Property Crime in The City and County of San Francisco 2016–2017

Applying GIS to Crime Pattern Theory

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- Emma Edholm
ABSTRACT

This study’s aim is to reveal statistically significant hot spots and temporal patterns of property crime in the City and County of San Francisco and to also analyse the relationship between property crimes and the environment in which these crimes occur by using Geographic Information System (GIS). Crime pattern theory was used as the framework for the analysis of environmental surroundings and occurrence of crime. This theory indicates that certain places can be crime generators and attractors. The result showed that there are hot spots of crime in the north-eastern part of San Francisco, and that crime in these high-risk areas are intensifying. Then, by visual examination of density maps of property crime and facilities, such as shopping centres, pubs/bars/nightclubs and Bay Area Rapid Transit stations, it is shown that these facilities can explain concentrations of crime in certain areas. Furthermore, this study shows GIS can be a practical tool to utilize when presenting data of crime when used in combination with social theories which focuses on the causes of crime occurrence.

Keywords: GIS, crime pattern theory, environmental criminology, hot spots of crime
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1. Introduction

Research shows that crime is not randomly distributed on a map. Instead, crimes can be concentrated in certain places while other areas are not affected by crimes as much (Sherman, Gartin, & Buerger, 1995; Eck, et. al., 2005; Cozens, Saville & Hillier, 2005). Crime is often concentrated to certain places or areas, these can be where people live and where they travel or move within a city (Brantingham & Brantingham, 2008). An example on concentrations of crime can be seen in a study by Sherman et al. (1989) where they looked at incoming calls from different addresses in Minneapolis during 1985. The study showed that 50.5% of all calls which were made to the police came from 3.3% of all addresses in the city. Also, over the course of one year there was at least one call was generated from 60% of all addresses within the city. Although, half of those addresses made only one call and no more. At the same time did the top 5% of all addresses generate an average of 24 calls each, which is about one every two weeks. Furthermore, the concentration of crime was discovered to be even greater when it came to predatory crimes. This includes robbery, criminal sexual conduct and auto theft. Out of the calls that were linked to these kinds of crimes were 100% concentrated to only 5% of the 115 000 street addresses in Minneapolis.

The concentrations of crime are called hot spots. Eck, et.al. (2005) argue that the term hot spot of crimes has no common definition, but there is a common understanding which mean that “an area that has a greater than average number of criminal or disorder events, or an area where people have a higher than average risk of victimization” (Eck, et. al., 2005, p. 2).
Environmental criminology is a gathering of theories which share an interest in crime and its immediate spatial surroundings (Hiropoulos & Porter, 2014). Researchers look at crime patterns and try to find and explain the environmental influences at the locations of which crime occurs. There are other theories of criminology which are focusing on biological development or/and social factors which influence criminal offenders, while this perspective is intent to research the occurrence of the crime itself. By the development of computerised mapping and spatial analysis techniques the environmental perspective has advanced. These spatial analyses are carried out in Geographic Information Systems (GIS), which hold, manage and visualise spatial data in a way which can considerably improve the ability to look more closely on the relationship of crime and place (Hiropoulus and Porter, 2014).

There are three premises when it comes to the environmental perspective of crime. Firstly, the surrounding environment has a significant impact on criminal behaviour. Individuals' behaviour is viewed as a result from person-situation interaction, and the environment plays an important part in the initiation of crime and on how it plays out. Secondly, crime does not occur randomly in space and time. Crime is distributed according to criminogenic environments’ locations and, therefore, concentrates close to crime opportunities and further environmental features which attract activities of crime. And lastly, finding the relationship between criminogenic environments and crime pattern is a valuable tool to prevent crime (Hiropoulus and Porter, 2014). Hiropoulus and Porter (2014) also mean that the field of environmental criminology gets a lot of critique, examples of those critiques are that it remains theoretically shallow and empirically narrow and that theories have a lack of depth.
When used in combination with relevant theories which a focus on the affecting factors of crime occurrence, GIS can be a powerful tool in visualising crime data. In this study GIS is used to give focus to the methodological practicality of environmental criminology. Specifically, the focus will lay on the city and county of San Francisco. In 2017 San Francisco saw a rise of property crime and had the highest property crime rate out of big cities in the USA (Cassidy & Ravani, 2018, Oct. 1). Leif Dautch—who is running for district attorney in San Francisco—tells The Economist (2019, 16 Feb) that “It feels like an epidemic because it is an epidemic”. Because of the rise of property crimes and the detailed data that was available was San Francisco seen as a significant study area for this analysis. In this study these kinds of crimes are studied through the visualization of spatial patterns by looking at the occurrence of crime in relation to its local surroundings. The study’s result can contribute to further understanding of crime occurrence and its surroundings, and the usefulness of using GIS when visualising and working with crime data.

1.1 Aim and Research Questions
The aim of this study is to, firstly, identify statistically significant hot spots and temporal patterns of property crime in the city and county of San Francisco in 2016–2017. Secondly, to visualise the relationship between the occurrence of crime and the locations in which they occur within the city and county by using GIS. This will be done through answering these research questions:

- How does the pattern of property crime look in relation to residents in the city and county of San Francisco 2016–2017?
- In which areas are there statistically significant hot spots of property crimes and what is the temporal pattern of those hot spots?
- Is there a clear relationship between density of property crime and environmental surroundings?
- Is GIS a practical tool to utilize when presenting crime data when used in combination with crime pattern theory?

2. Previous studies and Theoretical Framework

2.1 Crime Pattern Theory

Environmental criminology is seen as a crucial part of the scientific study of spatial patterns in crime, environmental awareness, and offender's perceptions and their mobility patterns (Mogavero & Hsu, 2018). There are many environmental criminological theories and one of them is crime pattern theory (Brantingham & Brantingham, 1981). Eck & Weisburd (2015) mean that this theory has been important for the understanding of crime and its distribution across space. The theory seeks to explain hot spots of crime by looking into the way that, in their everyday lives, offenders seek and find opportunities to commit crimes (Hiropoluos & Porter, 2014).

Crime pattern theory includes both routine activities theory and rational choice perspective and focuses on spatial movement (Mogavero & Hsu, 2018). Routine activities theory can be explained as a crime triangle. Sherman (1995) compares it to a triangle much like the three elements of fire, i.e. oxygen, heat, fuel. All three components are needed to start a fire. As for a crime to occur, the theory means that a target, an offender, and lastly, an absence of a guardian is needed. Guardians are defined as people
who can protect targets from crime. This includes formal authorities like public police and security guards, but it can also be a friend or a family member (Eck & Weisburd, 2015). Even though a lot of other factors can play a big part in the occurrence of crime, the theory indicate that these three components are the bases of crime occurrence.

Rational choice perspective concludes a range of criminological perspectives, i.e. classical and economic theories of crimes (Cote, 2002). The theory means that “crimes are the result of broadly rationalized choices based on analyses of anticipated costs and benefits” (Cornish & Clarke, 1986, p. xviii). Instead of having a focus on what makes criminals unique and stand out from others, the theory concentrates on the criminal event itself and what situational factors influence the crime to occur (Cote, 2002).

Crime pattern theory includes three main concepts; nodes, paths and edges (Hiropoulos & Porter, 2014). Nodes are the locations of which people travel to and from. These nodes can be shared by many people; thousands of people do their shopping at the same mall, or work in the same office complexes, or go watch movies at the same cinema. They also mean that nodes can be junctions of major paths, i.e. railway terminals, bus stops. They are areas where people leave one path to go on another (Brantingham & Brantingham, 1984). It is either at or close to these nodes that crimes are committed since a lot of people gather or move through those places (Brantingham & Brantingham, 1995).

Paths are what shape routine activities, everyday life and also special events; they are what determine how people move (Brantingham & Brantingham, 1995). These movements are spatial biased; people do not
move randomly within a city, region or a country (Brantingham & Brantingham, 1984). People spend much time on their routine paths. They travel to and from school, work, shopping, entertainment, etc. It is also possible that, on these paths, offenders search for criminal targets and people become victims of crime. A city’s traffic and transit pattern does influence the distribution of certain crimes. Crimes tend to cluster close to traffic arteries, which creates hot spots at or nearby, for example, bus stops, subway exits, etc. (Brantingham & Brantingham, 1995).

The boundaries of areas where people live, work, go shopping or go to seek entertainment are called edges (Hiropoulos & Porter, 2014). Brantingham & Brantingham (1984) mean that physical and perceptual edges are everywhere. They can be considered as physical barriers, i.e. land bordering on a river or a road with another land use on the other side. Or they can be perceptual, like the uneasiness a person can feel when entering areas which are unknown.

Brantingham and Brantingham (2008) mean that crimes do not occur completely randomly in time, space or society, nor do they occur randomly across neighbourhoods, social groups, or during peoples’ daily activities or lifetimes. This is because there are hot spots and cold spots. Places where a large amount of people gathers are categorized as crime generators and attractors (Brantingham & Brantingham, 1995). Meaning that these places produce crime by creating a concentration of people at a certain time. Crime generators do not necessarily attract people because of a criminal motivator, nor are they related to any crime types which any of these people who go there might end up committing. Examples of these places can be shopping centres, sport stadiums, entertainment districts, etc. These places produce crime by creating a concentration of people at a
certain time. Then there’s also crime attractors. These are areas are known for having a high chance for successfully committing crimes and therefore attract offenders. Facilities that are considered crime attractors gathers possible victims either at them or in their closest surroundings. These kinds of places can be bars or shopping centres. Particularly those that are close to major public transport exchanges are sensitive to crime occurrences. They also mean that places can be identified as both crime attractors and generators, meaning there are areas that don’t have to be recognised as one or the other but can be both (Brantingham & Brantingham, 2008).

Brantingham & Brantingham (2008) also mean that the urban backcloth has an important effect on how crime is patterned in a city. Certain land-use, individuals’ socio-economic status, or which economic forces the city is driven forward by are categorized as elements of the backcloth. Also, an urban backcloth is not static; a city and its people activity are very different during day- and night-time. For example, some entertainment nodes are closed during the night, while other’s open in the evening or on the weekends. Shopping centres, for example, are open during the day, while bars open and attract people in the evenings and during the night. This is the underlying rule of crime pattern theory since crime generators and attractors are created by high flows of people who move on paths to and thorough nodal points. They also mean that it is no longer plausible to argue that crime happens randomly. For example, bar fights do occur more commonly on Friday or Saturday nights than on weekdays; income tax evasions cluster close to due dates; shoplifting is more common in certain stores and occur more frequently during a certain set of hours in the day.
Since crime pattern theory deals with large areas, such as communities, square blocks and census tracts, it is appropriate for this study since it looks at the occurrence of property crime at the precinct level, i.e. concentrations of crime in neighbourhoods within the city. This theory is also very well-suited for data visualisation through Geographic Information Systems. And since this study’s aim is to examine the relationship between property crime and the environmental surroundings at which they occur, crime pattern theory is seen as a fitting framework to use for this study. This can give further understanding of crime and place, and be useful in the work with preventing crime.

2.2 Crime and Place

The interest in crime and space is not new; studies of this have been acknowledged since the early nineteenth century (Cozens, Saville & Hillier, 2005). Quetelet (1835) and Guerry (1833) are two researchers who studied and mapped out areas in French cities which had a high potential for crime to occur. They studied the relationship between social factors in areas, such as poverty and level of education, and arrest rates. In the 1930’s researchers at University of Chicago mapped out crimes committed by juveniles by pinning out, by hand, each juvenile delinquents’ residence in Cook County, Illinois. Via this strategy could Shaw and McKay (1942) see that certain areas of the city had high crime rates that were consistent over several decades (Anselin, et. al., 2008). Although, Eck & Weisburd (2015) mean that the early studies of the relationship between crime and place took a macro approach, meaning they looked at crimes from a point of view of regions, states, cities, neighbourhoods, communities, etc., while recent studies are more focused on a micro-level relationship between crime and place (Eck & Weisburd, 2015). These studies first started at identifying the relationship between crime and urban design. C.R.
Jeffery’s ‘crime prevention through environmental design’ started out as an independent theory about place-based crime prevention but is today being applied to spatial planning worldwide (Cozens, Saville & Hillier, 2005). Although, the studies then broadened and a wider set of characteristics of the physical space was accounted for. Also, then were the opportunities of the criminal taken into consideration as well. They saw a distinction between the locations in which crimes occurred and the larger geographical areas, i.e. city, neighbourhood, community, etc. In this micro context places are seen as specific locations within a larger social environment. These locations can be either a small area, for example, right next to an ATM, or a bigger area such as a shopping strip (Eck & Weisburd, 2015).

Research shows that land-use as well as the location of certain facilities play an important role in the shaping of the behavior of humans and in setting the stage for crime to take place (Groff, 2011). The land use characteristics that is seen as one of the most consistent when it comes to describing hot spots is the presence of entertainment venues (Anselin, et.al., 2008). Ceccato (2009) mean that areas such as night-life districts are vulnerable to crime. Roneck and Maier (1991) found a strong connection between higher crime rates and the number of taverns and lounges in city blocks of Cleveland. In Sherman, et al. (1989) study of incoming calls to the police in Minneapolis five out of the top ten hot spots had bars. Another study by Deryol et.al (2016) made a statistical test of the development of hot spots and how paths, nodes and environmental backcloth have an effect on their formation. The analysis was made on the city of Cincinnati, Ohio. A total of 33 105 crime incidents was used stretching over a time period of 2010 to 2012. The Euclidean distance was used to measure the distance between the location of the crime to the
closest carry-out liquor store/on-premises drinking establishment, and bus route. The result showed that the distance to nodes which sold liquor and the distance to closest bus stop was significant and could be related to the crime incidents. It also showed that the interaction of liquor establishments, bus stops, and crimes had varied effects in different neighbourhoods. For example, neighbourhoods which were characterized by a higher level of commercial density had a stronger negative effect on crime occurring. Also, Stucky and Ottensmann (2009) mean that neighbourhoods which have commercial land-use, residential areas with tall buildings and a high population density have a risk for higher crime rates than other areas. Furthermore, locations which work as transportation hubs are running on a higher risk to have more common occurrences of crime (Ceccato, 2009).

Along certain streets people might take another look over their shoulder or lock their cars, while on other streets, they will not. This proves that there’s an understanding that crime is not evenly distributed on a map. And although, people might sometimes be wrong about the risks of crime in certain areas, they do not mistake that the risk of becoming a victim of crime is not geographically constant (Eck, et.al, 2005). This study can give a further understanding of crime distribution and its possible relation with certain facilities and movements of people.

3. Study Area

3.1 The City and County of San Francisco
San Francisco, officially the city and county of San Francisco, is located on a peninsula between the San Francisco Bay and Pacific Ocean in northern California, USA. It is located right at the heart of The Bay Area which includes nine counties that surrounds the San Francisco Bay (see figure 1).
Within the Bay Area there is a population of approximately 7 million people (Bay Area Census, 2019). The Bay Area does not have a typical metropolitan area with just one city centre which is surrounded by suburbs, instead is the population spread throughout several cities and suburbs. The city and county of San Francisco got its municipal charter in 1850 after the Gold-rush in 1848 which lead to an increase of the population from 800 to 30 000 in only two years (Nationalencyklopedin, 2019). As of 2016 the city and county had a population of 864 800. In 1906 big parts of San Francisco was destroyed by an earthquake (US Geological Survey, 2019). It is located on top of the San Andreas Fault which results in a high risk of earthquakes in the area. Also, San Francisco is seen as unique since it is full of different geographic elements and filled with people of various backgrounds and different cultures (San Francisco Urban Planning, 2019). Chinatown in San Francisco is the most-known Chinese community in the United States, for example (Britannica, 2019). Moreover, San Francisco is known for its tolerance for diversity and is seen as a mecca for the HBTQ community (Encyclopedia, 2019).

The cityscape is of a classic American grid street plan which is spread over a much hilled terrain which has given the city its characteristic steep streets (NE, 2019). Within the city and county there are 41 neighbourhoods which has been officially identified by the San Francisco Planning Department (DataSF, 2019a) (see figure 2). On the northern tip of the county and city is the Presidio, a park and a former U.S. Army military fort which overlooks the Golden Gate Bridge. Also, in the northern part of San Francisco you will find the Pacific Heights, which is known to be a wealthy neighbourhood. Then there is North Beach where you’ll find Fisherman’s Warf and Pier 39 which attract a lot of tourists. South of North Beach lies the city centre which include Chinatown, the Financial
District/USF and Tenderloin. To the west of Downtown is the Western Addition that is known for its well-restored Victorian homes. Close to the city centre there’s districts like Haight-Ashbury, birthplace of the 1960’s counterculture movement; Mission District, which holds the city’s largest Hispanic population; Castro, the mecca for the HBTQ community; and the South of Market district which is a commercial area that has attracted lots of start-up firms in the high-technology- business. Stretching five kilometres from Ocean Beach towards the heart of the city is Golden Gate Park which is the city’s largest urban park of a total of 406 hectares (Encyclopedia, 2019).

The most populated neighbourhood is Sunset/Parkside. This is also one of the largest neighbourhoods and consists mostly of urban residential houses. It has a population of 65 001–85 000. Mission is the next most populated neighbourhood. The neighbourhoods with the least population are, firstly, Lincoln Park, Golden Gate Park, and McLaren Park, which is understandable since these are the city and county’s park areas. But there are also neighbourhoods which are residential which has a low population, these are Lakeshore, Glen Park, Twin Peaks, Mission Bay, Chinatown, North Beach and Treasure Island with a population of 0–15 000 (see figure 3)

As for transportation to, from and within San Francisco there is the Bay Area Rapid Transit (BART) which provides a commuter rail service with 46 stations which connect San Mateo County, the city and county of San Francisco and the East Bay Area. There’s a total of eight stations within the city and county of San Francisco (Encyclopedia, 2019). Powell Street Station, Montgomery Street and Civic Center are the busiest stations, both within the city but also out of all stations within the whole transit system,
with Powell Street Station being the one with most people departing and arriving (BART, 2019) (see figure 4).

Figure 1 Overview map of counties in San Francisco Bay Area (source: own figure)
Figure 2 Neighbourhoods within the city and county of San Francisco (source: own figure)

Figure 3 Population in each neighbourhood in San Francisco (source: own figure)
3.2 Crime in the City and County of San Francisco

In 2017 FBI released crime statistics which showed that property crime had declined in the US from 2016 but San Francisco saw a rise (Federal Bureau of Investigation, 2018). In this study the focus will be of property crime since these kinds of crimes in San Francisco has been increasing and in 2017 the city had the highest per capita property crime rate of any major city in the USA, which is just a continuation of a trend which has been going on for a couple of years. There were 54,356 property crimes in 2017, which is an increase from 2016 where up to 47,402 property crimes occurred, this is according to FBI Statistics (2019). 54,356 property crimes in 2017 corresponds to 6,168 crimes per 100,000 people in the city and county of San Francisco. In comparison with the 100 most populated cities in the USA, the average crime rate per 100,000 people was 3,582 in 2017 (Federal Bureau of Investigation, 2018).
Lonely Planet (2019) recommend being careful in districts such as Tenderloin, South of Market, The Upper Haight and the Mission during night-time. Smarter Traveler (2018) also mean that Tenderloin, Mission District and Union Square are areas where your attention should be on high alert; especially at night. Tenderloin is a neighbourhood which has for long been known for its street drug trade.

4. Method
The analysis of this study was made with a quantitative spatial analysis to detect patterns of crime in the city and county of San Francisco between the years of 2016–2017. This was done by using property crime data which were geocoded and managed in the geographical information system ArcGIS Pro 2.2.1. The property crime data was then analysed to see if there were statistically significant hot spots of crime within San Francisco, how the temporal pattern over the course of the two years had changed, and if there was any clustering of property crime close to or around criminogenic environmental factors which are specified in the crime pattern theory.

4.1 Workflow
A multi-step spatial analysis was done to be able to visualise the distribution of property crime in the city and county of San Francisco. Firstly, a hot spot analysis was made to see which clusters of property crime in San Francisco were statistically significant. Moreover, an emerging hot spot analysis was done to be able to see how clusters of property crime have changed over the time period of 2016–2017. Then a Kernel density analysis was made of the property crime data to detect patterns of clustering. Three of these analyses were made. One analysis of all property crimes that had occurred 2016–2017. And then the crimes
were divided into day- and night-time. Day time stretched from 06:43 to 20:30 and night-time from 20:31 to 06:42. This was done to be able to compare crime pattern during the day and night within San Francisco. To select at what hour the property crimes would be divided into day and night an average sunset and sunrise time was calculated. This was done by taking the time of sunset and sunrise on the first day of each month in 2016, and then the time for sunset and sunrise on the 15\textsuperscript{th} day of each month in 2017. This was done to get a more precise average time for sunrise and sunset. If only the first day of each month would have been used, the average time would have been more generalised. An average of these collected times was then calculated. For sunrise the average time of 06:43 was used, and for sunset 20:31. Daytime property crimes were a total of 80 179 and night-time property crimes added up to 32 533. The crimes were divided by the number of hours in which they occur to normalize them. Meaning, the crimes which occurred between 06:43 and 20:30 were divided by 13,8 since that’s the time period used for day crimes in the study. Crimes which then occurred during the day were divided by 10,2, while all property crimes were divided by 24, i.e. the total amount of hours in one day. These Kernel density maps were then normalised with the population density to see how the relation between property crime and the city and county’s residents look like. The Kernel density of property crime was also used in the final analysis were different facilities overlaid on top to see if there was any relationship between the density of property crime and nearby facilities.

4.2 Data
To be able to detect and analyse property crime patterns in San Francisco crime data from DataSF’s website was downloaded. This website’s aim is to give easy access to data for San Francisco residents, employers,
employees and visitors (DataSF, 2019b). The crimes were reported between 01/01/2016 and 12/31/2017. These dates were chosen since San Francisco saw a high increase of property crimes from 2016 to 2017; from 47 402 to 54 356 (Federal Bureau of Investigation (2019a) (see figure 5). They were chosen to see how the distribution of these kinds of crimes looked like in San Francisco. Federal Bureau of Investigation (2019b) mean that property crimes include the offenses of larceny-theft, burglary, motor vehicle theft, and arson. Therefore, these four crimes were filtered and downloaded from the crime data base at DataSF. In all 112 712 reported crimes were used in the analysis. Included in this data was the place the crime occurred, the date and time for when it occurred, and a description of the crime. This data was then geocoded in GIS. This is a method by which an address is given precise geographic coordinates (Anselin, et.al., 2008). It should be noted that the crime data don’t include if the crime was solved or if it was reported legitimately. Also, the data only include crimes which have been reported, and therefore, you can assume that the data does not represent all property crimes that happened in San Francisco in 2016–2017. Not all crimes get reported. It should also be notified that crime data in the USA are shown at an intersection level, meaning that crimes that has occurred on properties or in buildings are moved to the closest street. Although, from an ethical standpoint this is a necessity since if the crime data could be tracked to buildings and properties it could therefore risk the identifications of individuals (Data SF, 2019b).
Also, although the property crimes have increased in San Francisco it is important to notify that it does not mean that all sub-crimes included in the category of property crimes has increased. Arson and larceny theft have seen an increase from 2016 to 2017 while burglary and motor vehicle theft have decreased. (See Appendix 1 for graphs of each sub-crime). The increase of property crimes is almost only dependant on the increase of larceny theft, which is the crime type included in property crimes with highest rates overall. The choice to still include all sub-crimes even though they have not all increased was made since, in overall, property crime has increased within San Francisco. See the change for all sub-categories in the appendix 1.
The data and shapefiles which were used in creating the maps were either downloaded from OpenStreetMap (2019a), DataSF (2019) or United States Census Bureau (2019a). United States Census Bureau provides current quality data about the country’s people, places and economy (United States Census Bureau (2019b). OpenStreetMap (2019b) is an open portal to geographic data all over the world. Data which was used from here include facilities and land area. The facilities used are bars/pubs/nightclubs, shopping centres and BART stations. It should be noted that OpenStreetMap is not run by any official authority but is edited and created by people around the world. Any official data of facilities was not found. Because no official data could be found there might be facilities left out of the analysis, but since OpenStreetMap is an open platform and anyone can add data to it, the most well-known and major facilities should be included in the data that was used. After having removed the shopping centres, pubs/bars/nightclubs and BART stations that were located outside of the study area a total of ten shopping centres and 409 pubs/bars/nightclubs were included in the data and used in the analysis. As for the BART stations, there are eight of them inside the city and county of San Francisco, which are the ones that are used in the analysis.

4.3 Ethics
It should be noted that crime data in the USA are shown at an intersection level, meaning that crimes that has occurred on properties or in buildings are moved to the closest street. Although, from an ethical standpoint this is a necessity since if the crime data could be tracked to buildings and properties it could therefore risk the identifications of individuals (Data SF, 2019b).
4.4 Limitations
Detected in the analyses were that property crimes which have not been given a clear location when reported have been moved to certain areas within the city and county. For example, Hall of Justice, which is located in the neighbourhood South of Market, is identified as an area with a high crime rate in the density maps. This building has 3,594 reported property crimes over the course of 2016–2017. But since the crimes are concentrated at this building its right to assume that these crimes might not been given a geographic location when reported, and therefore was Hall of Justice assigned as the crimes geographic place. This data can give a misleading result since it gives the illusion that some areas have a much higher crime density than they actually do. Also, since these crimes probably happened somewhere else, it could also affect the result because they are not included in the areas of where they actually occurred. It also seems like property crimes which have happened in Golden Gate Park and the Presidio have been moved to the outside of the parks since the data is moved to the closest street of where the crime occurred. Especially notable is the northeast entrance to the Golden Gate Park where 593 crimes have been given the same geographic coordinate. Lastly, on Treasure Island a cluster of crimes can be seen, these might be related to crimes which has occurred at the harbour on Treasure Island and still been given the same address within the data. This data is still included in the analysis since it was detected through the analysis.

4.5 Kernel Density
A common function to use to move from an individual point location to a much smoother representation of crime is the Kernel density function (Anselin et.al, 2008). It is a tool in GIS which out of polyline or point features calculates a magnitude-per-unit area, i.e. it creates a continuous
surface out of point or line locations (ESRI, 2019a). The output is in the form of a raster. Figure 6 shows an illustration of how the input is transformed using the Kernel density tool (ESRI, 2019a)

When using the tool, a cell size must be set. This determines the resolution of the output by calculating the point density for each cell, starting from the centre of the cell. For this analysis a cell size of 10m was used. This is because the distance between the points consisting of property crimes had a minimum distance of 10m between each other. If the distance was shorter the points had been snapped together and shared the same geographic coordinates. Next, each distance between the centre of the cell and the points are weighted by the search radius. If no specific search radius is defined it is calculated based on the spatial configuration and the number of input points. This default setting is called the Silverman’s Rule of Thumb (ESRI, 2019a). In this analysis a search radius of 238m was used which was calculated by the default setting. A Kernel density map was also done on the population of San Francisco. Here, the same cell size was used, but the search radius was set to 1 728 meters. This was done because the points that were furthest apart were a distance of 3 457 meters, so to ensure that the source radius would meet the distance was divided by half.
4.6 Optimized Hot Spots
Since Kernel density is a somewhat descriptive approach for finding hot spots of crime, meaning it only visualises the data, it is necessary to see where statistically significant hot spots of crime are located within the study area. When identifying spatial patterns, you can look from a global or local level. At a global level the entire study area is examined as a whole, while on a local level different parts of the study area are examined separately. By using hot spot analysis you’re given a more refine result of patterns since it is on a local scale (Mitchell, 2005). The tool ‘optimized hot spot analysis’ finds statistically significant spatial clusters of low and high values, i.e. cold and hot spots, by the help of Getis-Ord-Gi* statistic. It therefore can detect areas which has a potential high risk for crimes to occur (ESRI, 2019b). To calculate Gi* all values of the neighbours are summed up and then divided by the sum of the values of all the features within the study area (Mitchell, 2005). In this analysis the output shows hot spots as areas where there is a statistically significant overrepresentation of property crime incidents. In comparison to the standard hot spot analysis tool in ArcGIS, ‘hot spot analysis (Getis-Ord-Gi*)’, this tool determines settings depending on the data characteristics and the spatial extent of the area. These settings are the distance band and the cell size (ESRI, 2019b). Because of this optimized procedure a cell size of 132m and a fixed distance band of 455m was determined. A fishnet grid was used as the method to aggregate the incidents. This means that only cells which have one or more incidents was part of the analysis.

4.7 Emerging Hot Spots
To be able to detect temporal trends in crime events over a period of time an emerging hot spot analysis was made. This analysis can be seen as a supplement to the optimized hot spot analysis since it unveils how hot
spots and cold spots have developed in a certain area over time. The tool analyses the amount of crimes within a certain distance. It then creates cold and hot spots categories depending on different temporal trends within the data. Examples of these are intensifying, diminishing, and persistent cold or hot spots (See Appendix 2 for all definitions) (ESRI, 2019c). This kind of analysis is good to use to detect trends of crimes. The detection of persistent or intensifying hot spots can be helpful to identify which areas have continuous crime activity, which could then receive extra attention for crime prevention. Meanwhile, diminishing hot spots can help in the understanding of already implemented crime prevention measures and their effectivity.

A space time cube must be created in order to do an emerging hot spot analysis. A space time cube consists of netCDF files which is created by a tool called ‘create space cube by aggregating points’ (ESRI, 2019d). It aggregates the features, in this case the crime data, into space-time bins and calculates the Getis-Ord Gi* for each bin (ESRI, 2019e). “Within each bin the points are counted and the trend for bin values across time at each location is measured using the Mann-Kendall statistic” (ESRI, 2019d, p. 1). In this analysis a time interval of one month was set, including a time period from 2016-01-01 to 2017-12-31, i.e. 24 time steps. When using the tool ‘emerging hot spot analysis’ a distance band has to be set. The distance which is chosen should be related to the scale of the analysis to be made. Whenever you are dealing with spatial clustering it is the evidence of underlying spatial processes. ‘Incremental spatial autocorrelation’ is a tool which is helpful for identifying a suitable analysis distance depending on those underlying spatial process (ESRI, 2019f).
Since the analysis made for this study focuses on crime events and their nearby locations a rather small distance is suitable. ‘Incremental spatial autocorrelation’ measures the intensity of spatial clustering at each distance, which is determined by the z-score. At some distances the z-score peaks. These peaks reflect a distance where the clustering are the most distinct (ESRI, 2019g). Figure 7 shows the output graph of the incremental spatial autocorrelation tool. As the figure shows, there were two peaks. The first one was selected since the analysis is focusing on crimes and their closest environment. By using this tool, a distance band of 100m was identified.

*Figure 7 Output graph of incremental spatial autocorrelation (source: own figure)*
5. Result

5.2 Overview of Crime in the City and County of San Francisco

In the years of 2016 and 2017 a total of 112,712 property crimes was reported in the city and county of San Francisco. The dominating crime type is larceny-theft which holds 78% of all property crimes while arson, burglary and motor vehicle theft share the other 22% (see table 1).

*Table 1 Property crimes in San Francisco 2016–2017 (DataSF, 2019b)*

<table>
<thead>
<tr>
<th>Crime Incident</th>
<th>Number of Incidents</th>
<th>Number of Incidents in %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arson</td>
<td>613</td>
<td>1%</td>
</tr>
<tr>
<td>Burglary</td>
<td>11,670</td>
<td>10%</td>
</tr>
<tr>
<td>Motor Vehicle Theft</td>
<td>12,154</td>
<td>11%</td>
</tr>
<tr>
<td>Larceny-Theft</td>
<td>88,275</td>
<td>78%</td>
</tr>
<tr>
<td><strong>TOTAL</strong></td>
<td><strong>112,712</strong></td>
<td><strong>100%</strong></td>
</tr>
</tbody>
</table>

As for the population density within the city and county there’s a higher concentration of people in the north-eastern part of the city, including neighbourhoods like Russian Hill, Chinatown, Nob Hill, Tenderloin and Western Addition (see figure 8). When looking at the property crimes per 1,000 residents in the city, neighbourhoods such as South of Market, Financial District/South Beach, North Beach, Russian Hill and Marina have a high crime rate per capita; between 2,6–600. Note that the area of 101–600 crimes per 1,000 residents is the location of Hall of Justice, which works, as mentioned before, as a centroid for crimes with no geographic location. There are also certain spots in which have a higher crime rate per capita in other neighbourhoods, such as Lakeshore and western parts of Golden Gate Park and Outer Richmond. The highest crimes per 1,000 residents in these areas re 26–100. Neighbourhoods with a lower crime rate per capita are Presidio, Treasure Island, Sunset/Parkside, Noe Valley, Excelsior and McLaren Park (see figure 9). When comparing property crimes per capita during the day and night the concentration of crimes per
capita are still higher in certain similar areas; the north-eastern part of San Francisco (see figure 10 and figure 11). But you can also see a clear difference in the south-eastern and western neighbourhoods during night- and daytime. It lowers in those areas during the night, leaving an even clearer high crime rate in the north-western neighbourhoods (see figure 11)

Figure 8 Population density in San Francisco 2017 (source: own figure)
Figure 9 Property crimes per 1000 residents in San Francisco 2016–2017 (source: own figure)

Figure 10 Property crimes per 1000 residents at day in San Francisco 2016–2017 (source: own figure)
5.2 Cluster and Hot Spot Analysis

At first, a point-map was created by the aggregated data. As figure 12 shows is that when using point data of this amount the problem of overlaying occurs, but there are still certain spatial patterns which can be observed; areas with higher or lower amounts of crime occurrences. Because of the high amount of point data, analysing patterns with a point-map can be very insufficient. A better understanding of the distribution of crime is given in maps for each type of crime, i.e. arson, burglary, motor vehicle theft and larceny-theft. Then a clustering of arsons can be detected in Tenderloin, Mission and Bayview Hunters Point. While burglary and motor vehicle theft have a more common spread throughout the city and county, with a higher clustering in the north-eastern neighbourhoods. The point-map displaying larceny-theft, which is the most common crime of all four, is still hard to detect any significant patterns in (see appendix 3-6).
By doing a Kernel density analysis a more distinctive pattern of potential crime risk zones in the city and county of San Francisco could be detected. The area where the three neighbourhoods (Financial District/South Beach, South of Market and Tenderloin) is where there’s the highest density of crime. As mentioned before, the Hall of Justice in South of Market has a high density of crime since crimes with an unknown location is given that building as a centroid location (see figure 13).

The optimized hot spot analysis shows significant hot spots of crime and in figure 14 it is notable that the hot spots which has been identified in the city and county of San Francisco cover mostly, but not completely, neighbourhoods such as North Beach, Russian Hill, North Beach, Financial District/South Beach, Nob Hill, Pacific Heights, Western Addition, Hayes Valley, Mission and South Market. Only the neighbourhood called Tenderloin is completely included in the significant hot spot. When comparing to the temporal development, the significant hot spots are identified as hot spots categorized as intensifying, meaning that property crime has increased in these areas during 2016–2017 (see figure 15). The majority of hot spots identified are intensifying hot spots, but there are also larger areas with consecutive, sporadic and oscillating hot spots. These hot spots are identified in Marina, Haight Ashbury, Castro/Upper Market, Mission Bay and Potrero Hill. Only a small area in the Financial District/South Beach has hot spots that are categorised as persistent, meaning that those areas have been statistically significant hot spots for 90% of the time-step interval. All other neighbourhoods in San Francisco, if significant, are regarded as cold spots. When comparing the Kernel density analysis with the optimized hot spot and emerging hot spot analyses it is visible that areas which have a high density of crime also are significant and intensifying hot spots.
Figure 12: Distribution of property crimes in San Francisco according to crime type 2016–2017 – Point map
(source: own figure)
Figure 13 Kernel density analysis for property crimes in San Francisco 2016–2017 (source: own figure)

Figure 14 Optimized hot spot analysis of property crimes in San Francisco 2016–2017 (source: own figure)
5.3 Surrounding Environment

To determine whether the environmental surroundings are criminogenic, crime generators and attractors (bars/pubs/nightclubs, shopping centres and BART stations) were overlaid on top of the Kernel density maps. Figure 16 displays shopping centres in the city and county of San Francisco overlaid on top of a density map displaying property crime density at day. Daytime, as mentioned before, is between 06:43 and 20:30. Shopping centres can be both crime attractors and crime generators. A visual inspection of the map does show that all shopping centres are in areas with a property crime density of 166–325 crimes or more. In Japantown there are four shopping centres, which in the map might be hard to distinguish since they are located close to one another. Although, all four of those shopping centres are in an area with a crime density of 326–650. In Financial District/South Beach there are two shopping centres which are also located in areas with a property crime density of 326–650. Another
two shopping centres are located in South of Market. The one in the north part of the neighbourhood is located in the area with the highest property crime density, which is a crime density of 1301–2 600 crimes, while the south one is in an area of crime density of 166–325. The last two, who are in Lone Mountain/USF and Lakeshore, which is further away from the city centre, are located in areas with a crime density of 166–325. Although, the one in Lakeshore is very close to an area of crime density of 326–650. It is also visible that the places of which these two shopping centres are located have a higher crime rate than its surrounding areas.

Next, facilities of bars, pubs and nightclubs were overlaid on top of the Kernel density map displaying property crime density at night, i.e. between 20:31 and 06:42 (see figure 17). There are more facilities of this type than shopping centres and they are more distributed throughout the city and county, but with a greater concentration in the north-eastern part of San Francisco. No area has a higher crime rate than 650 during the night. The areas which have a crime rate of 326–650 are in neighbourhoods such as Nob Hill, Mission and South of Market. Although, the area in South of Market is the location of Hall of Justice, which as mentioned before, is used as a centroid for reported crimes which has no geographic location. What is clear in this map is that where there is a cluster of pubs/bars/nightclubs there are a higher crime density, while where there are lone bars/pubs/nightclubs the crime density is 15–25.

Lastly, the subway stations of BART were placed upon the Kernel density map which displays the density of all property crimes in the years 2016–2017 (see figure 18). Major nodes for transit are categorised as crime attractors since they are seen by offenders as a way to easily move in and out of an area. The transit line, which goes from south to north in the city
and county, has a total of eight subway stations. The six most northern ones are located in areas with a property crime density of 86–1300. While the 2 most southern ones are located in areas with a lower property crime density of 16–25 and 26–50. Most clearly you can see a higher density of crime surrounding the stations called Powell Street, Civic Center and 16th Street Mission. Powell Street is in an area where the property crime density is at 651–1300 while its surrounding areas is at 326–650. Civic Center has a property crime density of 326–650 and its surrounding areas have 166–325. 16th Street Mission is in an area of 166–325 while its surrounding areas have a property crime density of 86–165. The same goes for 24th Street Mission station and Glen Park station which, although at a lower crime density, also has a higher density at its location than in comparison to its surroundings. The last two, Embarcadero and Balboa Park are the only two were you can’t see a clear pattern of higher property crime density at their locations.

Figure 16 Kernel density map with locations of shopping centres in San Francisco (source: own figure)
Figure 17 Kernel density map with locations of bars/pubs/nightclubs in San Francisco (source: own figure)

Figure 18 Kernel density map with locations of BART stations in San Francisco (source: own figure)
6. Discussion
This study aimed to identify significant hot spots and temporal patterns of property crimes in the city and county of San Francisco, and to also see if there was any clear relationship between crimes and their environmental surroundings. This was done by using Geographic Information System (GIS). The analysis showed that certain areas in San Francisco do have distinct spatial patterns of property crime. All three analysis (optimized hot spot, emerging hot spot and Kernel density) shows that the occurrence of crime is the most common in the north-eastern part of the city and county. The optimized hot spot analysis established which areas were statistically significant hot spots between the years of 2016–2017, when the property crime rates heightened. The emerging hot spot analysis then clarified which temporal patterns there were of property crime in San Francisco. It also identified that the hot spots identified through the optimized hot spot analysis where intensifying hot spots, meaning that crime had risen during the time period of 2016–2017 in those areas.

The Kernel density analysis also showed a high density of crime in the same regions as to where the hot spots were identified, but there were also other areas within the city and county which had a high density of crime. By overlaying certain facilities some of these areas’ higher crime rate could be explained. Even though the analysis of crime generators and attractors and their effect on crime was based on descriptive analyses, it shows that crime pattern theory can be useful as a framework for clarifying hot spots and their environmental surrounding. All shopping centres in the analysis were identified in areas of higher crime rates, some of them are also the possible reason for a higher crime rate, since surrounding areas had less crime density. Of course, there are many factors that play part in the happening of crime events, but a shopping mall do attract a lot of people
which can generate crime. Several researches have pointed out before that the built environment and the human activities within an area can have great effect on the distribution of crime. This also applies to the case of San Francisco.

Also seen in the analysis is that there’s a clear pattern of a higher property crime density during the night where there are several pubs/bars/nightclubs, only in areas where there are lone pubs/bars/nightclubs the property crime density is lower. As Brantingham & Brantingham (2008) say it is more likely that crime occur at or close to bars/pubs/nightclubs during the night. Lastly, the three busiest BART stations were all in areas of high crime density and you could also see a clear higher density of property crime at the location of 6 out of 8 stations in comparison to their surrounding areas. This adds up to Ceccato’s (2009) saying that areas that work as transportation hubs are more vulnerable to crime. Also, Powell Street Station is the BART station with the most travellers departing and arriving, which also then indicates that the area where this station is located at a place where there is a lot of people activity. Crime pattern theory is built upon the bases that crime occurs at nodes where a lot of people gathers, and also that big transit points, just like subway stations, are crime generators and attractors (Brantingham & Brantingham, 1995). Also, Stucky & Ottermann (2009) mean that areas with a high population density also have a higher crime rate than other areas, which is also supports the findings in all three analysis. The statistically significant hot spots, the intensifying hot spots and the highest property crime density were all detected in the area of which has the highest population density. These areas are also
Of course, since most of these facilities are mostly concentrated in the area where there are significant hot spots which are intensifying, you can’t say that one facility out rules another facility’s effect on criminality. But the result of this study still shows that it is possible to detect patterns of crime in relation to its surrounding environment. By dividing the crimes by day and night hours the change in crime pattern dependent on time becomes even clearer. During night-time, for example, the density of crime at some shopping centres decreases, which supports Brantingham & Brantingham’s (1995) saying of how crime occurrence is affected by how much people activity a location has during certain times of the day.

In the Kernel density analyses, there are also areas of high density which are not explained by the facilities chosen in this study. An example is North Beach, which has a high density of property crime but are also clearly a statistically significant hot spot. This can be explained that in this area Fisherman’s Wharf and Pier 39 are located. These are two big tourist attractions which also indicates that the area gathers a big amount of people. To evolve this study more facilities could have been used to identify crime pattern, for example, tourist attractions.

One could argue that even though the result shows that place does matter, spatial and social developments within these areas of high crime are not stationary. But with the emerging hot spot analysis it shows that the areas of which has the highest density of crime also are intensifying hot spots, meaning that crime is increasing. Therefore, even though there might have been social and spatial development in the time period the analysis is based upon, crime has still risen. Moreover, one could look at the areas within the city and county where crime has decreased to see what
characteristics or spatial and social developments could have been given the effect of crime lessening.

I believe, GIS is a practical tool to use when presenting and examining crime data when used in combination with relevant social theory which explains the causes of criminality. The analyses that was done in this study – both statistically significant and visually – shows that spatial patterns of crime can be visualised through GIS.

Furthermore, in this study property crimes were divided into day and night through a calculated average sunset and sunrise. Further research could use the same method but be even more precise. Brantingham & Brantingham (2008) mentions, for example, that crime at bars is more usual during weekend evenings since there are more people who gathers there during that time of the week. Identifying how hot spots of crime change over the course of the day, month, or year may play a major role in the development of combating crime since it is a way of knowing how to distribute resources, i.e. police men, guards, etc. Also, by looking at socio-economic and demographic factors in the areas of high crime rates can lead to an even better understanding of the pattern of crime. As Brantingham & Brantingham (2008) states, the backcloth of the city also has a high effect on the occurrence of crime, i.e. the land-use, individuals’ socio-economic status, or what economic forces which are driving the city forward. Additionally, you could probably apply the knowledge which has been gathered from this study onto different places and cities and see similar results.
7. Conclusion

The city and county of San Francisco saw a rise of property crimes between the years 2016–2017; from 47 402 to 54 356. The aim with this study was to, by using Geographic Information System (GIS), identify significant hot spots and temporal patterns of property crime within San Francisco. It was also to visualise if there was any relationship between the occurrence of crime and its environmental surroundings. This was done by comparing the density of property crime within the city and county to principles of the crime pattern theory and certain facilities which the theory identifies as crime generator and attractors. The result showed that property crime is most concentrated in the north-eastern part of San Francisco, and in these areas the crimes were rising during the time period. Also, patterns of higher density of property crimes near facilities such as shopping centres, bars/pubs/nightclubs and subway stations were also identified. The study’s result supports the usefulness of GIS when presenting crime data when used in combination with relevant social theory with the objective to explain crime occurrence. Further on, this study can contribute to a better understanding of the distribution of property crime when taking environmental surroundings into consideration, and how crime occurrences changes over the course of a day.
References


Bay Area Rapid Transit (2019) Ridership Reports. Received 2019-05-11 from: https://www.bart.gov/about/reports/ridership


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Appendix

Appendix 1: The change in sub-crimes included in property crimes in the city and county of San Francisco 2016–2017 (source: Federal Bureau of Investigation, 2019a).
<table>
<thead>
<tr>
<th>Pattern Name</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Pattern Detected</td>
<td>Does not fall into any of the hot or cold spot patterns defined below.</td>
</tr>
<tr>
<td>New Hot Spot</td>
<td>A location that is a statistically significant hot spot for the final time step and has never been a statistically significant hot spot before.</td>
</tr>
<tr>
<td>Consecutive Hot Spot</td>
<td>A location with a single uninterrupted run of statistically significant hot spot bins in the final time-step intervals. The location has never been a statistically significant hot spot prior to the final hot spot run and less than ninety percent of all bins are statistically significant hot spots.</td>
</tr>
<tr>
<td>Intensifying Hot Spot</td>
<td>A location that has been a statistically significant hot spot for ninety percent of the time-step intervals, including the final time step. In addition, the intensity of clustering of high counts in each time step is increasing overall and that increase is statistically significant.</td>
</tr>
<tr>
<td>Persistent Hot Spot</td>
<td>A location that has been a statistically significant hot spot for ninety percent of the time-step intervals with no discernible trend indicating an increase or decrease in the intensity of clustering over time.</td>
</tr>
<tr>
<td>Diminishing Hot Spot</td>
<td>A location that has been a statistically significant hot spot for ninety percent of the time-step intervals, including the final time step. In addition, the intensity of clustering in each time step is decreasing overall and that decrease is statistically significant.</td>
</tr>
<tr>
<td>Term</td>
<td>Description</td>
</tr>
<tr>
<td>----------------------</td>
<td>--------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Sporadic Hot Spot</td>
<td>A location that is an on-again then off-again hot spot. Less than ninety percent of the time-step intervals have been statistically significant hot spots and none of the time-step intervals have been statistically significant cold spots.</td>
</tr>
<tr>
<td>Oscillating</td>
<td>A statistically significant hot spot for the final time-step interval that has a history of also being a statistically significant cold spot during a prior time step. Less than ninety percent of the time-step intervals have been statistically significant hot spots.</td>
</tr>
<tr>
<td>Historical Hot Spot</td>
<td>The most recent time period is not hot, but at least ninety percent of the time-step intervals have been statistically significant hot spots.</td>
</tr>
<tr>
<td>New Cold Spot</td>
<td>A location that is a statistically significant cold spot for the final time step and has never been a statistically significant cold spot before.</td>
</tr>
<tr>
<td>Consecutive Cold Spot</td>
<td>A location with a single uninterrupted run of statistically significant cold spot bins in the final time-step intervals. The location has never been a statistically significant cold spot prior to the final cold spot run and less than ninety percent of all bins are statistically significant cold spots.</td>
</tr>
<tr>
<td>Intensifying Cold Spot</td>
<td>A location that has been a statistically significant cold spot for ninety percent of the time-step intervals, including the final time step. In addition, the intensity of clustering of low counts in each time step is increasing overall and that increase is statistically significant.</td>
</tr>
<tr>
<td>Type</td>
<td>Description</td>
</tr>
<tr>
<td>----------------------</td>
<td>--------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Persistent Cold Spot</td>
<td>A location that has been a statistically significant cold spot for ninety percent of the time-step intervals with no discernible trend, indicating an increase or decrease in the intensity of clustering of counts over time.</td>
</tr>
<tr>
<td>Diminishing Cold Spot</td>
<td>A location that has been a statistically significant cold spot for ninety percent of the time-step intervals, including the final time step. In addition, the intensity of clustering of low counts in each time step is decreasing overall and that decrease is statistically significant.</td>
</tr>
<tr>
<td>Sporadic Cold Spot</td>
<td>A location that is an on-again then off-again cold spot. Less than ninety percent of the time-step intervals have been statistically significant cold spots and none of the time-step intervals have been statistically significant hot spots.</td>
</tr>
<tr>
<td>Oscillating Cold Spot</td>
<td>A statistically significant cold spot for the final time-step interval that has a history of also being a statistically significant hot spot during a prior time step. Less than ninety percent of the time-step intervals have been statistically significant cold spots.</td>
</tr>
<tr>
<td>Historical Cold Spot</td>
<td>The most recent time period is not cold, but at least ninety percent of the time-step intervals have been statistically significant cold spots.</td>
</tr>
</tbody>
</table>
Appendix 3: Point map for arsons in the city and county of San Francisco 2016–2017 (source: own figure)
Appendix 4: Point map for burglaries in the city and county of San Francisco 2016–2017 (source: own figure)
Appendix 5: Point map for motor vehicle thefts in the city and county of San Francisco 2016–2017 (source: own figure)
Appendix 6: Point map for larceny-thefts in the city and county of San Francisco 2016–2017 (source: own figure)