses, ranges, city, etc.) for a county. They are part of the product of TIGER/Line shapefiles and can be downloaded from U.S. Census Bureau website (http://www.census.gov/geo/maps-data/data/tiger-line.html).

Several parameters require to be specified in order to perform geocoding correctly and appropriately. According to Leitner and Helbich (2011), who did a spatial-temporal analysis in the City of Houston to study the impact of hurricanes on crime, the spelling sensitivity was set to 80, the minimum candidate score and the minimum match score were set to 75 and 60, respectively. These three parameters are utilized jointly in ArcGIS for geocoding to help find an appropriate and accurate match address for each crime incident location. The matched or tied point will be assigned an address which has the highest match score from the candidate addresses and the unmatched point will not be assigned an address. The same user-defined geocoding parameter settings as in Leitner and Helbich (2011) are applied in this research and are shown in Figure 3.2.

Using this set of parameters, the match rates for the nine crime types and the total of all Part 1 Crimes are all close to or above 95%. According to Ratcliffe (2004), this is a sufficiently high match rate. In comparison, an increase of the minimum match score to 80 and keeping the other parameters unchanged would have resulted in match scores of less than 90%. Table 3.3 presents the match rates after geocoding.

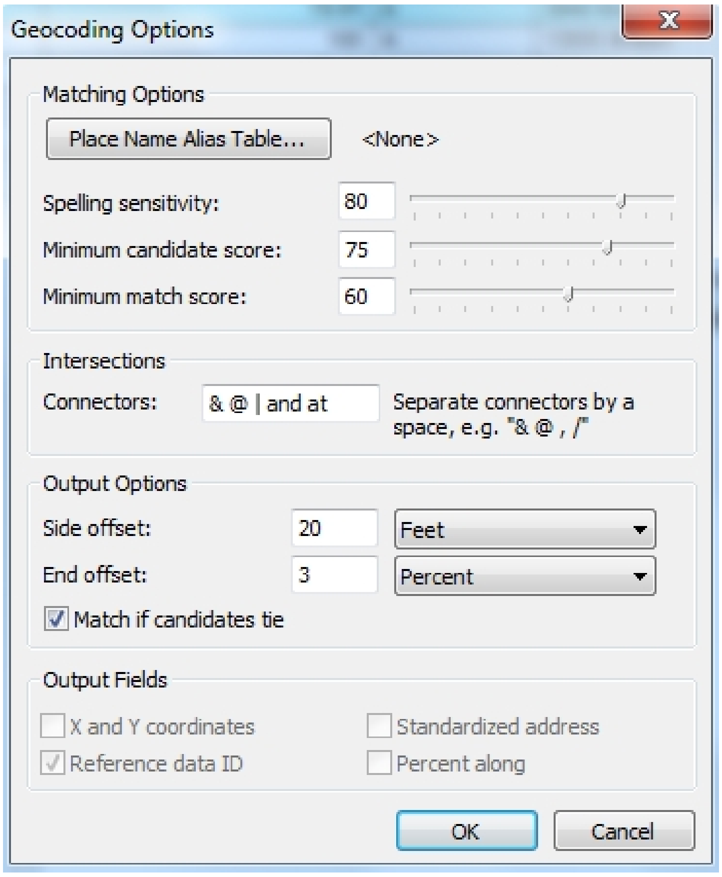

Figure 3. 2 Geocoding parameters setting window in ArcGIS 10.2

After geocoding, all crime locations with unmatched addresses were removed and not included in the subsequent analysis of this research. Table 3.4 shows the number of crime incidents and the corresponding percentages for nine crime types and the overall Part 1 Crimes after completion of the geocoding process.

After geocoding, robbery, aggravated assault, burglary, larceny-theft, and auto theft again total to close to 99% of all Part 1 Crimes. Since after geocoding all crime incident locations are assigned X and Y coordinates, crime locations can now be used to conduct spatial and temporal hotspot analysis.

Table 3. 3 Match rates for nine Part 1 Crime types for the year 2011 and 2012 after geocoding

UCR Code	Type of Crime	Match Rate 2011	2012
00	Murder and Non-negligent Manslaughter	99%	96%
01	Manslaughter By Negligence	94%	89%
02	Forcible Rape	95%	96%
03	Robbery	96%	96%
04	Aggravated Assault	97%	97%
05	Burglary	96%	96%
06	Larceny-Theft	94%	94%
07	Auto Theft	96%	95%
09	Arson	95%	95%
	All Part I Crimes	95%	95%

Table 3. 4 Number and percentage of crimes for nine Part 1 Crime types for the year 2011 and 2012 after geocoding

UCR Code	Type of Crime	Number of Crimes and Percentage 2011	2012
00	Murder and Non-negligent Manslaughter	223 (0.18%)	235 (0.19%)
01	Manslaughter By Negligence	16 (0.01%)	39 (0.03%)
02	Forcible Rape	786 (0.63%)	616 (0.50%)
03	Robbery	8128 (6.51%)	9043 (7.31%)
04	Aggravated Assault	12024 (9.63%)	10892 (8.81%)
05	Burglary	26732 (21.41%)	25593 (20.70%)
06	Larceny-Theft	64580 (51.71%)	63782 (51.59%)
07	Auto Theft	12258 (9.82%)	13269 (10.73%)
09	Arson	131 (0.10%)	157 (0.13%)
	All Part I Crimes	124878	123626

CHAPTER 4 SPATIAL PREDICTIVE ACCURACY MEASURES

Three spatial predictive accuracy measures are commonly used in the area of crime analysis, which include the hit rate, the Predictive Accuracy Index (PAI) and the Recapture Rate Index (RRI). To compare how accurately these techniques work to predict where and when crimes may occur in the future, each spatial predictive accuracy measure (hit rate, PAI, RRI) is calculated in this thesis research to represent the relative accuracy level of each technique. Also, the literature indicates that crime types have an effect on the predictive accuracy (Chainey et al, 2008; Hart and Zandbergen, 2012). For this reason, the three spatial predictive accuracy measures (hit rate, PAI, RRI) will be computed and examined for five different crime types, including aggravated assault, auto theft, burglary, larceny-theft, and robbery.

4. 1 Measures of Spatial Predictive Accuracy

The first measure of predictive accuracy is the hit rate. This measure is calculated as the percentage of new crimes that occur within the areas where crimes are predicted to occur (Chainey et al, 2008). The higher the hit rate, the more accurate the hotspot technique is. This measure is easy to calculate and to understand. However, the larger the hotspot area, the higher the likelihood is that a higher number of future crimes would fall into it. The hit rate does not thus take the area of the hotspot into consideration. This could make the results less meaningful to law enforcement agencies. For instance, a hit rate can be calculated that exceeds 90%, but the hotspot areas also make up more than 90% of the study area. It is unlikely for the police to patrol such a large area because of limited resources and manpower. Thus, a measure which considers the size of hotspots vis-à-vis the size of the study area is needed to better evaluate the predictive accuracy. This is accomplished with the next measure, which is the Predictive Accuracy Index.

Predictive Accuracy Index (PAI) was first introduced by Chainey et al (2008). It was created to address the problem the hit rate may produce. In other words, the PAI takes the sizes of hotspots and the study area into consideration. It is defined as the ratio of the hit rate to the proportion of the study area that consists of hotspots in the retrospective year (Hart and Paul, 2012). The formula (4-1) is as follows:

$$PAI = \frac{hit\ rate}{proportion\ of\ hot\ spot\ area} = \frac{n/N}{a/A} \qquad (4-1)$$

where *n* is the number of new crime incidents which fall into predicted hotspot areas from the retrospective year, *N* is the number of new crimes in the whole study area, *a* is the total area occupied by hotspots, and *A* is the size of entire study area. Compared to the hit rate, the PAI could weaken the effect of study area on producing meaningless information to police's tactical determination. Again, a larger PAI value means a hotspot mapping method that is more accurate for predicting crime.

The third predictive accuracy measure is the Recapture Rate Index (RRI). It was proposed by Levine (2008) in a response to Chainey et al.'s newly invented PAI. The RRI does not take the sizes of hotspots or the study area into consideration. The index is calculated by dividing the ratio of hotspot crime counts for 2011 and 2012 by the ratio of the total number of crimes for each year (see formula 4-2 below):

$$RRI = \frac{hotspot\ crime\ ratio}{total\ crime\ ratio} = \frac{n1/n2}{N1/N2} \qquad (4-2)$$

where *n*1 is the number of crimes in hotspot areas for year 2011, *n*2 is the number of new crime incidents for year 2012 which took place in predicted hotspot areas, *N*1 is the total number of crimes for year 2011, and *N*2 the total number of crimes for year 2012. Similar to the hit rate and the PAI, a larger RRI corresponds to a more accurate hotspot mapping method for crime prediction.

The following image illustrates an example of the calculation of the three predictive accuracy measures.

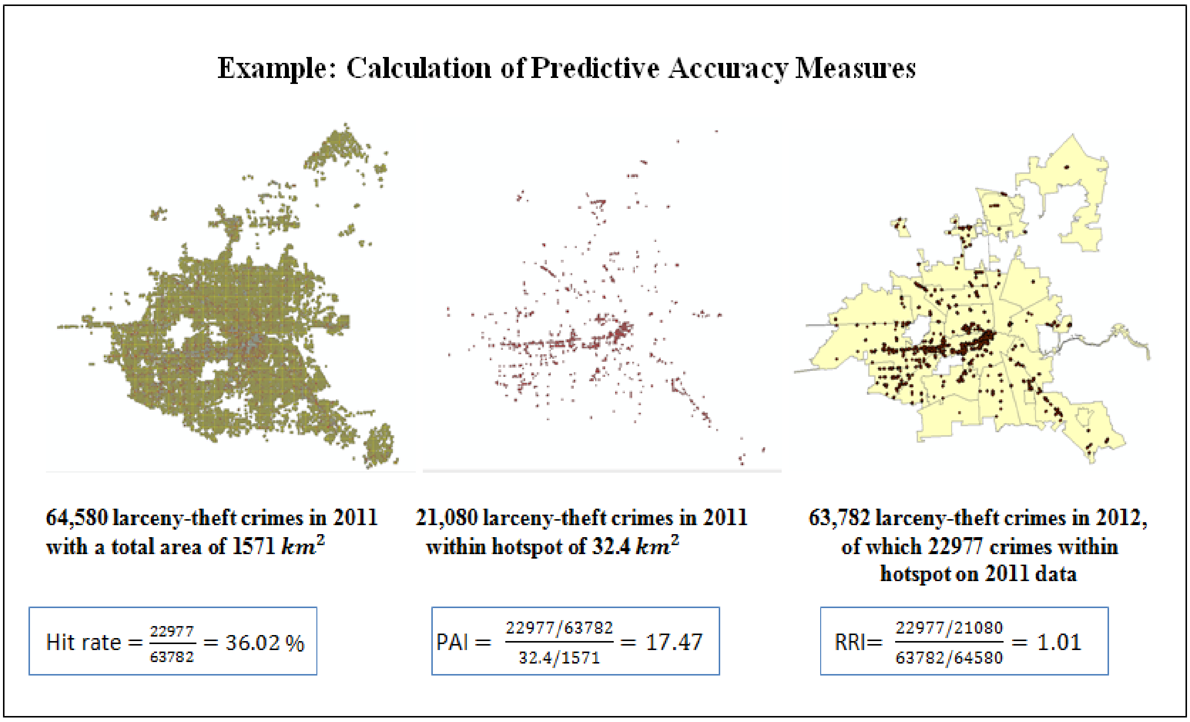

Figure 4. 1 Calculation of the three predictive accuracy measures

4. 2 Hotspot Methods and Parameters

After introducing the three measures of predictive accuracy, the eight hotspot methods will be discussed one by one in much detail.

Eight hotspot mapping methods were selected in this research to create hotspot maps. These eight methods were chosen because of their availability (for example in ArcGIS or in other programs that are easily accessible), popularity (whether they have been commonly applied by other crime analysis researchers or practitioners), and their comprehensiveness (this set of eight methods includes two risk-based hotspot mapping methods in order to consider the effect of population density on crime prediction). The selected eight methods include risk-based thematic mapping, grid thematic mapping, spatial and temporal analysis of crime (STAC), nearest neighbor hierarchical clustering (NNHC), risk-adjusted nearest neighbor hierarchical clustering, kernel density estimation (KDE), local Moran's I statistic, and Gi* statistic (Table 4.1).

Table 4. 1 Polygon and point pattern analysis methods and their corresponding outputs

Methods	Data Type	Hotspot Mapping Results
Thematic Mapping	Polygon	Census Tracts
Risk-Based Thematic Mapping	Polygon	Census Tracts
Grid Thematic Mapping	Point	Grids
STAC	Point	Ellipse
NNH	Point	Ellipse
Risk-Based NNH	Point	Ellipse
Kernel Density Estimation	Point	Grids
Local Moran's I	Polygon	Census Tracts

These eight hotspot mapping techniques can be classified as non-risk-based methods and risk-based methods. Non-risk-based methods include grid thematic mapping, STAC, NNHC, KDE, local Moran's I and Gi*. The other two are risk-based.

The grid thematic mapping technique is put forward to deal with the problem of the effect of different sizes and shapes of enumeration areas on crime counts or crime rates. This is accomplished by placing a uniform grid over the study area with each grid cell having the same size and shape (usually a square). Different to risk-based thematic mapping, where each area has a crime rate associated with it, in grid thematic mapping each cell can display a value that is either a crime count or a crime rate. It is possible to display crime counts with this mapping approach, since all cells of the regular grid have the same size and shape.

The Spatial and Temporal Analysis of Crime (STAC) method is one of the earliest tools available for crime analysis (Illinois Criminal Justice Information Authority, 1996). It was initially developed as two computer programs, which include the Time Analyzer and the Space Analyzer. The Space Analyzer is aimed to help crime analysts find and locate the hotspot areas by creating ellipses placed over the study area. Now this function was integrated into CrimeStat 4.0, which is a software specifically developed to perform spatial and temporal crime incidents analysis (Levine, 2004).

The nearest neighbor hierarchical clustering (NNHC) method uses a hierarchical clustering routine to create a hierarchy of hotspots based on several user-defined criteria, including the minimum number of points that a cluster should consist of. NNHC is based on the nearest neighbor analysis technique and hotspots consist of groups of points that are closer than expected under spatial randomness (Eck et al., 2005). The clustering routine will repeat until all points are grouped into a single cluster or the clustering criteria fail (Levine, 2004). The clustering criteria are based on two parameters, which need to be selected by the user.

The kernel density estimation has been agreed by several researchers as being the most suitable hotspot mapping technique (Chainey and Ratcliffe, 2005; Chainey et al., 2008). It is also a very popular method among crime analysis practitioners. It is one of the continuous surface smoothing methods which interpolate values based on intensity values of known points. It works by first imposing a regular grid with a specified cell size over points across the study area. Then, a user-defined three-dimensional kernel function of a user-defined search radius will visit each point and calculate densities for all the cells within the search radius. The final kernel density estimate for one cell is then calculated by summing up all values obtained from all kernel density functions for that particular cell. This method is preferred by many practitioners in part due to its nicely visualized mapping results and its availability in most spatial analysis and GIS software packages.

Local indicators of spatial association (LISA) are a set of statistics, which are widely employed by crime analysts. These statistics are proposed because traditional global statistics which explores the spatial association across the whole study area offer little insight into the location, relative scale, size, shape and extent of hotspots (Chainey and Ratcliffe, 2005). The local Moran's I is based on covariance and identifies a Moran's I value for each zonal area so that the area can be examined as being different or similar to its neighbors. The definition of "neighbors" has to be specified by users. It can be either adjacent areas or areas negatively weighted based on the distance from the observation area (Anselin, 1995).

The Gi and the Gi* statistics are another set of LISA statistics. The difference between these two statistics is that the Gi* statistic considers the effect of the value of the point itself in the calculation of the Gi* values, while Gi does not. Gi* is more popular to be utilized by crime researchers and analysts. It was thus selected instead of Gi as one of two hotspot mapping methods in this thesis research as one hotspot mapping method.

Thematic mapping is widely used for showing administrative or enumeration areas by cartographers and crime analysts in order to obtain an overview of the spatial distribution of crime incidents. It works by assigning graduated colors to different statistical areas. In crime analysis, these areas are usually associated with attributes such as crime rates. It requires users to specify a classification scheme whereby areas with similar values are grouped together. In ArcGIS, several classification methods are provided. They include natural breaks, equal interval, quantile, standard deviation, manual classification, etc. Choosing an appropriate classification method and the corresponding class boundaries is important in crime analysis research. Different classification schemes will place crime events into different categories, and will change classification boundaries. After the classification scheme is specified, the risk-based thematic map can then be produced based on the crime rates associated with each statistical area. Crime rate, rather than crime count, is used as the value based on which a thematic map is created because it is more appropriate for the purpose of crime analysis.

The risk-adjusted nearest neighbor hierarchical clustering (risk-adjusted NNHC) method is developed on the basis of the nearest neighbor clustering (NNHC) routine, which is discussed above and the kernel density estimation, which is discussed below. The risk-adjusted NNH clustering method introduces an intensity or weight field. For many police purposes, for example, as discussed in risk-based thematic mapping, the population distribution plays an important role in where crime hotspots occur. In this research, the intensity field is the population of each census tract. The risk-adjusted NNH clustering routine will dynamically adjust the threshold distance based on the distribution of the population rather than relying on the user-defined threshold distance. The clusters of points which are closer than what would be expected according to a baseline population will then be identified by the routine as risk-based hotspots (Levine, 2004).

The type of data and the mapping result vary for different methods. Points and administrative polygons are two types of data used and census tracts, grids and grids are three forms of mapping results.

The data used in this section are the reported crime events for 2011 and 2012 in Houston, TX. Since the effect that crime types have on hotspot technique's predictive accuracy will be studied in the next section (Section 4.2), the total number of Part 1 Crimes data was analyzed in this section.

4. 3 Comparison of Predictive Accuracy Measures Across Hotspot Mapping Methods

Since different techniques are based on different theories, concepts, and set of parameters, their resulting outputs, namely, the hotspot maps, are thus somewhat different from each other. The statistically significant hotspot area produced using one technique maybe lacking statistical significance using another method or even turning into a coldspot, when considering the population at risk. The study area for all methods is the same, namely, the City of Houston, TX. The hotspots produced by risk-based thematic mapping and local Moran's I use census tracts as their unit of observation. Grid thematic mapping, Gi* and KDE show their results in the form of a regular grid. Finally, STAC, NNH clustering and risk-adjusted NNH clustering methods exhibit their results in the form of ellipses. Also, it can be seen from the results in Figure 6. 1 – 6. 8 that the local Moran's I, grid thematic mapping, NNH clustering and risk-adjusted NNH clustering yield more hotspots than the other methods.

After having compiled all hotspot maps, the three measures of predictive accuracy (hit rate, PAI, and RRI) can be computed. The formulas for all three measures were given in Section 4.1. Table

6.2 presents the results of the three predictive accuracy measures across the eight hotspot crime mapping techniques. Table 6.1 lists the parameter settings for each cluster method.

When interpreting the hit rate as one measure to assess the predictive accuracy for various hotspot methods, it obviously needs to be kept in mind that the four methods, which produced the highest number of hotspots and largest hotspot sizes, are better at predicting future crime events, since a higher number of new crime events would be located inside these retrospective hotspots. In contrast, the PAI, which takes the study area and the hot spot sizes into consideration, yields the best results with the kernel density estimation and the Gi* statistic. Finally, the RRI predicts future crimes the best with the risk-adjusted nearest neighbor hierarchical clustering method and the kernel density estimation.

It should be kept in mind that these results are based upon a large dataset consisting of nine different crime types. These results may be applied by the police for tactical decision making. For example, if the results are presented to the general police officer in the city of Houston and the main purpose is to reduce overall crime for the entire city, the results shown in this section might be potentially suitable. However, if the purpose is to effectively allocate resources by a police decision maker in order to control the number of one particular crime or crimes, then additional studies about the effect of individual crime type on the predictive accuracy needs to be studied.

Table 6. 1 Hotspot mapping methods parameters

Methods	Parameters		
	Cell Size	Search Radius	Threshold
Risk-Based Thematic Mapping	N/A	N/A	Greater than 1 standard deviation
Grid Thematic Mapping	200m	N/A	10%
STAC	200m	750m	15 points, first order
NNHC	N/A	250m	15 points, first order
Risk-Adjusted NNHC	200m	250m	15 points, first order
KDE	200m	250m	Greater than 3 standard deviation
Local Moran’s I	N/A	N/A	Greater than 99.9%
Gi*	200m	283m	Greater than 99.9%

Table 6. 2 Measures of predictive accuracy for eight hotspot mapping methods

	Crimes in 2011		Crimes in 2012		Total (km^2)		Predictive Accuracy		
Hotspot Mapping Techniques	In 2011 Hotspot	In Study Area	In 2011 Hotspot	In Study Area	Area of 2011 Hotspot	In Study Area	Hit Rate (%)	PAI	RRI
Risk-Based Thematic Mapping	1890	124022	1979	122785	94.26	1625	1.61	0.28	1.06
Grid Thematic Mapping	64889	124251	61550	123028	65.63	1571	*50.03*	11.98	0.96
STAC	15389	124878	9323	123626	11.25	1571	7.54	10.58	0.61
NNHC	100398	124878	65879	123626	105.34	1571	*53.29*	7.95	0.66
Risk-Adjusted NNHC	38058	124878	48558	123626	85.31	1571	*39.28*	7.23	*1.29*
KDE	23565	124878	28070	123626	18.44	1571	22.71	*19.34*	*1.20*
Local Moran's I	57488	124022	55836	122785	401	1625	*45.47*	1.84	0.98
Gi*	21628	124251	20580	123626	18.86	1571	16.65	*13.87*	0.96

4. 4 Comparison of Predictive Accuracy Measures Across Crime Types

The dataset in this research contains nine Part 1 Crime types. However, as shown in Table 3.4, after geocoding, only five of the nine crime types possess more than 5% of the total number of crimes each. These are robbery, aggravated assault, burglary, larceny-theft and auto theft. This section will study how crime types affect predictive accuracy testing the same eight hotspot mapping techniques as applied in Section 4.2. To be consistent across each crime type, the parameters selected for each hotspot mapping technique remain the same. The three measures of predictive accuracy were calculated for each combination of any one of the five crime types and eight hotspot mapping techniques. Table 4.2 shows the results of the three predictive accuracies for each of the 40 combinations (5 crime types x 8 mapping techniques).

The results clearly show that different crime types have an effect on the predictive accuracy. For example, hit rates for larceny-theft are higher than for any of other four crime types. This may be because larceny-theft has by far the highest percentage (52%) among all five crime types. However, when using the PAI, robbery tends to be as accurate or more accurate than any of the other four crime types. Finally, the RRI is again highest for larceny-theft.

It is also interesting to answer the questions which crime type has a higher predictive accuracy for one particular hotspot mapping technique, or which hotspot mapping technique is more accurate at predicting future crimes for any or most of the crime types. To answer the first question, the STAC method can be taken as an example. When using STAC as the hotspot mapping technique for all five crime types studied, the predictive accuracy is higher for larceny-theft than for any of the other four crime types. In order to answer the second question, it can be shown that the NNH clustering and the kernel density estimation outperform all other mapping techniques at predicting future crime events across all five crime types.

When taking crime type into consideration, the three predictive accuracy measures change substantially across eight hotspot methods. But from the perspective of hotspot methods, the three measures vary moderately across five crime types. The results of the three predictive accuracy measures by nine crime types and eight hotspot methods are presented in Table 4.2. In general, hit rate and PAI for robbery appear to be higher among five crime types. When using RRI as the predictive accuracy measure, however, larceny-theft is the crime type which can be predicted more accurately.

One objective in this thesis research is to find a single best hotspot method which is better at predicting future crime events. A modified version of Table 4.2 is shown in Table 6.3, Table 6.4 and Table 6.5 in order to locate the best method for each individual crime type based on three predictive accuracy measures.

By examining the hotspot methods' ability to predict future crime events across five crime types, findings are different from the above and may provide valuable advice to police decision makers. Kernel density estimation method is consistently the best method at predicting future crime events for all five crime types when RRI is used as the predictive accuracy measure. Nearest neighbor hierarchical clustering method could be generally regarded as the most accurate hotspot method for crime prediction when PAI is the measure. When hit rate serves as the predictive accuracy measure, the best hotspot method varies for different crime types at predicting crime incidents in the future.

Table 6. 3 The hit rate for the combination of five crime types and eight hotspot mapping techniques. The value in bold represents the highest value among the eight hotspot methods for each crime type

	Hit Rate				
	Robbery	Aggravated Assault	Burglary	Larceny-Theft	Auto Theft
Risk-Based Thematic Mapping	0.26	0.16	0.15	2.69	0.95
Grid Thematic Mapping	26.16	24.08	*33.42*	*49.58*	30.04
STAC	9.9	7.17	6.89	9.84	7.03
NNHC	10.87	14.21	22.72	47.02	13.92
Risk-Adjusted NNHC	1.17	2.93	10.73	26.62	4.25
KDE	18.18	19.15	19.29	23.24	20.53
Local Moran's I	*48.84*	*51.31*	32.34	24.70	*30.22*
Gi*	9.63	7.90	14.31	15.52	9.93

Table 6. 4 The PAI for the combination of five crime types and eight hotspot mapping techniques. The value in bold represents the highest value among the eight hotspot methods for each crime type

	PAI				
	Robbery	Aggravated Assault	Burglary	Larceny-Theft	Auto Theft
Risk-Based Thematic Mapping	0.09	0.06	0.06	0.46	0.29
Grid Thematic Mapping	27.27	23.61	14.33	15.12	21.98
STAC	12.78	8.26	8.67	16.08	9.82
NNHC	*54.39*	*36.78*	*19.96*	15.78	*49.93*
Risk-Adjusted NNHC	34.1	34.33	17.47	13.93	25.39
KDE	29.26	23.67	19.04	*28.80*	24.07
Local Moran’s I	2.87	1.92	1.01	1.73	1.26
Gi*	32.06	26.85	19.19	23.34	27.94

Table 6. 5 The RRI for the combination of five crime types and eight hotspot mapping techniques. The value in bold represents the highest value among the eight hotspot methods for each crime type

	RRI				
	Robbery	Aggravated Assault	Burglary	Larceny-Theft	Auto Theft
Risk-Based Thematic Mapping	0.47	0.69	0.95	1.09	0.96
Grid Thematic Mapping	0.72	0.76	0.81	0.93	0.81
STAC	0.57	0.53	0.56	0.63	0.54
NNHC	0.52	0.6	0.59	0.68	0.60
Risk-Adjusted NNHC	0.58	0.88	1.01	1.23	0.94
KDE	*1.01*	*1.10*	*1.11*	*1.15*	*1.12*
Local Moran's I	0.92	0.97	0.98	1.01	0.97
Gi*	0.81	0.82	0.89	0.95	0.87

CHAPTER 5 SPATIAL-TEMPORAL PREDICTIVE ACCURACY MEASURES

In this chapter, the discussion of the spatial analysis of crime will be extended to spatial-temporal analysis. Similar to the previous chapter on spatial analysis, which compared eight crime hotspot mapping techniques to explore the spatial distribution of five crime types, in temporal analysis mapping techniques have been widely adopted to identify temporal patterns of crime. One simple idea is to use to compare a pair of timestamps to detect changes of crime clusters in the temporal dimension. For example, in a research conducted by Leitner and Helbich (2011) to investigate the impact of Hurricane Rita and Hurricane Katrina on crime, the Kulldorff's scan statistics was used to detect spatio-temporal crime clusters over two periods, namely before and after the landfall of both hurricanes. Another example is given by Bowers and Johnson (2003), who developed statistical testing structures to access crime prevention before and after some specific measures have been implemented.

Choosing a pair of timestamps could produce problems of underestimating the importance of time in the distribution of crime clusters, particularly for distinguishing stable and fluid clusters (Nakaya and Yano, 2010). Consequently, larger time periods have been chosen by some researchers. A time interval of an hour, day, week, month, season, or year are most commonly used by researchers. For example, Rengert's study (1997) concluded that crime cluster patterns varied based on different periods of time within one day. Nakaya and Yano (2010) chose one month as the time interval in their study to explore a 3-D hotspot mapping method for visualizing crime clusters.

In this research, the data were provided by the Houston Police Department on a monthly basis. The dataset ranges from Jan. 2011 to Dec. 2011 (12 months). Thus it was decided to use one month as the time interval. Figure 5.1 shows the reported monthly numbers of crimes (all Part 1 Crimes) in Houston, TX in 2011.

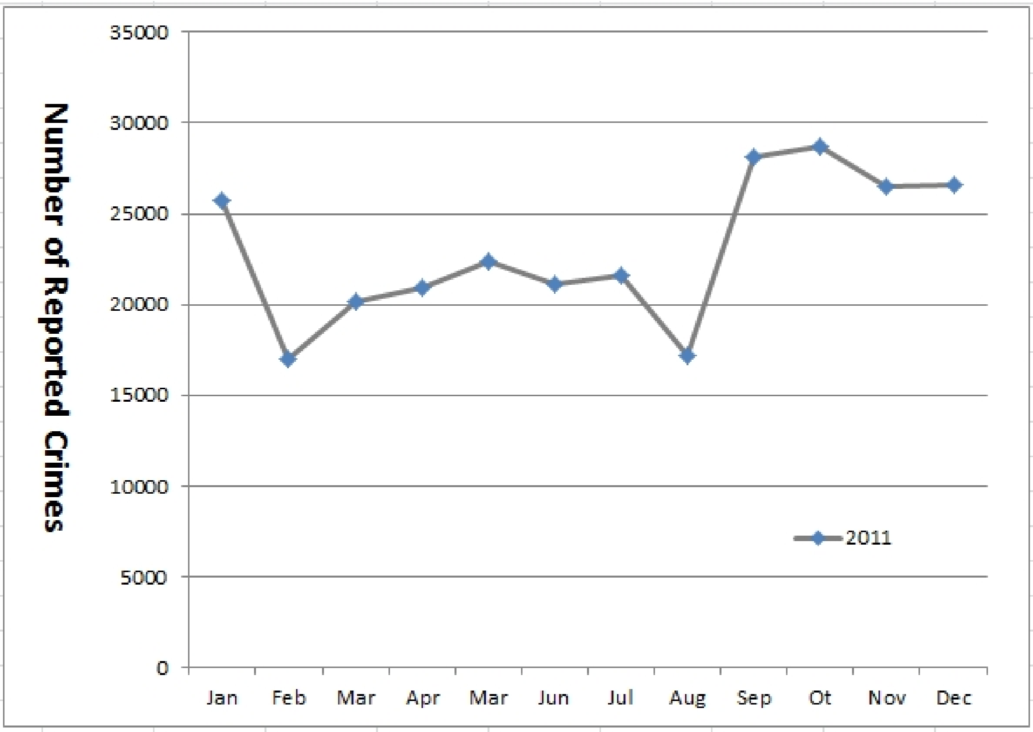

Figure 5. 2 Monthly trends of Part 1 Crimes in Houston, TX in 2011

In the previous chapter, I used three predictive accuracy measures (the hit rate, the PAI, and the RRI) to evaluate the performance of the eight spatial hotspot mapping methods in predicting future crimes. In terms of assessing the predictive accuracy of the spatial-temporal hotspot mapping methods, these three measures are not applicable since they do not take the time factor into account. Hence, the spatial-temporal predictive accuracy measures must contain a time factor.

Nowadays, no specific spatial-temporal predictive accuracy measure have been provided or applied in the literature. Without the use of this specified measure, it would be difficult to be able to evaluate which spatial-temporal hotspot mapping method outperforms the other, or if one spatial-temporal hotspot mapping technique results in a higher accuracy in the crime prediction in the future.

5. 1 Measures of Spatial-Temporal Predictive Accuracy

The definition of the spatial-temporal prediction accuracy measures could derive from the three commonly used spatial predictive accuracy measures. Since the time factor has to be taken into consideration, and the ways of how this time factor be considered vary, there exist different variants of spatial-temporal predictive accuracy measures. In this research I will provide several different definitions of this measure.

Similar to the hit rate, the spatial-temporal hit rate could be defined as the percentage of new crimes that occur within the areas where crimes are predicted to occur divided by a time factor.

Since in this research the time stamp is one month, we can count the number of the months in which crimes are predicted to occur divided by 12 months. The result could be the time factor. The formular is as follows:

$$\frac{\dfrac{number\ of\ crime\ in\ 2012\ falling\ into\ spatial - temporal\ hotspots\ in\ 2011}{all\ 2012\ crimes}}{\dfrac{sum\ of\ temporal\ months}{12\ \ month}} \qquad (5-1)$$

If we look further into how we calculate the time factor, we could find that several months (these months are associated with the predicted crime clusters) actually occur more than once while others do not occur at all or just occur once. Considering this, we can calculate the time factor as the division of the number of the months in which crimes are predicted to occur and the sum of the month that occurred greater than or equal to once plus 12 for each month. The adjusted formular for (5-1) is as follows:

$$\frac{\dfrac{number\ of\ crime\ in\ 2012\ falling\ into\ spatial - temporal\ hotspots\ in\ 2011}{all\ 2012\ crimes}}{\dfrac{sum\ of\ temporal\ months}{\sum_{1}^{12} 12 + sum\ of\ the\ month\ that\ occured\ greater\ than\ or\ equal\ to\ once}} \qquad (5-2)$$

In formular (5-3), the time factor is calculated as the sum of temporal months divided by number of clusters times 12.

$$\frac{\dfrac{number\ of\ crime\ in\ 2012\ falling\ into\ spatial - temporal\ hotspots\ in\ 2011}{all\ 2012\ crimes}}{\dfrac{sum\ of\ temporal\ months}{number\ of\ clusters * 12\ \ month}} \qquad (5-3)$$

Similarly, if we keep the time factor unchanged as (5-1), and we calculate the hit rate for each twelve months, then we get the following formular (5-4):

$$\frac{\sum_{i=1}^{12} \dfrac{\substack{number\ of\ crime\ in\ 2012\ falling\ into\ spatial - temporal \\ hotspots\ in\ each\ month\ of\ 2011}}{all\ 2012\ crimes\ in\ each\ month}}{\dfrac{sum\ of\ temporal\ months}{12\ \ month}} \qquad (5-4)$$

If we keep the calculation of the hit rate unchanged as (5-4), and change the way we calculate the time factor. Then we get formular (5-5). In the numerator and denominator of the formular (5-5), we calculate for each of the twelve months and then sum them up.

$$\frac{\sum_{i=1}^{12} \dfrac{\substack{number\ of\ crime\ in\ 2012\ falling\ into\ spatial - temporal \\ hotspots\ in\ each\ month\ of\ 2011}}{all\ 2012\ crimes\ in\ each\ month}}{\sum_{i=1}^{12} \dfrac{sum\ of\ temporal\ months}{12\ \ month}} \qquad (5-5)$$

Formulars (5-1) to (5-5) are all based on the time stamp, here, one month. For the spatial-temporal hotspot analysis, predicted crimes are spatial-temporal clusters. Normally, the number of these spatial-temporal clusters are no more than 20. Thus, if we could calculate the number of crimes and the sum of temporal months for each cluster and then sum them up we then could get formular (5-6) and (5-7).

In formular (5-6), the numerator is calculated as the sum of the number of new crimes that occur within the areas where crimes are predicted to occur for various clusters divided by all the new year's crimes. The denominator is calculated by the sum of temporal months for each cluster divided by the number of clusters times 12.

$$\frac{\dfrac{\sum_{i=1}^{number\ of\ clusters} number\ of\ crime\ in\ 2012\ falling\ into\ spatial-temporal\ hotspots\ in\ each\ cluster\ of\ 2011}{all\ 2012\ crimes}}{\dfrac{\sum_{i=1}^{number\ of\ clusters} sum\ of\ temporal\ months\ for\ each\ clusters}{number\ of\ clusters * 12\ month}} \quad (5-6)$$

In formular (5-7), the time factor is calculated as the sum of temporal months divided by 12 months.

$$\frac{\dfrac{\sum_{i=1}^{number\ of\ clusters} number\ of\ crime\ in\ 2012\ falling\ into\ spatial-temporal\ hotspots\ in\ each\ cluster\ of\ 2011}{all\ 2012\ crimes}}{\dfrac{sum\ of\ temporal\ months}{12\ \ month}} \quad (5-7)$$

5. 2 Comparison of Different Spatial-Temporal Predictive Accuracy Measures Using Space-Time Scan Statistic

The space-time scan statistic has been one of the most widely used methods in the analysis of spatial-temporal data. It is derived from the space scan statistic which is aimed to identify spatial clusters by imposing circular windows with various radii to scan across the study area (Kulldorff, 1997). Each circular window with a particular radius assigned to it will cover sets of neighboring areas and a likely candidate of including a hotspot or cluster. In accordance with Kulldorff (1997), the formula to calculate the spatial scan statistic is as follows (formula 5-1):

$$S = \frac{max_z L(Z)}{L0} \qquad (5-1)$$

where S is the spatial scan statistic. Z is the set of circles of the scanning windows. L(Z) is the likelihood ratio for circle Z. $L0$ is the likelihood ratio under the null hypothesis. S is essentially the maximum likelihood ratio of all circles divided by the likelihood ratio computed from the null hypothesis. Thus, the cluster contained in the circle with the maximum likelihood scan statistic is also the most likely cluster. Furthermore, in order to test the distribution of the test statistic, whose actual distribution remains unknown, Monte Carlo simulations are utilized. Under the null hypothesis that cases within the study area taking place at random following a user-defined model, the program then calculates values of the scan statistic for both the real dataset and the simulated datasets (Zeng et al., 2004). If the calculated value of the scan statistic of the real dataset is more than 95% of all the values, then the identified cluster or hotspot is significant at 95% level.

The spatial-temporal scan statistic is based on the spatial scan statistic. The spatial scan statistic is viewed as a 2D crime map, which uses a circular window scanning the study area. While after adding a time factor the spatial-temporal scan statistic employs a 3-D cylinder to scan the area both horizontally and vertically. The circular window now serves as the base of the cylinder and time is measured by the height.

In this research the Kulldorff's spatial-temporal scan statistic is used to detect crime clusters in space and time. The software used to apply Kulldorff's scan statistic is SaTScan which was developed by Kulldorff (Kulldorff, 2001, 2005). The input data are X, Y coordinates (the spatial component) and the date (day) when the crime happened (the temporal component).The space-time permutation model was chosen in the analysis. Other settings were not changed from the defaults provided in SaTScan. The dataset used here is all Part1 Crimes from January 2011 to December 2011. One month was selected as the temporal unit. The calculation in SatScan is very time-consuming. It took more than 62 hours on a computer (i5-2400QM CPU, 3.10 GHz, 8 GB RAM) to perform the Kulldorff's spatial-temporal scan statistic.

After the introduction of Kulldorff's scan statistic, I then apply the formulars (5-1) to (5-7) to calculate the values of the newly-designed spatial-temporal predictive accuracy measures. The results are shown in Table 5.1.

From the results we can see that the values of the various spatial-temporal predictive accuracies are relatively small compared to the spatial predictive accuracy measures. This could be addressed by introducing some constant value into the formulars. The different measures for different crime types are relatively consistent. For example, Burglary always has a largest value for various spatial-temporal predictive accuracy measures among different crime types.

Since these measures were only applied to the space-time scan statistic, more spatial-temporal hotspot mapping methods should be utilized to obtain a better assessment of the appropriateness and correctness of these newly designed measures.

Table 5.1 Results of the spatial-temporal predictive accuracy measures for each crime type using Kulldorff's space-time scan statistic

Space-Time Predictive Accuracy	Overall Part1 Crime	Aggregated Assault	Auto Theft	Burglary	Larceny Theft	Robbery
(5-1)	1.55(%)	0.48(%)	3.69(%)	6.79(%)	1.74(%)	2.99(%)
(5-2)	0.20	0.03	0.24	0.32	0.22	0.06
(5-3)	0.26	0.03	0.15	0.28	0.24	0.06
(5-4)	1.46(%)	0.40(%)	3.15(%)	6.72(%)	1.58(%)	2.80(%)
(5-5)	0.14	0.01	0.15	0.21	0.13	0.04
(5-6)	0.24	0.03	0.11	0.27	0.22	0.05
(5-7)	1.53(%)	0.48(%)	3.67(%)	6.75(%)	1.73(%)	2.98(%)

CHAPTER 6 CONCLUSION

With the advance of Geographic Information Systems (GIS) and crime theories, crime hotspot mapping and analysis have been drawn increasing attention. Crime researchers and practitioners have put a lot of effort into studying how crime hotspot mapping can be used to assist police decision makers with allocating their limited resources and manpower to areas where crime events are most likely to occur. This thesis research used all 2011 and 2012 reported Part1 Crimes data from the city of Houston, TX. Eight hotspot mapping methods were employed to produce hotspot maps and their corresponding predictive accuracies for all Part 1 Crimes combined. In addition, nine individual crime-type hotspot maps were created and the predictive accuracies were calculated. For each crime type, the “best” method among the eight hotspot mapping techniques was identified, after comparing the predictive accuracy results across the eight mapping techniques with each other. In addition, spatial-temporal analysis using hotspot plots and Kulldorff’s space-time scan statistic were performed for the same crime dataset, and study area. Maps showing crime clusters which were statistically significant, both spatially and temporally, were created.

The results from this research could provide valuable suggestions for law enforcement agencies in Houston to adapt their decision-making strategy based on the type of crime involved. For example, if an area is predicted to have a high rate of robbery, then a deterrent force, such as the armed police patrol, should be used to control this area. Also, the hotspot map and its predictive accuracy for all crime types combined will help the police allocate their limited resources more effectively and efficiently. For instance, if an area is predicted to have a high rate of multiple crime types, then this place should be paid most attention to by the police. If one area is predicted to have a high rate of burglary, but another is predicted to have a similarly high rate of assault, then the area with the predicted high rate of assault should receive more patrols in the future.

The results in this thesis research indicate that the type of hotspot mapping method chosen markedly affects the predictive accuracy. Moreover, by using different measures of predictive accuracy, the extent to which hotspot methods affect predictive accuracy results varies, as well. For example, the hit rate yields the best predictions with the grid thematic mapping method. However, the kernel density estimation (KDE) method predicts future crime incidents the best if the PAI and the RRI are applied. Since the KDE method also yields a hit rate, this method could thus be identified as the most accurate method at predicting all Part 1 Crimes combined.

The kernel density estimation and the nearest neighbor hierarchical clustering are the two methods which result in the highest RRI and PAI across the five crime types selected. In contrast, for the hit rate, no single hotspot method consistently possesses the highest prediction across the five crime types.

In terms of the temporal factor, seven spatial-temporal predictive accuracy measures were designed. And the Kulldorff's space-time scan statistic was used to calcite the values of these new measures. While the validity and correctness of these measures remain further verified, they offer some possible alternatives to researchers if they are conducting researches related to the comparison of different spatial-temporal hotspot mapping methods.

One issue which has to be drawn particular attention to is related to the sampling method. In most of the social work study, the dataset used in the analysis consist of all observational records, which is to say, no sampling process was conducted to select the dataset to be analyzed. The approach used in this thesis research could be considered to be a social work approach. While in the field of engineering, a random design study is usually conducted to randomly select the records to be included in the analysis. The experimental design requires the knowledge of statistics. Further research could be focusing on this engineering approach.

Of course, this thesis research has some limitations. First, the crime data analyzed are limited to the nine Part 1 Crime types, which may not provide useful information for the analysis of other crime types. Second, the study area of this research is limited to the city of Houston, TX. The implications from the results of this research may thus not be applicable to other urban study areas. Third, although in this research the effect of hotspot methods and crime types on predictive accuracy has been investigated, other issues (e.g. study area, parameter settings, threshold selection, geocoding quality, etc.) may also contribute to the resulting predictive accuracy. Finally, the time span of the spatial-temporal analysis is two years, which may not be sufficient for preforming a credible and accurate spatial-temporal hotspot map for predicting future crimes.

Accordingly, future research could emphasize the following aspects. First, variations of other factors, such as the study area, parameter settings, and the threshold selection could be examined to investigate the effect that these factors have on the ability to predict future crimes. To implement this, crime data from alternative urban study areas should be evaluated, and a series of different sets of parameter settings and threshold selections should be investigated and their predictive accuracy results compared with each other. Second, Part 1 Crimes can also be categorized as violent or non-violent crimes. Redoing the analysis from this research with these two crime categories could also be carried out. Hotspot methods not selected for this thesis research could also be applied. Third, for spatial-temporal analysis, cluster maps for each of the five of the nine individual crime types could be produced rather than just for the overall Part 1

Crimes combined. Finally, more researches will be done further to obtain a better design of the spatial-temporal predictive accuracy measures. For example, the area factor or other factors could also be included in the calculation of measures. Further researches could also be focused on the validation of these newly designed measures. To accomplish this, more spatial-temporal hotspot mapping methods and more study areas are needed.

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