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Maria Camacho Doyle

Forecast: Crime with a chance of feeling unsafe

Examining unsafety (crime and fear of crime) within the context of the surrounding environment

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Abstract

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In environmental criminology, various methods exist to forecast unsafety. Some are more complex than others. To determine their practicality, we must compare the accuracy of simple, transparent, and functional methods with slightly more complex methods and those requiring more data collection.

The overall aim of the current dissertation was to examine the relationship between crime history, environmental and neighborhood characteristics in forecasting unsafety, both crime and fear of crime, in various geographical locations. Study I compared the predictive accuracy of two methods using historical crime exposure and different crime-time-periods for violent and property crimes. Study II compared the predictive accuracy of prior crime, place attributes, ambient population, and community structural and social characteristics for various crime types. Study III examined the relationship between violent and property crime, as well as community structural and social characteristics, and different types of fear of crime.

The findings of the current dissertation suggest that, overall, a one-size-fits-all approach is not effective. Simpler methods are generally comparable to more complex ones in long-term crime forecasting at the micro-level. However, at the neighborhood level, social integration plays a significant role in determining levels of perceived safety and fear of crime.

Keywords: Hotspot-Mapping, RTM, Micro-Place, Neighborhood, Prediction-Accuracy, Prediction-Efficiency, Violent-Crime, Property-Crime, Perceived-Unsafety, Fear of Crime, Avoidance

"Success is no accident. It is hard work, perseverance, learning, studying, sacrifice and most of all, love of what you are doing or learning to do."

Pelé

What an exhilarating, educating, privileged, stressful, and just plain fun journey that has come to an end. I had several quotes to choose from describing my years as a PhD student before finally landing on Pelé's excellent description. But a few of the following almost made the top page, as they do an almost equally good job: “That which does not kill us, makes us stronger”.😁 Friedrich Nietzsche. “It always seems impossible until it is done”. Nelson Mandela. “Failure is only the opportunity to begin again, this time more intelligently”. Henry Ford. “Our greatest glory is not in never falling, but in rising every time we fall”. Confucius. Alongside me on this journey there have been countless people that I feel gratitude towards.

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Table of Contents

List of papers

This thesis is based on the following studies, referred to in the text by their Roman numerals.

I. Camacho Doyle, M., Gerell, M., & Andershed, H., 2021. "Exploring Violent and Property Crime Geographically: A Comparison of the Accuracy and Precision of Kernel Density Estimation and Simple Count". *Nordic Journal of Studies in Policing,* 8:1, 1-21.

II. Camacho Doyle, M., & Gerell, M,. "Exploring Hotspots of Violent and Property Crime in Malmö, Sweden". Manuscript submitted for publication.

III. Camacho Doyle, M., Gerell, M., & Andershed, H., 2022. "Perceived unsafety and fear of crime: The role of violent and property crime, neighborhood characteristics, and prior perceived unsafety and fear of crime". *Deviant behavior*, 43:11, 1347-1365.

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List of abbreviations

PAI Predictive Accuracy Index

RRI Recapture Rate Index

PEI Predictive Efficiency Index

PEI* The constrained Predictive Efficiency Index

IRR The Incidence Rate Ratio

KDE Kernel Density Estimation

SC Simple Count

RTM Risk Terrain Modeling

MAUP The modifiable areal unit problem

CPT Crime pattern theory

MCS Malmö Community Survey

PredPol The predictive policing company

ANN Average Nearest Neighbor

NnH The nearest neighbor hierarchical clustering technique

STAC The spatial and temporal analysis of crime technique

1 Introduction

The right to be safe and to feel safe when out in public, is of utmost importance for any person, in any city (UN-Habitat, 2012, 2019, 2021). To be safe, could regard avoiding the actual risk of becoming a victim of crime and to feel safe could regard the perception of safety or fear, among other things. Both crime and perception of safety are important dimensions of unsafety, affecting both people and cities. Consequently, for people to be safe and to feel safe when out and about in public, crime prevention, aided by correct crime forecasts, and increasing perceptions of safety, based on correct information, should be one goal for the commonweal in any city.

The actual risk of becoming a victim of crime is directly related to actual crime incidents and can be measured through crime statistics. In Sweden, there are about 1.5 million crimes reported to the police every year according to the National Council of Crime Prevention in Sweden (NCCP, 2022). 'Everyday crimes' such as theft, property damage, residential burglary, and assault comprise about three quarters of these crimes (Police authority, 2022a). 'Everyday crime' is hence frequent and affects a lot of people. Being victimized of assault and residential burglary for example, can have both health related (Dustman & Fasani, 2016; Fowler et al., 2009; Janke et al., 2016; Ornstein, 2022), and financial consequences (Johnston et al., 2018; Ornstein, 2022). Crime is thus a problem for people being victimized. Crime is likewise a problem for society, as it is costly, no matter how you choose to do the analyses (NCCP, 2017). In Sweden over the course of a year, public environment assault cost society between 16.5 billion ($1.51 billion) and 83.2 billion SEK ($7.60 billion) depending on the severity of the assault being committed (NCCP, 2022; Nilsson & Waedskog, 2011). In the US, over one year, assault cost about $334.5 billion, arson cost $2.3 billion, and vandalism cost $10.8 billion (Miller et al., 2021). In any sustainable society these types of crimes need to be prevented, and thus first accurately forecast, as it involves such costs for society at large, as well as for individuals.

The perception of unsafety or fear, rather simplified, can be an expression of fear of crime. Perceived unsafety is related to both physical and mental health problems and can furthermore limit people's physical (i.e., walking in said neighborhood) and social activity (see e.g., Amerio & Roccato 2007; Dolan & Peasgood 2007; Golovchanova et al., 2021; Hale 1996; Jackson & Stafford 2009; Stafford et al., 2007) due to an unwillingness to leave the house because of fear, for example. All people in a city should have an equal opportunity to move around and use the public place (Ceccato et al., 2020a). Even though a place is publicly accessible to everyone, like a park, a town square, a street corner, perceived unsafety can impede this accessibility and unequally so (Gray et al., 2011; Jackson & Gray, 2010). Cues in the environment, such as desolate places, shrubs, no lights, can trigger fear in some people (see e.g., Ceccato & Bamzar, 2016; Ceccato et al., 2020b) making them avoid the place all together or at certain times. In Sweden, 80 percent of the population (16–84 years) believe that crime has increased in the last three years and 45 percent worry about crime in society (NCCP, 2021). Twenty-eight percent feel unsafe and 35 percent worry that a relative or friend will be victimized. In any sustainable society, not only crime and victimization but also perceived unsafety should be prevented, and thus first accurately localized geographically.

Prevention, informed by correct geographical forecasts, will thus increase equality, as some places (see e.g., Andresen et al. 2017; Weisburd et al., 2004) and some people (see e.g., Grove et al., 2012; Hoppe & Gerell, 2019) are victimized more often than others and the accessibility of the public place is somewhat unequal (see e.g., Ceccato et al., 2020a). Prevention rather than reaction then, should be the goal when curtailing unsafety at places (UN Agenda 2030; UN-Habitat, 2012, 2019, 2021). To be effective when working with prevention, one must first make correct assessments, identifying potential hotspots of unsafety by a correct forecast. It is therefore of utmost importance to know with some accuracy and precision where future unsafe locations might appear, as this will inform preventive strategies. For this preventive reason, it is fortunate that crime is not evenly distributed in any city. Crime rather sticks to certain smaller geographical locations, hotspots, over time (see e.g., Curman et al. 2014; Haberman, 2017; Levin et al. 2017; Weisburd et al. 2004; Wheeler et al. 2016). It might also be the case that there are equivalent hotspots of unsafety as regards to perceptions of safety (see Jakobi & Pòdör, 2020; Kronkvist, 2022; Nasar & Fisher, 1993; Ogneva-Himmelberger et al., 2019; Pánek et al., 2019). That is, small locations that increase fear of crime, persisting over time.

There are different ways to understand and identify hotspots of unsafety geographically. Local crime history can be used to pinpoint where future crime events might take place (Chainey et al., 2008; Eck et al., 2005) and where perceived unsafety is higher (Kuen et al., 2022). Another way is to use place characteristics such as closeness to, or density of bars, restaurants, and bus stops to try to forecast crime (Caplan et al., 2011; Caplan et al., 2015) or perceived unsafety (Kronkvist, 2022). Adding information regarding the social status of the overall neighborhood might also contribute to a more accurate forecast for both crime (Browning et al. 2004; Mazerolle et al. 2010; Morenoff et al. 2001; Sampson 2012) and perceived unsafety (Brunton- Smith et al., 2014; Brunton-Smith & Sturgis 2011). It is furthermore likely that multiple reasons at different neighborhood, and place-levels combined, make these unsafe places appear. Because of this there are different ways of identifying these unsafe places. Depending on theoretical standpoint, different types of data need to be collected and different ways of analyzing the data exists.

For practical purposes though, it is important to establish that the time, effort, and finances put into collecting more data gives a higher forecast accuracy for both actual safety and perceived safety, compared to simply counting past crimes in the location. In some recent studies, models with a lot of data collected and included such as the presence/density of apartments, restaurants, and neighborhood poverty etcetera, only slightly outperformed simply counting past robberies in Dallas (Wheeler & Steenbeek, 2021) and a traditional hotspot map of burglaries in Belgium (Rummens & Hardyns, 2020). However, a study from Fukuoka, Japan (Ohyama & Amemiya, 2018) showed that including additional data, such as the presence of parks, restaurants, and convenience stores, was far more effective than using crime counts alone for forecasting theft from vehicles.

In general, research on the amount of data required for accurate forecasts is slightly ambivalent. It appears that reasonably simple methods with less data could render good results, though not necessarily the best (see also Lee et al., 2020). Therefore, the overall aim of the current dissertation was to focus heavily on real-world applicability and practical insights. It aimed to compare the forecast contribution of crime history alone using various time-periods, as well as environmental and neighborhood characteristics in relation to unsafety, both crime and fear of crime.

1.1 Definitions

1.1.1 Safety and Unsafety

There is no universal definition of perceived safety/unsafety or fear of crime. Safety covers a risk management (Aven, 2016; Khan et al., 2015), criminological and a public health (Heber, 2007, 2008) perspective and normally feelings of safety are seen as the presence of safety, trust and security and the absence of worry, risk, and fear. In the current dissertation the actual risk of becoming a victim of crime, measured through crime statistics, and the perception of safety or fear of crime regardless of crime victimization will be considered when unsafety/safety is mentioned. The term *actual safety* pertains to the objective risk and likelihood of experiencing a crime in a certain place and will be based on crime statistics. The term *perceived safety* relates to people's or groups' affective and emotional fears. How unsafe, fearful of crime people perceive themselves to be. Unsafety will be viewed as the opposite of safety. This definition of unsafety, including the definitions of *actual safety* and *perceived safety* is in concordance with the UN-Habitat's approach to Safer Cities (2012, 2019, 2021) as well as previous literature (Ceccato et al., 2020a). Researchers in the fear of crime field do distinguish between actual safety and perceived safety (see Cordner, 1986; Dubow et al., 1979; Ferraro & LaGrange, 1987; Hale, 1996; Wilson & Kelling, 1982). A place can have no crime and still be seen as unsafe (Ceccato & Lukyte, 2011; Ferraro, 1995; Gray et al., 2008; LaGrange et al., 1992; Pain et al., 2006). An unsafe location can be seen as unsafe due to it being perceived as unsafe only or because there is a lot of crime there. It is important to distinguish between actual safety and perceived safety as they are separate phenomena. However, environmental factors can play an important role in affecting both actual safety and/or trigger perceived unsafety. In conclusion, in the current dissertation the definition of unsafety will hence regard both crime and fear of crime. *Perception* of safety/unsafety on the other hand will regard different aspects of *fear of crime*.

1.1.2 Place and Space

Place, a word that we use in conversations semi-daily, is in research not as straight forward. "Although a place must be smaller than the space that contains it, places do not have to be small" (Weisburd et al., 2016:17). Sweden can be a place in Europe (space), Malmö a place in Sweden (space), Möllevången a place in Malmö (space) and a particular street in Möllevången or Möllevångstorget a place in Möllevången (space). In criminological research, place is just one concept among others (space, areas, settings, and zones) used in relation to the geographically defined location of interest. In the study of geography on the other hand, place can be seen as absolute, relative, and relational or a combination of these (Harvey, 1973, 2006). Absolute place, that is fixed, and immovable could be measured, as in the current dissertation, using the exact latitude and longitude of crime incidents and information on land use patterns, including residential, commercial, industrial, and open spaces. Relative place, how one place relates to other places in terms of distance, connectivity, and interaction could be measured using proximity to crime hotspots, infrastructures aiding movement to and from the area and, as in the current dissertation, proximity to areas with low-income levels, unemployment rates, and poverty or age ratio of the neighborhood. Relational space, how social networks, communication, and interactions shape a place could be measured using data on neighborhood level fear of crime, gang-activity and as in the current dissertation, collective efficacy. In the current dissertation the definitions place, micro-place and location are used interchangeably (Study I & Study II) but still referring to the same thing: the defined geographical location of interest. The micro-places in Study I & Study II represent a small part of space and are operationalized as grid-cells. Micro-place grid cells are hence the main unit of analysis in both Study I and Study II. As the area is larger in

Study III the definition neighborhood (meso-level) is used for the defined geographical location of interest. Furthermore, places in the current dissertation are defined as places where citizens have access, such as parks, neighborhoods, town squares or streets in Malmö. Places where people can be victimized and/or have perceived unsafety (or fear) triggered due to characteristics of the surrounding environment.

1.1.3 Hotspots of crime and fear of crime

A crime hotspot can be defined as a small geographical location with a high concentration of crime incidents over time (Sherman & Weisburd, 1995). It does seem as if there might be an equivalent of hotspots for perceived safety (Curtis et al., 2014; Doran & Lees, 2005; Kronkvist, 2022; Guldåker et al., 2023). That is micro-places with a persistent level of high perceived unsafety.

1.1.4 Prediction and Forecasting

In the current dissertation the term forecasting will be used interchangeably with prediction. Forecasting one dependent (outcome) variable using multiple independent (predictor) variables, in a linear fashion. There is dispute in different fields on how to use the terms forecast and prediction (see Silver, 2012). In general, in the spatial crime analysis field, prediction has been used interchangeably with forecast, as their purpose is seen as the same (see Kounadi et al., 2020). A common term used is predictive policing (Groff & La Vigne, 2002; Haberman & Ratcliffe, 2012; Mohler et al., 2015), where the police use algorithms and computer systems (such as PredPol) to analyze big data, in decisions where to deploy police officers. Though the term predictive policing has become criticized as of late, due to a lack of transparency in the proprietary programs. One such criticism is that predictive policing can reinforce existing racial biases in the criminal justice system (Lee et al., 2020; Sullivan & O'Keeffe, 2017). Other disciplines, such as seismology (which the ETAS algorithm of PredPol is based on), differentiate between the two terms, prediction being firmer and forecast being more like a probability such as a weather forecast, 60 percent chance of rain tomorrow.

1.2 Understanding unsafety (crime and fear of crime)

1.2.1 Actual safety

The risk of becoming a victim of crime is a worldwide problem, as crime is a major part of every society. All countries have a problem with crime to some degree. The costs and effects of crime affect everyone to some extent and some people and places more so, whether it be through pain and suffering, lower quality of life, property losses, loss of income, increased security expenses and so on (see e.g., Dustman & Fasani, 2016; Fowler et al., 2009; Janke et al., 2016; Miller et al., 2021). These effects could be both short-term and long-term, for both the individual (see e.g., Johnston et al., 2018; Ornstein, 2022) and society (see e.g., Kirk & Laub, 2010; Miller et al., 2021; Sharkey & Sampson, 2015). Certain crime types coined 'everyday crimes' are more common than other crime types, even across countries (see e.g., NCCP, 2022; FBI, 2022; Office for National Statistics, 2022 a,b; Statista, 2022a,b). Common 'everyday crimes' are both property crimes such as theft and vandalism and violent crimes such as assault and robberies. The financial cost for society alone is one reason to work with preventing these 'everyday crimes', simply due to the sheer number of crime incidents. A cross-country comparison made by the UN in 2003 with 31 countries included, showed different types of crime to be important to some extent in all included countries (UNODC, 2003). In sum, all societies have crime to some extent. Both public environment violence and property crimes are quite common and frequent across cities and countries. These crimes are quite costly, consequently we should work to identify the hotspots of crime to be able to prevent them.

1.2.1.1 Different types of crime

There are many different types of crime, as well as different ways of categorizing the types of crime. One category is 'everyday crime' (mass crimes). Everyday crimes include but is not limited to theft, vehicle theft, burglary, property damage, drunk driving, drug crimes, assault, and fraud (Police authority, 2022a). 'Everyday crime' comprises a minimum of 75 percent of all reported crimes every year.

It is hence frequent crime affecting many people and is quite costly from a societal perspective.

In the current dissertation 'everyday crime' will be in focus. More specifically, violent crime including public environment assault and street robbery and property crime including illegal fire setting, property damage, theft, vehicle theft and residential burglary. Violence was chosen as it accounts for most of the societal financial cost (Miller et al 2021). For comparison everyday property crimes were chosen, as property crimes are frequent and include crime types affecting a large group of people in society. Drug crimes are excluded as this crime type is somewhat different in comparison. Drug crimes include possession, personal use and organized crime with drug manufacturing and distribution etcetera (Police authority, 2022b).

1.2.1.1.1 Public environment violence

Violent crime (see NCCP, 2022) comprised 854 crimes per 100 000 residents reported in Sweden 2020. Public environment violence is considered an 'everyday crime'. Hence, it is quite common (see e.g., NCCP, 2022) and quite costly (see e.g., Miller et al 2021). Public environment violence is a problem not only for the citizens being victimized and their immediate surroundings but also for the fabric of the greater neighborhood (Kirk & Laub, 2010; Sharkey & Sampson, 2015). Public environment violent crime has been shown to contribute to neighborhood definition. One study including neighborhoods across 22 cities, in the US, revealed that neighborhood violent crime levels and especially robbery and aggravated assault, strongly predicted residents' perceptions of crime in that area (Hipp, 2010). High levels of perceived violence explained why people moved out of the neighborhood (Hipp & Steenbeek, 2016). Neighborhood level violent crime did also reduce neighborhood property values (Hipp et al., 2009).

Crime is usually not the whole problem; it is a part of the problem. Nevertheless, there have been studies that show both direct and indirect consequences of living in violent neighborhoods. In one longitudinal study, comparing children from more violent neighborhoods with peers from safer neighborhoods, long-term, academic results were affected (Burdick-Will, 2016). Students from violent neighborhoods fell behind students from safer neighborhoods in standardized math and reading test scores as they progressed through school. The impact of one standard deviation increase, in neighborhood violence, over time, became more noticeable. Other studies show that witnessing neighborhood level violence has been associated with mental health problems such as depression, anxiety, and aggression in young people (Buckner et al., 2004; Buka et al., 2001; Weisburd et al., 2018). For example, according to self-report data, an estimated 14.8 percent of individuals residing in areas with high rates of violent crime exhibit signs of moderate depression or meet the criteria for a diagnosis of PTSD (Weisburd et al., 2018). In contrast, only 6.5 percent of residents living in areas with low crime rates experience similar mental health challenges.

Witnessing neighborhood level violence has also been associated with fear of further victimization (Leshem & Weisburd, 2019) and the risk of additional violence (Buka et al., 2001; Farrell & Zimmerman, 2018). Living in high violence neighborhoods increased the risk of direct exposure of violence or indirect through family or friends, or even routinely hearing gunshots erupt near one's home. This may induce trauma and emotional stress for residents. Physical and mental health problems have been associated with direct and indirect exposure to violence (see e.g., Curry et al., 2008; Dustmann & Fasani, 2016; Harding, 2009; McGarry & Walklate, 2015; Ruback & Thompson 2001; Schaefer et al., 2018; Turanovic & Pratt, 2015; Turanovic, 2019). Direct and indirect exposure to violence has also been associated with a lower quality of life (McDougall & Vaillancourt, 2015; McGarry & Walklate, 2015; Ruback & Thompson 2001) and potential developmental problems (Fitzpatrick et al., 2005; Harding, 2009; Gorman-Smith & Tolan, 1998). For example, when examining neighborhood violence as a mediator between neighborhood disadvantage and high school graduation and teenage pregnancy, there was a 14.1 percent reduction in the odds of high school graduation for each one-standard-deviation increase in neighborhood violence, and a 7.6 percent increase in the odds of teenage pregnancy (Harding, 2009). Furthermore, lower income in adulthood has been related to living in areas with higher violent crime rates (and lower SES) for a longer period (Chetty & Hendren, 2015). Looking at more immediate risks of violent crime such as aggravated assault, a bar fight might result in premature death (Mazzerole et al., 2012).

In sum, preventing public environment violence both in the night life districts and in low socioeconomic areas would be beneficial, from a sustainability perspective, for a healthy and more equal society. Not only for the citizens being victimized and their immediate surroundings but also for the greater neighborhood and society. Consequently, it is important to identify these hotspots of violence as we can work proactively to prevent them.

1.2.1.1.2 Property crime

A lot of property crime types, such as property damage, theft, and vehicle theft are considered as 'everyday crime'. Hence, they are quite common (NCCP, 2022, 2023a), with 7932 crimes per 100 000 residents reported in Sweden 2020. Property crimes are also quite costly (Miller et al., 2021). Burglary is considered "everyday crime" (Police authority, 2022a). Longitudinally, victimization whether violent or property has been associated with security perceptions, trust, and neighborhood satisfaction (Janssen et al., 2021). Burglary has been described as a crime that has a powerful impact on its victims (Mawby et al., 1999; Mawbe, 2001; Mawby & Walklate, 1997). Lower levels of perceived health and physical wellbeing have been related to being victimized of burglary, especially in older victims (Britt, 2001; Norris & Kaniasty, 1994; Norris et al., 1997). Lower life-satisfaction has also been related to property crime victimization (Ambrey et al., 2014; Staubli et al., 2014). However, as an example only repeat victimization of property crime seemed to be important in relation to feelings of unsafety (β =.116, $p<0.05$), worry about crime (β =.151, $p<0.001$) and avoidance behavior over time (β =.070, $p<0.05$), and the effect was smaller than that of violent victimization (Janssen, et al., 2021).

The relationship between property crime victimization and perceived unsafety has been examined in several studies, and the findings have been mixed. Some studies have found a positive relationship, indicating that higher rates of reported property crimes are related with greater perceived unsafety (Zhao et al., 2015). On the other hand, other studies have reported no significant relationship between property crimes and perceived unsafety (Franklin et al., 2008). Furthermore, research has shown that neighborhood-level burglary rates are linked to perceived unsafety (Wilcox-Rountree & Land, 1996a; Wilcox-Rountree & Land, 1996b), fear specific to burglary (Wilcox-Rountree, 1998), and defensive behaviors (Wilcox-Rountree & Land, 1996b). However, it is also important to note that a separate study did not find such a relationship between neighborhood level property crime and worry about crime (Franklin et al., 2008). Overall, the literature on the relationship between property crime victimization and perceived unsafety shows varying findings, with some studies suggesting a positive relationship, while others report no significant relationship. Similarly, the impact of neighborhood-level property crime on fear of crime also yields mixed results. Previous research highlights the complexity and variability of these relationships and the need for further research to gain a thorough understanding of the issue.

There is also the disputed notion (O’Brien et al., 2019) that certain property crimes such as vandalism, that is graffiti, breaking windows, damaging public or private properties, and illegal fire setting, that is “signal crimes” and “signal disorders” indirectly led to more neighborhood level crime (Wilson & Kelling, 1982) and hence should be prevented to not lead to further crime. Early on, Wilson and Kelling's (1982) explained the main ideas behind what we now call the broken windows theory. In short, untended disorders increase fear of crime in real time and over time. If residents perceive their neighborhood as being disorderly, seeing cues such as vandalism, graffiti, and burnt down cars can indicate larger problems, such as a lack of governmental control, and carelessness of their fellow neighborhood residents. This perceived lack of governmental control and carelessness of their fellow neighborhood inhabitants, in turn, can make residents perceive/fear they are at greater risk of becoming victims of crime and making them stay off the streets (Hunter, 1978; Wilson & Kelling, 1982) contributing to less capable guardians with eyes and ears. The disorder cues can furthermore encourage continued criminal activity (nobody cares anyway) and discourage crime prevention efforts carried out by residents. A negative spiral of fear and neighborhood decline can be found on blocks (Wilson & Kelling, 1982), and in neighborhoods (Skogan, 1986; 1990) with more disorderly cues. Hence, curtailing these property crimes could lead to a break in the negative spiral and hence prevent further crimes in the area. In general, disorder can be categorized into two different groups: social disorder, which includes behaviors like public drinking, rowdy youth, and loitering in public places, and physical disorder, which includes issues such as broken windows, graffiti, vandalism, rundown buildings, vacant houses, and accumulated trash.

It is not clear if disorder has a causal effect on more serious crime, or not (see Harcourt, 2005; Sampson & Raudenbush, 1999, 2004; and O'Brien, 2019 for meta-analysis). In a European context, a direct influence of disorder on crime has been found (Mellgren et al., 2010; Wikström et al., 1997) with social trust partially mediating this relationship. The results also suggested that different contexts can affect the relationship between disorder, collective efficacy, and crime. Furthermore, that there might be smaller micro-neighborhood differences within the greater neighborhood. The recent meta-analysis (O'Brien, 2019) did not show that disorder led to increased aggression or more negative attitudes towards the neighborhood, when independent assessments of disorder and fear of crime were used. Studies included in the meta-analysis that claimed such effects often had weaker research designs and failed to consider other important factors such as socioeconomic status and collective efficacy, hence overestimating the perceived relationship between disorder and fear of crime.

Whether property crimes lead to more serious crime and increased fear of crime, or not, they are costly in and of themselves (see Miller et al., 2021; NCCP, 2017). Direct costs can refer to the financial losses for individuals, businesses, and society. These costs can include the value of the stolen or damaged property, costs associated with insurance claims and payouts, expenses related to property repairs or replacements, and the cost of law enforcement and the criminal justice system in investigation and prosecution of such crimes. Indirect costs are harder to quantify monetarily but can still be great. They can include the broader economic and social consequences of property crimes. Indirect costs can include decreased property values in affected areas, increased insurance costs for individuals, psychological impact on victims leading to decreased wellbeing and quality of life, and the strain placed on public resources and services to address crime prevention and victim support.

In sum, preventing property crimes remains crucial and beneficial not only for the individuals who are victimized and their immediate surroundings but also for the broader neighborhood and society. Therefore, it is essential to accurately identify hotspots for various types of property crimes to assess their potential relationship to future criminal activity and overall safety concerns. By doing so (accurately identifying hotspots), proactive measures can be implemented to mitigate the occurrence of property crimes and enhance overall community safety.

1.2.2 Perceived safety

One would expect that when crime rates are high, fear of crime would also be high, and conversely, when crime rates are low, fear of crime would decrease accordingly. However, research has shown that the relationship between crime and fear of crime is not as straightforward. For example, fear of crime in the USA has remained consistently high, despite a significant decline in crime rates over the past two decades (Dugan, 2014; Rader, 2017). The rates of murder, rape, and stolen property has steadily decreased between the years 1980 and 2013 (Snyder & Mulako-Wangota, 2015). At the same time the percentage of people afraid of walking alone in their neighborhood at night (40 percent in 1980 and 37 in 2013) has stayed similar (Dugan, 2014) and there has been a slight increase in the belief that crime in the neighborhood is increasing (37 percent in 1983 and 41 in 2013). Partly, because of the discord between levels of crime and fear of crime in society, fear of crime has become a significant social issue and a topic of research in and of its own (see e.g., Box et al. 1988; Rader, 2017) as well as a political issue (Farrall et al., 2009).

In Sweden, there has been a stable level of reported crimes, with yearly fluctuations, over a 10-year period (NCCP, 2023a). The yearly national crime survey (NCCP, 2023b) shows that perceived unsafety remained relatively steady from 2007 until 2015, in 2016 there was a notable increase. Since 2016, there has been a stable level of perceived unsafety with occasional minor fluctuations, in 2020, 23 percent felt unsafe. Looking at levels of 'belief' that crime is increasing in society, 80 percent of respondents believed this in 2020. This 'belief' of increased crime decreased from 2007 until 2014, followed by an increase in 2015. The belief that crime is on an increase has since 2015 remained stable at around 80 percent of respondents. Furthermore, in 2020, 26 percent of respondents reported frequently altering their route or mode of transportation due to concerns about being a victim of crime (NCCP, 2021). Likewise, 14 percent often refrained from engaging in certain activities and 8 percent reported that their overall quality of life was impacted by their worries about becoming a crime victim. There was a significantly higher proportion of women than men that frequently chose an alternate route or mode of transport and refraining from activities due to fear of crime victimization. There was 27 percent that expressed concerns about burglary (very often or quite often), and this proportion has remained relatively stable over recent years. Furthermore, 12 percent (similarly across gender) indicated that they very often or quite often worry about becoming a victim of assault. With reporting this information regarding the number of fearful individuals in the US and Sweden, a caution is warranted, the measurement of fear of crime is not without problems.

1.2.2.1 Different types of perceived safety

There is no universal definition of perceived safety or fear of crime. The term fear of crime, commonly used, can be seen as an umbrella term covering several aspects. Generally, three aspects of fear of crime can be found in recent literature; affective, behavioral, and cognitive (ABC) (see e.g., Farrall et al., 2009; Fattah & Sacco, 1989; Greve et al., 2018; Jackson & Gouseti, 2014; May et al., 2010; Rader, 2004; Rader et al., 2007; Rader et al., 2014).

The affective aspect (A). The affective aspect regards how frequently one has feared becoming a victim of a specific crime (see e.g., Abdullah et al., 2015; Franklin & Franklin, 2009; Franklin et al., 2008; Lane et al., 2014; Yuan & Mcneely, 2017) preferably measured with frequency and magnitude of the fear episodes (see Farrall & Gadd, 2004a, b, c; Farrall et al., 2009; Hinkle, 2015).

The behavioral aspect (B). The behavioral aspect regards changes in behavior. Both avoidant behaviors, if one has limited or changed their behavior due to fear of crime (avoiding going places alone or at night), and defensive behavior, if one has done a specific action (installing extra locks) to reduce their fear (Rader et al., 2007). The behavioral aspect hence regards the precautions people do or do not take to guard against crime (see e.g., Gray et al., 2011; May et al., 2010; Rader et al., 2007; Wilcox-Rountree & Land, 1996b).

The cognitive aspect (C). The cognitive aspect of fear regards the perceived risk of being victimized. Usually measured by how likely is it that one will be mugged, raped, burglarized etcetera (see e.g., Brunton-Smith et al., 2014, Hinkle, 2015). Worrying about becoming a victim of crime could be regarded as another cognitive facet (Brunton-Smith & Sturgis, 2011; Skogan, 1999). Worry can also be seen as another affective aspect, as one of many emotional reactions, fear, worry and anxiety (Jackson & Gouseti, 2014). Worry hence overlap between the different definitions in research.

As there have been several different definitions and measurement approaches in the fear of crime field (Andreescu, 2010; Farrall et al., 1997; Ferraro, 1995; Ferraro & LaGrange, 1987; Hale, 1996; Heber, 2007; Wilson & Kelling, 1982; Zhao et al., 2002), this has also been accompanied by some criticism regarding the methodological aspects of measuring safety, including definitions, data collection, and data analysis (Farrall et al., 1997; Ferraro, 1995; LaGrange & Ferraro, 1987). There is a hence a lot of literature regarding the affective and cognitive aspects of fear of crime and the correct way to measure them (see e.g., Farrall et al., 1997; Farrall et al., 2009; Ferraro, 1995;

Lagrange & Ferraro, 1987; Gray et al., 2011; Hale, 1996; Hough, 2004; Jackson, 2005; Mesch, 2000; Rader et al, 2007; Wilcox -Rountree & Land, 1996a; Warr, 2000).

Fear of crime, however, continues to be a commonly used indicator to measure people's safety and unsafety. There is an assumption that there is a connection between fear of crime and feelings of unsafety (see NCCP, 2021). Historically, fear of crime was mostly defined as the perception of risk, indicating a likelihood of becoming a victim of a specific crime (Ferraro, 1995; Ferraro & LaGrange, 1987; LaGrange et al., 1992). However, research revealed that this definition differs significantly from the emotional response associated with the anticipation of victimization (Mesch, 2000; Rader et al., 2007; Wilcox-Rountree & Land, 1996a; Warr, 2000; Wyant, 2008). Nevertheless, both historically, and in contemporary times a common question employed in various contexts, such as national safety surveys, serves to gauge either a broader assessment of perceived safety (see Greve et al., 2018) or an individual's cognitive perception of the threat of crime (see Skogan in 1999). This is frequently measured by how safe one feels while being out alone in one's neighborhood at night (see e.g., Breetzke et al., 2015; Franklin et al., 2008; Hinkle, 2015; Wyant, 2008; Zhao et al., 2015). Using the perceived safety measurement typically renders a more fearful response, than more specific questions regarding cognition, affect or behavior change limited to time, crime, place, and frequency do (see e.g., Farrall & Gadd, 2004 a,b,c; Farrall et al., 2009, Hinkle, 2015).

Researchers in the fear of crime field do distinguish between actual safety and perceived safety (see Cordner, 1986; Dubow et al., 1979; Ferraro & LaGrange, 1987; Hale, 1996; Wilson & Kelling, 1982), as is done in the current dissertation. Actual safety pertains to the objective risk and likelihood of experiencing a crime and can be based on statistical data, while perceived safety relates to people's or groups' affective and emotional fears. These perceptions of unsafety and fear of crime are subjective and vary depending on factors such as time, location, and the people present in the environment (Farrall et al., 1997; Ferraro, 1995; LaGrange & Ferraro, 1987). This variability makes the measurement of safety challenging. In one example, from

Cytadela Park in Poland, results revealed that perceived unsafety varied depending on factors such as time of day and the people present in the environment (Bogacka, 2020). There was a noticeable difference in the perception of safety between day and night. During daytime, 84.9 percent of respondents reported feeling safe, while this number significantly dropped to 25.7 percent after dusk. Conversely, 3.6 percent indicated feeling unsafe during the day, and 36.5 percent expressed feeling unsafe after dark. The response "difficult to say" was most frequently chosen at nighttime. The top factors that influenced feelings of unsafety were alcohol consumption, the presence of homeless and vandalism. Appropriate lighting, the presence of known other and video surveillance on the other hand increased safety perceptions. Another example from Sweden also revealed that perceived unsafety varied depending on situational factors such as time, location, and the people present in the environment (Doyle et al., 2016). Respondents perceived themselves as less fearful during the daytime than during nighttime. A uniformed presence, regardless of uniform, increased the perceived safety feelings at nighttime, in a vibrant nighttime situation, as well as in a desolate park and a tunnel, but not during the day.

It is important when reading reports on fear of crime and perceived unsafety to remember, that depending on how fear of crime has been defined and concurrently measured, including specifiers of the situation or not, different amounts of people will be perceived as fearful (see e.g., Andreescu 2010; Farrall et al., 1997; Ferraro, 1995; Ferraro & LaGrange, 1987; Hale, 1996; Heber, 2007; Wilson & Kelling, 1982; Zhao et al. 2002).

Regardless of the apparent measurement issues, fear of crime has been linked to various physical and mental health problems (see Amerio & Roccato, 2007; Baum et al., 2009; Dolan et al., 2005; Dolan & Peasgood, 2007; Golovchanova et al., 2021; Hale, 1996; Jackson & Stafford, 2009; Kruger et al. 2007; Stafford et al., 2007; Whitley & Prince, 2005; Ziersch et al., 2005) such as anxiety (Whitley & Prince, 2005) and depression (Golovchanova et al., 2021; Kruger et al. 2007). For example, residents with higher levels of fear of crime were almost twice as likely to experience mental health issues as people with less fear of crime (Stafford et al., 2007). Fear of crime also contribute to increased stress (Jackson & Stafford, 2009) and is associated with lower quality of life, life satisfaction, and subjective wellbeing (Adams & Serpe, 2000; Cohen et al., 2009; Dolan & Peasgood, 2007; Golovchanova et al., 2021; Hale, 1988, 1996; Stafford et al., 2007; Ziersch et al., 2005). Fear of crime has furthermore been linked to a decrease in social integration (Hinkle, 2013), as well as having a potential negative role in neighborhood crime and decay (Hale, 1996; Skogan, 1986; Wilson & Kelling, 1982). Additionally, fear of crime can impact an individual's sense of mastery, trust (Adams & Serpe, 2000; Jackson & Stafford, 2009; Skogan & Maxfield, 1981), and limit their range of activities (Amerio & Roccato, 2007; Dolan & Peasgood, 2007; Hale, 1996; Jackson & Stafford, 2009; Skogan & Maxfield, 1981; Stafford et al., 2007) making them not leave the house due to fear for example.

Based on the previously mentioned studies, there are several reasons to prevent perceived unsafety, and thus to first make a correct identification of unsafe locations. One reason is an improved well-being. Fear of crime can have negative effects on individuals' physical and mental health (see e.g., Amerio & Roccato, 2007; Baum et al., 2009; Dolan & Peasgood, 2007; Golovchanova et al., 2021; Hale, 1996; Jackson & Stafford, 2009; Kruger et al. 2007; Stafford et al., 2007; Whitley & Prince, 2005; Ziersch et al., 2005), leading to heightened stress, anxiety, and a reduced quality of life. By preventing fear of crime, people can experience an improved overall wellbeing and a greater sense of safety in their daily lives. Another reason for prevention, and a correct geographical forecast, is to promote community cohesion and collective efficacy. Fear of crime can erode the peoples' trust and social ties within communities (see e.g., Abdullah et al. 2015; Brunton-Smith et al., 2014; Brunton-Smith & Sturgis 2011; Hinkle, 2013, 2015; Markowitz et al. 2001; Swatt et al. 2013). By addressing and preventing fear of crime, communities can raise a sense of safety, trust, and cohesion among residents, which in turn can strengthen community bonds and promote societal collaboration. Preventing perceived unsafety can also encourage resident participation and engagement in their neighborhood. Fear of crime can limit peoples' activity range (Amerio & Roccato, 2007;

Dolan & Peasgood, 2007; Hale, 1996; Jackson & Stafford, 2009; Skogan & Maxfield, 1981; Stafford et al., 2007) in public places and hinder their participation in community activities. By creating safer environments, people might be more likely to engage in various social, recreational, and public activities, leading to a more vibrant and inclusive community life. There might also be economic benefits to preventing perceived unsafety. High levels of fear of crime might deter businesses, tourism, and investment, resulting in negative economic consequences for a neighborhood (Ceccato & Wilhelmsson, 2011, 2012; Hale, 1996; Skogan, 1986; Wilson & Kelling, 1982). By addressing fear of crime, communities can create safer and more attractive environments for businesses, residents, and visitors, which in turn can influence the economic development of said neighborhood. Lastly, preventing fear of crime can add to crime prevention efforts (Hale, 1996; Skogan, 1986; Ren et al., 2019; Wilson & Kelling, 1982). Addressing fear of crime can create a sense of public safety and therefore encourage active involvement in crime prevention initiatives. When people feel safe and empowered, they are more likely to report suspicious activities, support community policing efforts, and take steps to secure their own homes and neighborhoods, thus contributing to overall crime prevention efforts.

In sum, preventing fear of crime/perceived unsafety, and first making a correct identification of unsafe locations, is essential for creating safer and sustainable communities, promoting social cohesion, encouraging community engagement, supporting economic growth/stability, and complementing crime prevention strategies. By accurately identifying potential fear hotspots, proactive measures can be implemented to mitigate the occurrence of unsafety and enhance overall community safety.

1.3 Hotspots of unsafety (crime and fear of crime)

Crime hotspots, small locations with a high concentration of crime, do exist (Andresen et al. 2017; Braga et al., 2019; Eck et al., 2005; Weisburd et al. 2004; Weisburd et al., 2009ab; Weisburd, 2015). These locations are often geographically limited in size (Caplan et al., 2011; Eck et al., 2005; Kennedy et al., 2011; Sherman et al., 1989; Weisburd et al. 2004; Weisburd et al., 2009ab) and cluster in small proportions of the city (Weisburd, 2015) in many cities (see Andresen et al. 2017; Braga et al. 2010; Haberman & Ratcliffe, 2015; Lee et al., 2020; Sherman et al. 1989; Weisburd 2015; Weisburd & Amram 2014; Weisburd et al. 2009ab, 2012; Umar et al. 2021; Wheeler & Steenbeek, 2021). One definition of a crime hotspot is a small geographical location with a high concentration of crime incidents over time (Sherman &Weisburd, 1995). It does seem as if there might be an equivalent of hotspots for perceived safety (Curtis et al., 2014; Doran & Lees, 2005; Guldåker et al., 2023; Kronkvist, 2022). Micro-places with a persistent level of high perceived unsafety have been found in the city of Malmö, Sweden (Kronkvist, 2022) and in Uppsala (Guldåker et al., 2023). These results, however, need to be further confirmed in other cities and in other contexts.

1.3.1 Issues relating to understanding the geography of hotspots

Though hotspots are geographically small locations with a persistently high number of crimes, there is not a consensus on how to define these hotspots (see e.g., Bernasco & Steenbeek, 2017; Chalfin et al., 2021; Gerell, 2021; Mohler et al. 2019). The size of the hotspot must be taken into consideration (see Eck et al., 2005; Gerell, 2017). The understanding of hotspots of crime and fear will depend on what type of geography is considered, see Figure 1. Hotspots can be defined based on specific street addresses, blocks, and even larger areas such as census – blocks and tracts, police districts (see e.g., Eck, 2005; Ramos et al., 2021; Rosser et al., 2017) or via smoothed ego-hoods, that is multiple areas (buffers) with overlapping boundaries (see e.g. Hipp & Boessen 2013; Kim & Hipp, 2020) or a place covering one percent of the study area (Wheeler & Steenbeek, 2021) to mention a few ways that size of the hotspot have been defined. Decisions regarding drawing boundaries around the units of analysis and deciding on the appropriate size (scale) of the units can have a major impact on results (see e.g., Gerell, 2017; Openshaw, 1984). The modifiable areal unit (MAUP) regards the two things already mentioned: zonation and scale (Openshaw, 1984). Zonation concerns the drawing of boundaries around the locations of interest, for example the boundaries of administrative neighborhoods or randomly drawn boundaries, ellipses, and convex hulls.

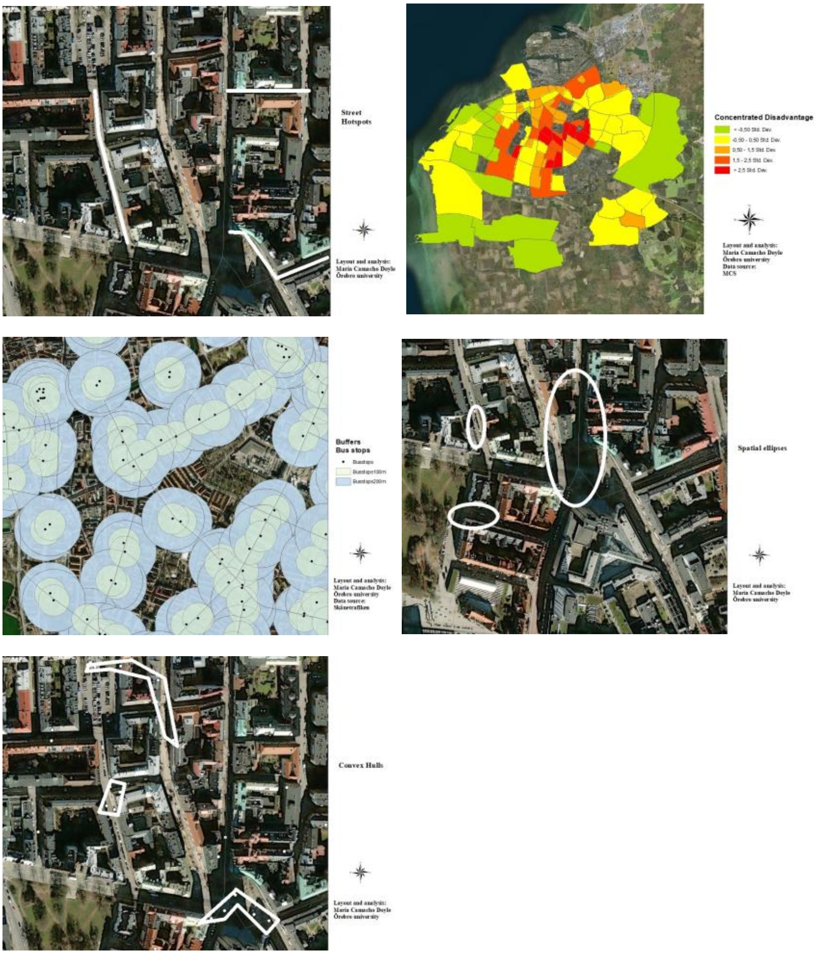

Figure 1. Type of geography. Top left, streets as hotspots. Top right, administrative neighborhoods. Middle left, buffers, bus stop with green 100-meter buffers and blue 200-meter buffers. Middle right, spatial ellipses. Bottom, convex hulls.

By changing the geographical boundaries of the location of interest, even reversed statistical associations have been attained (see Openshaw, 1984). Boundaries can furthermore be fuzzy, as crime for example might be higher around the edges between different types of places (see e.g., Brantingham et al 2009; Brantingham & Brantingham 1995). There might be more similarities than differences over the drawn borders. Scale regards the size of the location of interest. The issue of scale is more researched in the criminological field than the issue of zonation (see e.g., Andresen & Malleson 2013; Flowerdew 2011; Gerell, 2017), this is due to the semi-recent emphasis on micro-place hotspots in the field (Braga et al. 2019; Sherman, 1995; Weisburd et al. 2004, 2006, 2009, 2010, 2014b), and the similar geographical notion of 'smaller is better' (Hipp 2010; Gerell, 2017; Oberwittler & Wikström 2009). Results might differ depending on the scale of the location put into the analysis. One example from Malmö showed that the smallest size was best for understanding where outdoor arson occurred when comparing the size of two administrative units: a medium sized Small Area Markets Statistics area (SAMS) and larger neighborhood area to a much smaller 50-meter grid cell size (Gerell, 2017). The medium size was not much better than the larger size.

Whether the two parts of MAUP is a problem or not, is inconclusive in previous research, with certain studies showing MAUP to be a problem (e.g., Hipp, 2007; Steenbeek & Weisburd, 2016), and others showing a more limited effect of MAUP on the results (Flowerdew, 2011). In sum, MAUP is important, as much is agreed upon (see Gerell, 2017), how important it is, however, is under debate.

Perceived safety has mostly been studied at the neighborhood level (see e.g., Kuen et al., 2022; Kronkvist, 2022). Only recently has the micro-level approach been adapted to the fear of crime literature. The argument for the micro-level foci is that street segments should be seen as their own social settings, like small-scale communities rather than just a size unit (Weisburd et al., 2012). The issues of zone and scale (MAUP) are likely of importance here too. Different results might be reached depending on the unit of analysis. It might be that residents are more likely to recognize and react to issues on the streets where they live, rather than what happens in the greater neighborhood (Weisburd et al., 2011a; Weisburd et al., 2011b). There is research that indicates that disorder, low collective efficacy, and crime are concentrated at specific street segments, showing variability from one street to another within the same community (Weisburd, 2015; Weisburd et al., 2012; Hipp, 2010; Weisburd et al., 2020). In a qualitative example from Malmö, three levels of geography were studied: micro-place (about 200 residents), micro-neighborhood (about 1000 residents), which included a slightly larger area but not exceeding two blocks; and neighborhood (about 3000 residents), included a geographical area larger than two blocks (Gerell, 2015). Here the results revealed that collective efficacy was more influential at both micro-level and micro-neighborhood than the larger neighborhoods which is typically examined. People have expectations regarding collective efficacy (cohesion and informal control) based on the places they interact with in their daily lives, as well as the people who inhabit those places. Another Malmö based study (Kronkvist, 2022) comparing 100-metre grid-cells, 200-metre grid-cells and 400-metre grid-cells found that the different operationalizations of micro-place had minimal influence on the results. The smallest unit had slightly higher concentrations of fear of crime, and the larger units had slightly lower concentrations. It was furthermore reasoned that these results were expected, as smaller units of analysis usually show stronger concentrations of fear of crime (Schnell et al., 2017; Steenbeek & Weisburd, 2016).

1.3.2 Challenges in evaluating safety levels at hotspots

Hotspots defined as geographically small locations with a persistently high number of crimes, leave a question of what 'a lot of crime' is, out of the definition (see Eck et al., 2005). A lot of crime has been operationalized as locations that has two standard deviations over the mean crime level (Chainey et al. 2008; Drawve 2016), a location that has above average crime (Eck et al., 2005), or locations with for example 20 or 50 percent of the total crime (see Bernasco & Steenbeek, 2017; Ramos et al., 2021). There is also the question of crime specific-, or crime general (multi-crime) hotspots, the crime diversity at place (Brantingham, 2016; Khorshidi et al., 2021). Crime-specific meaning that one crime type occurs in a specific location, such as residential burglary in a residential area. Crime-general meaning that several types of crimes occur in the same location. Such as disorder, assault, and street robbery in a nightlife district. One study from Philadelphia showed that hotspots of different crime types typically do not overlap (Haberman, 2017). This is echoed in a few other studies from Vancouver (Andresen, 2009; Andresen & Linning, 2012; Andresen & Malleson, 2011, 2013). Other studies show a weak mixture of crime diversity at street-segments in Minneapolis (Weisburd et al., 1992), and micro places in London with a few thousand residents (Quick & Brunton- Smith, 2018) with some places being crime specific and other crime general. A recent study from St. Louis recommends looking at crime general hotspots however, rather than at specific crimes, when it comes to crime prevention, as the crime types that diverge from crime general places are usually crimes that occur relatively infrequently (Lentz & Brantingham, 2021). Lastly, also affecting both forecasting and prevention, the occurrence of different types of crimes in a particular area are not necessarily connected or influenced by each other (Brantingham, 2016). For example, a residential burglary and a drug offense occurring in the same location may not be directly related or influenced by each other. Different types of crimes occurring in the same location can reflect the environmental cues present throughout that area, such as mobility hotspots, rather than being driven by direct connections between the different types of crime.

Having knowledge about the law of crime concentration at places can be used to strategically allocate police resources (Braga et al., 2019) and as a basis for forecasting crime (Mohler et al., 2015). However, when there are more places than crimes in the analysis there is a risk of falsely confirming the law of crime concentration at places (Bernasco & Steenbeek, 2017; Chalfin et al., 2021; Mohler et al., 2019). When there are more places than crime, clustering of crimes can be observed even though a random distribution exists. Crimes that are rarer can furthermore appear to be even more concentrated than other more common crimes (Hipp & Kim, 2017), simply because a small number of places will account for most, if not all the crimes. This will constitute a problem for studies that use small units of analysis such as street segments or census blocks (e.g., Andresen & Malleson 2011), and individual addresses (e.g., Sherman et al. 1989). This becomes important because the effectiveness of crime prevention at places relies on the degree of actual crime concentration, and the accurate forecast. If we overestimate the importance of place, there is no actual crime clustering, an unnecessary focus on place-based interventions may hinder other effective non-place-based crime prevention strategies.

What constitutes a lot of crime is echoed in the fear of crime literature, how many are fearful. If survey questions do not include crime-specific fear (Ferraro & LaGrange, 1987; Hale, 1996), information regarding the specific location and situation (Ferraro & LaGrange, 1987; Fisher & Nasar, 1992, 1995) or tapping into the wrong construct, fear levels will be, and have been overstated (Farrall., et al 1997; Gibson et al., 2002; Gray et al., 2008; Hinkle, 2015; Wilcox-Rountree & Land, 1996a). A lack of consensus regarding the measurement of fear of crime remains in the field (Hinkle, 2015; Yuan & McNeeley, 2017). Nevertheless, if fear levels are overstated, the same risk of falsely confirming a potential law of fear concentration at places applies. All this considered to correctly measure hotspots of unsafety, it is still important to try to identify the hotspots of unsafety with some accuracy.

1.4 Theoretical framework

Identifying hotspots of unsafety is not the same as understanding them. Firstly, individuals themselves are at the root of human actions which can include actual safety; offending and some victimization, and reactions, which can include perceived unsafety. There is a lot of research on both individual level correlates of crime (see e.g., Basto-Pereira & Farrington, 2022) and fear of crime (Doran & Burgess, 2012; Farrall et al., 2009; Hale, 1996; Rader, 2017). However, human actions and reactions do not occur without context. This context can include both the immediate, and the greater environment. In criminology there are two somewhat different theoretical approaches that attempt to explain the non-random distribution of crime over space at different spatial scales, community criminology and environmental criminology. Community criminology and environmental criminology with its theoretical approaches can be used to describe both the occurrence of actual safety and perceived safety.

The fact that geographical location matters in crime consistency, and different explanations of the crime consistency have been put forward for quite some time. Mapping and trying to understand crime geographically, dates to France and Belgium (Balbi & Guerry, 1829 and Quetelet, 1847 as cited in Weisburd et al. 2009a), and Chicago (Shaw & McKay, 1942, 1942/1967) to mention a few. The early studies on where crime occurs were mostly focused on meso-geographic levels, comparing regions, cities, or neighborhoods. In the 1970s, 80s and 90s, large strides in understanding the geography of crime were taken as smaller micro-geographic level locations, so called hotspots, came into the spotlight (Sherman et al. 1989; Weisburd et al. 2004; Weisburd et al., 2009b). In recent times, multi-geographic level approaches have been developed to take the interaction of the larger meso-approach (neighborhoods) and the smaller micro-approach (specific place in neighborhood) into account, that is, place in neighborhoods (Tillyer et al. 2021; Wilcox & Tillyer, 2018), when explaining crime across time and space. Taking different levels of explanation into account is pertinent, as it is likely that different aspects of the environment at different geographical levels interact rather than work independently.

Perceived unsafety and related measures, have been studied for more than 40 years (Farrall et al., 2009; Rader, 2017), the focus early on was on what fear of crime was, and was not, and how to correctly measure it (see e.g., Farrall et al., 1997; Farrall et al., 2009; Ferraro & LaGrange, 1987; Gray et al., 2012; Hale, 1996; Hough, 2004; Jackson, 2005). When it also became apparent that there was a contradiction in actual victimization and fear of crime, researchers began to study why this was (Rader, 2017). Since then, the strand of research that focus on why people are fearful has focused mainly on mechanisms that occur at the individual level (see e.g., Lane et al., 2014; May & Dunaway, 2000; Schafer et al., 2006; Rader et al., 2012) and the community level (see e.g., Markowitz et al., 2001; O'Brien et al., 2019; Robinson et al., 2003; Wyant, 2008). Lately, contextual factors at the micro-geographic level have also been studied in relation to perceived safety (Guldåker et al., 2023; Kuen et al., 2022; Kronkvist, 2022). In short, based on earlier research, some of the differences seen in perceived unsafety between neighborhoods (see e,g., Ivert et al., 2013; Ivert et al., 2015) can theoretically be because individuals are different and differently prone to fearful responses (Gabriel & Greve, 2003; Jackson, 2009, 2015), or because conditions in the neighborhoods themselves such as low collective efficacy (Abdullah et al. 2015; Brunton-Smith et al., 2014; Brunton-Smith & Sturgis 2011; Hinkle 2015; Markowitz et al. 2001; Swatt et al. 2013), disorder (Brunton-Smith et al., 2014; Brunton-Smith & Sturgis 2011; Hinkle 2015; Lane et al. 2014; Robinson et al. 2003; Wyant, 2008) or actual crime rates (Doran & Burgess, 2012; Hale, 1996; May & Dunaway, 2000; Schafer et al., 2006) trigger a fearful response in the individual (Brantingham et al., 1995).

1.4.1 Community criminology

In community criminology, the structural patterns of the broader neighborhood aid in the understanding of why places become hotspots, and it is linked historically to the Chicago school and specifically the social disorganization theory (see Shaw & McKay 1942; Thrasher 1927). The social disorganization theory posits that a high population turnover, concentrated disadvantage, and an ethnic heterogeneity affect disorder (Shaw & Mackay, 1942 based on ideas by Burgess, 1925: Park, 1925ab, developed by Kornhouser, 1978). This relationship between structural neighborhood characteristics and deviance is mediated by community cohesion and social control. One example being the inability of residents to organize against disorderly behavior, due to a lack of cohesion because residents continually move in and out of the neighborhood. In short, places that are more socially disorganized will have more crime. Places with more social organization will have less crime. The understanding of what predicts crime is usually on the meso-level and comparisons are made on the neighborhood, census tract, police district level.

Contemporary elaboration of the social disorganization theory (Shaw & McKay 1942/1969; Kornhouser 1978), with the inclusion of informal social control has led to for example the collective efficacy theory (Sampson & Groves 1989; Sampson et al., 1997). Strong cohesion and informal control in the neighborhood will lead to high collective efficacy and likely to less crime in the neighborhood. The three pillars of social disorganization theory – high population turnover, concentrated disadvantage, and ethnic heterogeneity – will predict the level of collective efficacy in said neighborhood (Sampson et al., 1997). Collective efficacy sees the social control that lies between the private and the public as key. That is, social control exercised by social networks such as churches, schools, social clubs, and the like (parochial control) (Hunter, 1978). Furthermore, it regards the substance of these social networks not just the mere existence of them (Sampson et al. 1997; Sampson 2012). These social networks should be inherited with cohesion and trust, leading to expectations of informal social control, that is the expectation that others will intervene if necessary. Collective efficacy could be used as a measurement of capable neighborhood guardianship and because of this collective efficacy might have a bigger effect on public crime incidents as opposed to private incidents of crime. In short, places with low collective efficacy are thought to have more crime and places with high collective efficacy less crime.

Perceived unsafety and related measures has theoretically been related to the described processes of social disorganization (Brunton-Smith et al., 2014; Brunton-Smith & Sturgis 2011; Haynes & Rader, 2015; Porter et al., 2012; Robinson et al. 2003; Wyant 2008) and collective efficacy (Abdullah et al. 2015; Brunton- Smith et al., 2014; Brunton-Smith & Sturgis 2011; Hinkle 2015; Kuen et al., 2022; Markowitz et al. 2001; Swatt et al. 2013). In short, places with low collective efficacy and/or high social disorder are thought to have more perceived unsafety and places with high collective efficacy and/or low social disorder more perceived safety.

Living in a high-crime area, due to high social disorder and low collective efficacy, can increase the risk of becoming a victim of crime both direct and/or indirect, which in turn can increase the perception of unsafety in said neighborhood (Barton et al., 2017). Residential (im-)mobility and ethnic heterogeneity can also correlate with perceived unsafety directly (Chiricos et al., 1997; Covington & Taylor, 1991; Skogan & Maxfield, 1981). A diverse neighborhood can induce fear of crime, due to a fear of the unknown neighbor (Katz et al., 2003; Lane & Meeker, 2000). 'Othering' is a process that can occur when individuals in said neighborhood do not have a relationship with their neighbors (Lane et al., 2014). The individuals see themselves as different from the ethnically or culturally 'others', which in turn can increase the fear of crime (Chiricos et al., 1997; Katz et al., 2003; Lane, 2002). In a similar vein, high collective efficacy through social cohesion and informal control and a similarly strong tie between neighbors can decrease fear of crime (Swatt et al., 2013) and the opposite is also true, low ties to the community, higher fear (Markowitz et al., 2001; Scarborough et al., 2010; Sampson et al., 1997). Hence, areas with high social cohesion, a collective community and low anonymity generally contribute to a higher sense of perceived safety (see, e.g., Farrall et al., 2009). If this explanatory model is correct, forecasting models that use neighborhood risk factors as predictors could possibly explain the level of perceived safety of residential areas as well.

1.4.2 Environmental criminology

Environmental criminology emerged in the 1970s and 1980s and encompasses a family of opportunity theories such as rational choice, routine activity theory, crime pattern theory and environmental design theory (Taylor, 1998; Wilcox & Gialopsos, 2015). Crime incidents and how opportunities are provided in the situation are in focus. Crime is not random across space and time. It is the highly situational opportunities provided in the context of the specific location that affects crime (Brantingham & Brantingham, 1981; Cohen & Felson, 1979). Crime incidents are crime type- and context specific (Cornish & Clarke 1986; Clarke 1980; Clarke, 1997). The specific patterns, dynamics, and attributes of the place within the neighborhood will contribute to opportunities for people to commit crime. The understanding of what predicts crime is usually on the micro-level as opposed to greater neighborhoods (Schnell et al., 2017; Steenbeek & Weisburd, 2016) as in community criminology. Comparisons are usually made on the level of specific addresses (e.g., Sherman et al. 1989) or street blocks or segments (e.g., Andresen et al.

2017; Bernasco & Block 2011; Braga et al. 2010; Curman et al. 2014; Roncek & Maier 1991; Weisburd et al. 2012).

A frequently referenced environmental theory in the crime forecast literature is the crime pattern theory (CPT). Crime, according to CPT, depends much on the context of the specific location (Brantingham & Brantingham, 1995). Much attention is nevertheless also paid to the broader environmental background of the location. Crime will happen around activity nodes, such as home, school and workplace. Crime will also happen on and around paths between these activity nodes, roads that link the home, school, and workplace environments and at the edges between different types of areas such as industrial areas and residential areas for example. The activity nodes are central places to people. Places where they go to school/work, the store, shopping mall. At these activity nodes potential victims and offenders meet due to their routine activities. A lot of people have similar routine activities, routine places, and routine paths between these nodes. This generates a high concentration of people in and around these places which creates opportunities for crime. Crime will also happen along the edges between different areas of different social status (Brantingham et al 2009; Brantingham & Brantingham 1995). Especially along edges with a great difference between the places, this might be due to unclear rules at such a place and/or the potential for guardianship is low. It can be along the edges of a parking lot and a travel center or bus station. Or at the edges between a park and residential area. Lastly, certain land uses attract and generate crime differently. What the location is used for and what people the location attracts. A foreclosure attracts different people than a greenery area. A mixed residential area attracts different people than private owned or rental apartments.

CPT furthermore differentiates between places that act as crime generators and crime attractors (Brantingham & Brantingham, 1993, 1995). Crime generators are environments, paths and/or situations where a lot of people move about and are drawn to. People are there primarily to go about their daily business, not to commit crime. However, an opportunity and/or situation to commit crime might present itself for crime-prone people. The sheer concentration of people and potential goods is what generates crime. Examples of crime generators are shopping malls and districts, entertainment districts, travel-nodes for example bus-, and train stops. Crime attractors on the other hand are environments and situations where it is known to be conducive to commit crime. It is places and times where motivated offenders are drawn due to the known opportunity to commit crime, such as open drug markets, areas with prostitutes, large unattended parking lots, shopping malls and entertainment districts. Some types of places could be both crime generators and crime attractors such as a shopping mall or bar.

CPT also attempts to explain fear of crime (Brantingham & Brantingham, 1995) through fear generators. Certain aspects of the specific location or neighborhood can act as a fear generator. Fear will increase in unknown areas when a lack of control over the situation is apparent, fear will increase in the dark, fear will increase in the presence of unknown others and an isolation from known others, fear will increase when the individual's pathway between nodes crosses those of scary-others, and/or fear will increase when problems, disorder or indicators of incivilities are clearly visible. One of the earlier explanation models of perceived unsafety (Brunton-Smith & Sturgis, 2011; Doran & Burgess, 2012; Hale, 1996; Jackson, 2006), regards the statistically calculated risk of vulnerability and actual vulnerability as key explanations for why people report perceived safety or not. Thus, according to this explanatory model, perceived safety should be related to the level of criminal activity (fear generator) in the area or by what people hear about the criminal activity in the area through others (fear generator).

Previous crime has been shown in some previous research (Luo et al., 2016; Rader, et al., 2012; Wilcox -Rountree & Land 1996a, b; Zhao et al., 2015), to be a potential contributing factor to why people experience unsafety. If this explanatory model is correct, forecast models that use criminal history as a predictor could possibly be able to explain part of the neighborhood level perceived safety as well. Perceived neighborhood disorder has been related to higher perceived neighborhood unsafety (see e.g., Brunton-Smith et al., 2014;

Brunton-Smith and Sturgis 2011; Hinkle 2015; Lane et al. 2014; Robinson et al. 2003; Wyant 2008). In short, untended neighborhood disorder increased fear in real time and over time. There has been some evidence that characteristics of the built environment can work as fear generators (see e.g., Ceccato et al., 2020b; Ceccato & Bamzar, 2016; Ceccato & Snickars; 2000; Houser et al., 2019). Places with fewer people can also be fear generating (Lorenc et al., 2013). Unsafe places, according to a sample of elderly people, vary (Ceccato & Bamzar, 2016). Unsafe places can both be locations with a lot of people and locations that are more desolate. In short, the perception of the location and how it is being used plays a role in perceived safety at that place (Costamagna et al., 2019), the built environment can have an impact on an individual's safety (Ceccato, 2016).

1.4.3 Community and environmental criminology combined

The community and environmental perspectives of criminology are seen as compatible nowadays, even though they are different at the fundamental level (see e.g., Gerell, 2018a; Hipp, 2016; Jones & Pridemore 2019; Tillyer et al., 2021; Weisburd et al., 2021; Wilcox & Tillyer, 2018). Consequently, these perspectives are now often combined in different ways to explain crime at different places (see e.g., Deryol et al., 2016; Dugato, 2022; Duru & Kim, 2021; Smith et al. 2000; Stucky & Ottensmann 2009; Taylor, 1998; Weisburd et al. 2012). This combination can be referred to as spatial-contextual criminology (Hipp et al., 2017). Spatial referring to the environmental, micro-place level and contextual referring to the community, neighborhood level (Hipp et al., 2017), the greater context of the spatial location. It is believed that choices made by offenders are based on both specific place variables, at the micro-level, as well as what greater context the place variables are located in. A bus stop (place variable) might be more prone to violence in an area where guardianship is low due to low collective efficacy (neighborhood variable) (Gerell, 2018a). Vandalism might be more appealing in proximity to playgrounds or schools (place variables) in an area with low socioeconomic status (neighborhood variable) (Newton & Bowers, 2007). High-density housing (place variable) might be prone to violence, especially in more disadvantaged areas (neighborhood variable) (Stucky & Ottensmann 2009). Spatial risk factors at the micro place level will relate stronger with crime in a context, like neighborhoods that have a great supply of opportunities due to potential offenders, targets, and a weak collective guardianship (Tillyer et al., 2021). Spatial risk factors at the micro level will relate weaker to crime in a context, like neighborhoods without such opportunities. CPT, although a place-level theory, does acknowledge that places are nested in neighborhoods, and that places have a "backcloth" (e.g., Brantingham & Brantingham, 1993, 1995, 2013; Bernasco & Block, 2011) making CPT implicitly multilevel. The specific locations are important, but as is the greater neighborhood. "We need to see both the tree and the forest" (Brantingham & Brantingham, 1993, p.6). In a spatial-contextual framework, both the trees, that is the micro-level crime generators, and the forest that is the neighborhood level variables, are seen as equally important.

1.4.4 The framework of the current dissertation: spatial-contextual criminology

When trying to identify, explain and forecast unsafety it is thus advisable to take different levels of explanation into account. The greater context (community perspective): the structural patterns of the overall neighborhood such as poverty, population heterogeneity, and collective efficacy as well as the specific spatial (environmental perspective) patterns, dynamics, and attributes of the place within the neighborhood itself, should be considered in explanations of hotspot consistency (see e.g. Bernasco & Block 2009; Braga et al., 2019; Braga & Clarke 2014; Gerell, 2018a; Weisburd et al., 2014ab; Weisburd et al., 2021). Consequently, both community (structural), and environmental (opportunity) theoretical levels are needed to understand unsafety at specific places. The framework of the current dissertation was therefore spatial-contextual criminology, with potential crime generators at both the environmental and the community criminology levels. More specifically, in Studies I, II, III, all independent variables included in analysis were based on the environmental level crime pattern theory (CPT), and community level theories of social disorganization theory and collective efficacy.

1.5 Forecasting unsafety (crime and fear of crime)

Early on Guerry (1833) and Quetelet (1847) studied crime distribution and found that crime was not evenly distributed geographically across crime types. They found that violent crime was highest in poorer rural areas and property crime was highest in wealthy, industrialized areas. They reasoned that opportunity, not poverty, caused property crime, because there was more to steal in wealthy regions. This was echoed later in Malmö (Werner, 1964) where property crimes were found to occur mainly in the city center where poverty was quite low. "Things are stolen, where there is something to steal, independent of where the criminal lives" (Werner 1964: 244).

Since the work of Guerry, Quetelet and Werner, many ways of forecasting crime have emerged. Some ways simpler, like putting digital pins, that represent crime incidents, on digital maps (Eck et al. 2005), others more advanced using mathematical algorithms and machine learning (Corcoran et al., 2003; Mohler et al., 2014; Rummens & Hardyns, 2020; Wheeler & Steenbeek, 2021). The most common methods of forecasting can roughly be classified into three different groups: retrospective hotspot maps, near repeat analysis and methods based on regression (Reinhart & Greenhouse, 2018). Retrospective hotspot maps and methods based on regression will be included in the current dissertation.

1.5.1 Retrospective hotspot mapping

Retrospective hotspot mapping is straight-forward, where there has been a lot of crime in the past, there will be a lot of crime in the future (see e.g., Eck et al., 2005). Crime history is the sole predictor. Usually, longer periods of crime history are used for analysis. All crime incidents from the past year, or the past two or three years or even more are used to forecast crime in a location. Retrospective hotspot mapping at the micro-place has been around for quite some time, an early overview can be found from 2002 (Groff & Lavigne, 2002). This mapping technique, using crime history to forecast crime is somewhat atheoretical (Groff & La Vigne 2002; Wheeler & Steenbeek, 2021). It is simple: crime begets crime. A few examples of these hotspot methods for identifying crime hotspots are as follows: The spatial and temporal analysis of crime (STAC) technique, that uses standard deviations to identify crime hot spots. With STAC you locate the densest groups of crime events, based on the scatter of crimes on the map (Levine, 2013). After identifying the densest groups of crime events (hotspots), these hotspots are displayed on a map by spatial ellipses or convex hulls based on the standard deviation (Levine, 2013; Eck et al., 2005). See Figure 1, for a visualization of spatial ellipses and convex hulls. The nearest neighbor hierarchical clustering technique (Nnh) identifies hot spot areas, not specific crime events. The NnH identifies spatially close groups of crime events. Grouping conditions must be defined, such as threshold distance between a pair of crime events and a minimum of crime events per group. Then only crime pairs closer to each other than the defined threshold distance will be selected for grouping. In addition, only groups containing the defined minimum of crime events will be selected for grouping. A regrouping process then continues until the grouping conditions fail. Lastly, the hot spots are displayed on a map by spatial ellipses or convex hulls (Levine, 2013).

Kernel density estimation (KDE) was created to be a technique to calculate the density of a histogram (Levine, 2013). In KDE grids are used instead of ellipses and convex hulls for analysis and visualization. A grid is put over the study area. In every grid cell, with a pre-specified grid cell size, every crime event is calculated. The closer an event is to the center of the cell; the higher density value is given to that event. The grid cell is then given a density estimate. This will result in a heat map with a variation of crime density, like a weather map, see Figure 2. This map will aid in identifying crime hot spots in a larger area (Levine, 2013; Eck et al., 2005). The most used retrospective hotspot map among researchers and practitioners is the KDE (Hart & Zandbergen, 2014; Kounadi et al., 2020). It is considered a relatively simple technique and perhaps that is why it is the most frequently used.

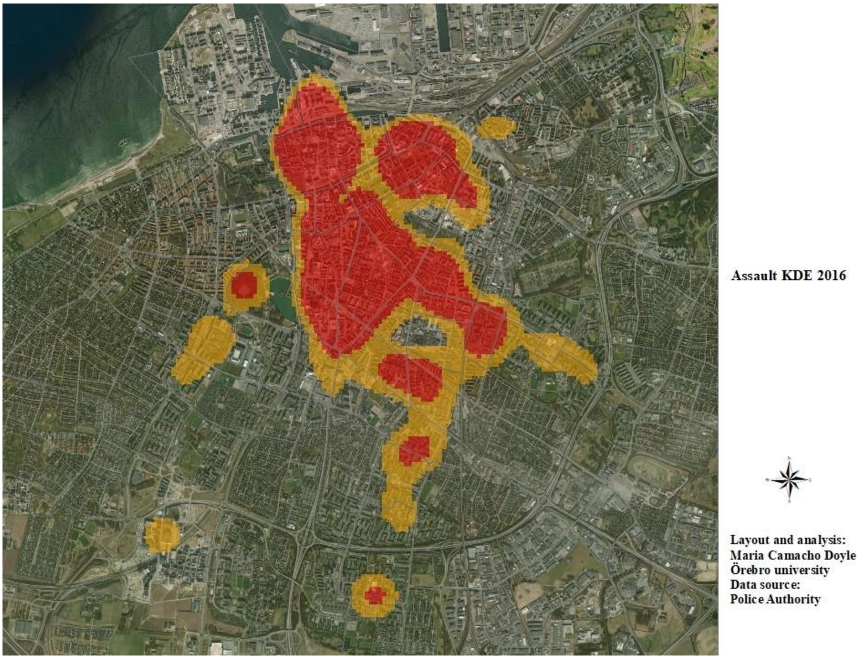

Figure 2. An example of a KDE based on assault 2016 to forecast assault in 2017, from Study II.

The effectiveness of retrospective hotspot maps in forecasting crime varies across crime types. In one study based in London using KDE, eight percent of the total crime amount was predicted, 12 percent of theft from vehicles and 20 percent of theft from persons (Chainey et al 2008). Another study from the US and using NnH, seven percent of the future gun crimes were forecasted (Drawve et al. 2016). Street crime seems to be the easiest to predict (Chainey et al., 2008). The retrospective techniques have been criticized for being a 'theoretic, a 'temporal, and static for example (Groff & La Vigne 2002).

1.5.2 Risk factors regressed onto crime

Another group of forecast methods are based on different types of risk factors regressed onto crime. The main idea is to identify potentially important environmental risk factors for a specific crime, in the specific location. Several crime types, both violent and property crimes, have been associated with the same set of risk factors (see e.g., Quick & Brunton-Smith, 2018). Common risk factors used for analysis are bars (Kennedy et al. 2011; Wheeler, 2019), liquor, and convenience stores (Wheeler, 2019), schools (Kennedy et al. 2016), public transit (Bernasco & Block 2011; Gerell, 2018a), banks, ATMs, and check cashing places (Haberman & Ratcliffe 2015; Kubrin & Hipp, 2016), public housing (Haberman et al. 2013), hotels and motels (Jones & Pridemore, 2019). These risk factors are sometimes used to forecast crime geographically in a linear matter(Caplan et al., 2011; Deryol et al. 2016). The risk factors can be measured via proximity, that is how close something is to something else. The risk factors can also be measured via density, that is the concentration of items within that space. Sometimes both proximity and density are important. There are, furthermore, likely interactions between different variables of the built environment, place variables, and social cohesion, a neighborhood variable (Hipp & Steenbeek 2016) or collective efficacy, usually a neighborhood variable (Gerell, 2018a) for example. These models based on regression are often driven by environmental criminology. Related theories such as crime pattern theory (CPT) (Brantingham & Brantingham 1993) and the routine activity theory (Cohen & Felson 1979) are used to explain why crime occurs at those places and what variables can be suitable for regression.

1.5.2.1 Risk Terrain Modeling

One way of analyzing the risk factors is to divide the study area into a geographic grid. Then theoretically and practically important risk factors for the specified crime type are calculated per grid cell. This is akin to risk terrain modeling (RTM) (see Caplan et al., 2015; Caplan et al., 2011). RTM, a spatial diagnostic method, was developed in 2010. RTM is a proprietary technique and uses the tool RTMDx (Caplan et al., 2013b), a for-profit software application, to ease the process of analysis of important geographical crime generators by automation. The first order of business in RTM is to identify all possible crime generators/risk factors for a specific crime type in the pre-decided location. These crime generators should be based both on empirical research but also the local knowledge of police (Caplan et al 2013a). Hence, many crime generators are collected. Crime history is normally not a part of the risk factors in risk terrain modeling but is used as the outcome measure. Likewise, neighborhood level risk factors such as concentrated disadvantage are usually not included in the RTM process. Somewhat simplified, after certain combinations of risk factors are found to be key in explaining future crime, through regression, a composite risk score is calculated. When risk values according to the risk composite have been assigned to each grid cell, you have a risk terrain map (see Caplan et al., 2015). This map tells us whether a particular place is a vulnerable place. See Figure 3.

Figure 3. An example of an RTM based on assault 2016 to forecast assault in 2017 from Study II.

Previous studies have shown RTM to be applicable to forecast general violence (Anyinam, 2015; Caplan et al., 2013ab; Giménez-Santana et al., 2018; Valasik et al., 2019), public assault (Kennedy et al. 2016, Kocher & Leitner, 2015), robbery (Barnum et al 2017; Caplan et al

2020; Drawve, 2016; Dugato, 2013; Garnier et al., 2018; Kocher & Leitner, 2015) auto theft (Kocher & Leitner, 2015) and residential burglary (Dugato et al., 2018; Yerxa, 2013) to name a few crime types.

1.5.3 Summary of forecasting methods

In summary, there are different methods to choose from when forecasting unsafety. Retrospective hotspot maps and RTM have been compared to see how useful they are at forecasting different types of crime such as violent crime, robberies, gun-crimes, residential burglaries, street crime, theft of- and from vehicles etcetera (see e.g., Chainey et al. 2008; Drawve, 2016; Drawve et al. 2016; Hart & Zandbergen 2012; Levine 2008; Van Patten et al. 2009). Two studies predicting robbery and gun-crimes respectively, compared different retrospective methods, such as KDE and NnH with RTM. KDE was more accurate in predicting future robberies and NnH more accurate in predicting gun crimes. RTM was the most precise in both cases (Drawve, 2016; Drawve et al., 2016). Using different methods together has been proposed, no matter what crime is being predicted (Caplan et al., 2013a; Kennedy et al., 2011; Van Patten et al., 2009). Some studies show that RTM is more accurate than retrospective hotspot mapping (Caplan et al., 2011; Kennedy et al., 2011). However, these studies did cross method comparisons without using a common reference point. The comparisons were done visually, by looking at the map, or forecast via a hit rate (Drawve, 2016). Methods that require more data collection than past crimes thus, do not always outperform simply counting past crime (Wheeler & Steenbeek, 2021) or KDEs (Rummens & Hardyns, 2020). But sometimes they do (Ohyama & Amemiya, 2018). When comparing different methods, using point, cluster, and density data, with different types of outputs, a shared reference value is recommended (see e.g., Chainey et al., 2008; Dugato 2013; Drawve, 2016; Drawve et al., 2016; Hart & Zandbergen, 2014; Van Patten et al., 2009; White & Hunt, 2022).

There is no standard hotspot method that is promoted over the others (White & Hunt, 2022). This might partly be due to the difficulty in assessing how good one hotspot map is compared to another. There is a lack of consistent terminology, what parameters to report and evaluation criteria, likely due to researchers coming from different backgrounds such as criminology, geography, computer science etcetera (Kounadi et al., 2020). This lack of consistency might contribute to the lack of consensus of what a good hotspot forecast is. Different accuracy metrics that have been used in the different research fields are Accuracy, Precision, Recall, F1-score, Area under the Precision-Recall Curve (PR-AUC), Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error, multinomial logistic regression accuracy and loss functions, the prediction accuracy index (PAI), the recapture rate index (RRI), the prediction efficiency index (PEI/PEI*) (see White & Hunt, 2022 for more information). Reference values generally used in the criminology field when forecasting crime geographically are the predictive accuracy index (PAI) value for examining how accurate the method is in finding the hotspot. The recapture rate index (RRI) value for examining how precise the method is in finding the hotspot over time. Plus, the prediction efficiency index (PEI/PEI*) for examining how well you did in your forecast, compared to how well you could have done. These accuracy metrics will be described in more detail in the method section.

Lastly, and in the vein of Kronkvist (2022) and Guldåker et al., (2023) perhaps there is a 'law of fear-concentration' as well (see also Ogneva-Himmelberger et al., 2019; Pánek et al., 2019) that can be forecast. Based on the social disorganization, collective efficacy theories and fear generators of CPT it might be possible to forecast places of perceived unsafety at the neighborhood level. A previous study (Houser et al., 2019) found that people that lived near crime attractors or generators perceived a heightened risk of crime victimization compared to those who lived further away even after controlling for demographic factors and neighborhood context. Another study (Glas et al., 2019), similarly found that people's feelings of unsafety were affected by the characteristics, the context, of the area they lived in. Ethnic diversity and economic status influenced feelings of safety in a larger area. While disorder influenced feelings of safety at a smaller, more micro-level area. In a third study (Kuen et al., 2022), fear of crime at the micro-level was studied in relation to for example street-level collective efficacy, social and physical disorder, and neighborhood concentrated disadvantage. Street level crime and social disorder were directly related to people's fear of crime.

1.6 Study relevance

Looking at the state of research today, to forecast unsafety properly in micro/meso places, one should use different types of crime/fear generators, at different levels (spatial scales) of explanation. Common crime/fear generators that appear in the literature are factors at the neighborhood level such as poverty, population heterogeneity, residential instability (Kim, 2018; Sampson et al. 1997; Quick & Brunton-Smith, 2018) and collective efficacy (Weisburd et al., 2014a). Collective efficacy might also be meaningful if measured at the micro-level spatial scale (Weisburd et al., 2021; Weisburd et al., 2020). Also, of importance are crime/fear generators of the built environment that affect land use, and the amount of ambient population that is flow of people at places. These crime generators could include amount of greenery, public housing, industrial areas, mixed living areas (see e.g., Sutherland et al., 2013). Specific place features, such as the proximity or density, or more likely both of bars (Kennedy et al. 2016; Wheeler, 2019), schools (Kennedy et al. 2016), public transit (Bernasco & Block 2011; Ceccato et al. 2015; Gerell, 2018a) and ATMs (Haberman & Ratcliffe 2015; Kubrin & Hipp, 2016). Further meaningful predictors are the effects from risky facilities that emanate out on to the street (Bowers, 2014), and the density of people (ambient population) using the area (Andresen, 2006; Gerell 2021). In addition, these crime/fear generators interact (Duru & Kim, 2021; Tillyer et al., 2021) and there could hence be different interaction effects to consider, for all included risk factors, at the different geographical levels (different spatial scales).

Making forecasts with a large amount of spatial data is very time-consuming and can also be quite costly. The data must first be collected and then processed. Using vast amounts of spatial data also introduces a lot of decisions that need to be made by the crime analysist that usually works with certain time constraints. For practical purposes we hence need to compare and establish that simple, transparent, and functional methods, such as a simple count of crime history, are not as accurate as slightly more complex methods and methods that require more data collection. Some earlier studies have not included a simple count of crime history when comparing different forecasting methods (Drawve 2016; Caplan et al., 2011; Chainey et al. 2008; Levine 2008). This is a problem, as simply counting crimes is both simple and cheap (Groff & La Vigne, 2002; Wheeler & Steenbeek, 2021). In addition to the simplicity argument, there is a historical persistence of crime at micro-place hotspots (Andresen et al., 2017; Curman et al. 2014; Weisburd et al. 2004; Wheeler et al. 2016) making crime history viable in forecasting unsafety, both crime and fear, depending on theoretical standpoint. Studies that include a simple count of crime history (Wheeler & Steenbeek, 2021), or other crime history information (Rummens & Hardyns, 2020) reveal that crime history perform quite well forecasting crime, when compared to methods that include more data collection. Others do not however (Ohyama & Amemiya, 2018). Earlier research is hence ambivalent, regarding how much data is needed to forecast unsafety. In general, reasonably simple methods do render good results, albeit not the best (see also Lee et al., 2020). Consequently, for practical purposes it is important to establish that the time, effort, and finances behind methods that require more data collection gives a higher forecast accuracy for unsafety both crime and fear of crime, compared to simply counting past crimes.

2 Aim

The overall aim of the current dissertation was to examine the relationship between historical crime data, environmental factors, and neighborhood characteristics in the context of forecasting unsafety. This examination was guided by crime pattern theory, social disorganization theory, and collective efficacy theory, with a strong emphasis on real-world applicability and practical insights. The dissertation will address various types of violent and property crimes, as well as different aspects of fear of crime. To achieve the overall aim, the following research questions were explored:

I. How do two different methods, simple count, and KDE (based on historical crime data), impact the predictive accuracy in forecasting various types of violent and property crimes? Additionally, to what extent does the amount of crime history influence prediction accuracy, regardless of the method used? The selection of the factors within the predictive models was informed loosely by the crime pattern theory. It was hypothesized that using more recent historical crime data from the past year would result in more accurate crime predictions compared to using older data and combining more historical data.

II. How does the predictive accuracy differ when using individual factors (e.g., prior crime, place attributes, ambient population, community structural and social characteristics), in isolation and when combined in forecasting various types of violent and property crimes? The selection and integration of the factors within the predictive models was informed by crime pattern theory, social disorganization theory, and collective efficacy theory. It was hypothesized that the inclusion of a broader set of variables, such as place attributes, ambient population, and community structural and social characteristics, would yield predictions of similar accuracy to historical crime data alone.

III. What is the nature of the relationship between violent and property crime, community structural and social characteristics, and different types of fear of crime (e.g., perceived unsafety, general and specific fear of crime, avoidant behavior)? The selection of the factors within the predictive models was informed by crime pattern theory, social disorganization theory, and collective efficacy theory. It was hypothesized that the inclusion of a broader set of variables, such as violent and property crime, community structural and social characteristics, would yield predictions of similar accuracy to historical crime data alone.

The overall hypothesis of the current dissertation thesis was twofold.

Prediction Hypothesis (Occam's Razor): In the context of forecasting unsafety, it was hypothesized that historical crime data, when considered on its own, would serve as a reliable predictor. This aligns with the principle of Occam's razor, emphasizing the simplicity and effectiveness of crime history in predicting various types of violent and property crimes and assessing dimensions of fear of crime.

Prevention Hypothesis (Variable Inclusion): In contrast to the first hypothesis, it was hypothesized that the inclusion of a broader set of variables, such as place attributes, ambient population, and community structural and social characteristics, would yield predictions of similar accuracy to historical crime data alone. However, this expanded set of variables will provide valuable insights for crime prevention strategies and interventions.

3 Method and Materials

3.1 Study design

Studies I, II, III were quantitative and deductive, hence numeric data was analyzed, and the theories aided in the collection of included variables. Observations were made to see if the theories were applicable in the current setting. The studies were hence of observational study design. Observational studies can only show associations, they cannot prove cause-and-effect relationships. To run an experiment to examine cause-and-effect relationships would have been beneficial but was not feasible. No interference or manipulation of the places was possible. Study I and II could be defined as within-cases longitudinal prediction studies. So, the same geographical units/locations were studied over time, cases hence being geographical places. The same predictor variables were collected at two time-points for all places, equally, based on the crime pattern theory and the theories of social disorganization and collective efficacy. The primary goal was to forecast future crimes and to explore the relationships among the various predictors. Extrapolation was made to make predictions beyond the range of the observed/existing data. Forecasts were made about future trends based on historical data. This design was chosen due to the overall aim, comparing the relationships among different predictors in relation to crime forecasting.

Study III was cross-sectional. The cross-sectional method allowed for a comparison of the many different predictor variables that were collected at the same time. As all collected variables, predictors, and outcome, were concurrent, it gave a snapshot of a point-in-time of the relationship between the predictor variables and the fear of crime outcomes. The different outcomes were related to specific types of violent and property crimes, and other major neighborhood level factors linked to fear, to make comparisons.

Data on crime history, neighborhood, and place characteristics known to relate to the outcomes of different types of unsafety both crime and fear of crime was collected simultaneously to the data on the outcomes. All included predictors (Study I,II,III) were based on the theories of collective efficacy, social disorganization (Sampson, 2012; Sampson et al., 1997; Sampson & Groves, 1989) and CPT (Brantingham & Brantingham, 1993; 1995) and previous research with comparable objectives (Brunton-Smith et al., 2014; Brunton-Smith & Sturgis, 2011; Ceccato & Uittenbogard 2014; Lee et al. 2020; Kuen et al., 2022; Quick & Brunton-Smith, 2018; Weisburd et al. 2014ab; Wheeler & Steenbeek, 2021).

3.2 The setting

The current dissertation has the municipality of Malmö in southern Sweden as study site, see Figure 4. Malmö was of interest for the current dissertation due to the applicability of the chosen theoretical perspectives.

Figure 4. Malmö municipality with administrative neighborhoods outlined.

For example, there are some similarities in Malmö to the zone-model (Burgess, 1925) which part of the social disorganization is based on (Shaw & McKay, 1942). That is that the city center is followed, at least partially, by a zone of disadvantage like the zone of transition (Werner 1964; Gerell, 2017). However, Malmö as compared to Chicago, where the social disorganization theory was developed, is a lot smaller geographically which obviously can influence how different predictors based on the theory relate to the outcome of interest. Furthermore, Malmö was of interest because, marginalization and social exclusion is a growing issue in the urban areas of Sweden (see Guldåker & Hallin, 2014; Sjöberg & Turunen, 2018) and perhaps more so in particularly exposed neighborhoods (a definition of these neighborhoods will follow, see also Guldåker et al., 2021; Police authority, 2021), which Malmö has four of. Malmö also has one area classified as a risk area. Compared to the rest of Sweden, Malmö has more crime, more unemployment, foreign born residents, and a younger population (Ekström et al. 2012; Malmö stad 2014; SCB 2020), that is children and youth groups in vulnerable areas, which increases the risk of more young people being recruited into crime. These are all similar to variables connected to concentrated disadvantage (Sampson, 2012; Sampson & Groves, 1989). Another example, collective efficacy, seem to operate in a similar way in the US and in Sweden (Sampson & Wikström, 2008) and in Malmö specifically (Gerell & Kronkvist, 2017), though the differences between groups in living conditions for example might be larger in the US. Lastly, place level indicators based on CPT seem relevant for unsafety for the context in Sweden, and Malmö specifically as well (Gerell, 2018a, 2021; Kronkvist, 2022) as specific crime/fear generators have been observed to forecast unsafety in micro places in Malmö.

Malmö is the third largest city in Sweden with an official population of 331 201 in June 2017 (SCB, 2017). Malmö is approximately 157 km^2 in size (SCB, 2018). Strictly geographically, the highest crime rates, highest population-, businesses-, night-life density, and the highest amount of ambient population, as measured through the annual number of people boarding local buses, are all in the northern parts of the city-center. Close to the city-center, on the south and east side, are neighborhoods that are considered disadvantaged due to higher unemployment and a lower median income. There is a strong relation of ethnic- and economic segregation in the city of Malmö

(Gerell, 2017), making it impractical to examine ethnic and economic segregation separately in the same statistical model. More affluent neighborhoods can be found to the west of the city center and further out in more rural parts of the municipality.

Since the mid-1970s, Malmö has faced several challenges (Guldåker & Hallin, 2014). Initially, during the mid-70s, the city witnessed a decline in population and economic difficulties. However, starting in the early 1990s, the population started to grow significantly, with more immigrants coming in. By 2012, about 45% of the population either originated from abroad or had at least one parent from another country. This population growth was particularly prominent in neighborhoods with affordable housing. In 2015, Sweden received a record number of asylum seekers and immigrants. Malmö, like other cities, experienced a noticeable increase in its population. This growth was once again particularly prominent in neighborhoods with affordable housing. Most people in Malmö live in apartments. While Malmö has become more attractive for various cultural activities, it has also become more divided economically, socially, and geographically over time.

When reflecting on generalizability, the specific setting of Malmö, but also Sweden in general, needs to be considered. In Sweden the National Operations Department's (NOA) of the police have made their own assessment of crime-exposed areas (Guldåker et al., 2021; Police authority, 2021). These areas are defined as exposed areas, risk areas and particularly exposed areas. The number of exposed areas, risk areas and particularly exposed areas changes over time, as the assessment of the areas and crime levels in the relevant areas change over time. A definition of the three will follow. In the exposed areas, a low socioeconomic status, living-segregation, lack of integration with the overall society and higher crime levels are a reality. According to the most recent report (Police authority, 2021) there are 61 exposed areas, and they are related to about 40 percent of all shooting reported in 2020, and a quarter of all car-related arsons. Higher levels of fear of crime can also be found in the exposed areas (NCCP 2018). The exposed neighborhoods are geographically small, approximating .02 percent of Sweden's total geographic area (Police authority, 2021).

These neighborhoods are characterized by social deprivation and offenders having an influence on the local community. This influence could be directly through threats and extortion against residents or people working in the community. Or indirectly through public violence and social unrest. The population in these areas are approximately 550 000 and comprises about five percent of Sweden's total population. To define these neighborhoods, statistics on deprivation such as unemployment, income, level of education etcetera is used in conjuncture with a survey with locally based police officers (see Guldåker et al., 2021). Out of the 61 exposed areas in Sweden, there are 20 areas considered particularly exposed areas. In these particularly exposed areas, the situation is considered critical with social structures parallel to the greater society, extremism, and a high concentration of criminals. The risk areas are at an intermediate level between the exposed and particularly exposed areas. They are exposed areas at risk of becoming particularly exposed areas. Out of the 61 exposed areas in Sweden, four are in the municipality of Malmö (Police authority, 2021). Three (out of the 20) particularly exposed areas, and one risk area are found in the municipality of Malmö.

Comparing Sweden to other Scandinavian countries, Sweden has a higher rate of immigration compared to Norway and Denmark (Pettersen & Østby, 2013). Also compared to other countries (such as the US), Sweden is considered an egalitarian country (see e.g., Barth et al., 2021; Lijphart, 2012), hence the economic differences between different groups of people are perhaps not as large in Sweden. Sweden does however have a greater problem with firearm related violence, compared to the rest of Europe (NCCP, 2021; Khoshnood, 2018, 2019) in recent years.

3.2.1 The specific setting in Study I

In Study I, Malmö was divided into 100-meter grid-cells, with a total of 16,737 grid-cells. The grid-cell size was based on a recommendation for KDE cell-sizes (Chainey, 2013), as KDE was the hotspot method chosen for comparison. The extent of the shorter side of the study area was divided by 150. So, approximately 15,400 meters divided by

150 = 103m², rounded down to 100-meter grid cells, resulting in a total of 16,737 grid cells (after being cut to the Malmö municipality border). Using a grid cell-size of one third of an average block face of the study area (Caplan et al., 2011; Hart & Zandbergen, 2014; Kennedy et al., 2011) does not work in Malmö municipality, as the block sizes in the inner-city and the suburban areas of Malmö municipality differ quite a bit.

3.2.2 The specific setting in Study II

In Study II, Malmö was divided into 50-meters grid cells with a total of 65,594 grid cells. See Figure 5. Both larger and smaller micro-places have been used in previous micro-place research. Some use cell-sizes of approximately 100-meters or above (see e.g. Drawve, 2016; Drawve et al., 2016; Kennedy et al., 2016; Mohler et al., 2015). Others use smaller cell-sizes of around 50 meters (Kennedy et al., 2011; Wheeler & Steenbeek, 2021). Malmö can be divided into 136 neighborhoods. Both grid-cells sizes and the neighborhood level were of interest for the current study.

Figure 5. Malmö with 50-meter grid cells. An RTM for assault 2017.

3.3.2.1 Changing the size of grid-cells

The choice of changing from 100-meter grid cells to 50-meter grid cells for Study II was based on the 'smaller is better notion' (Hipp, 2010; Oberwittler & Wikström, 2009; Schnell et al., 2017; Steenbeek & Weisburd, 2016). In addition, one earlier study from the same setting, Malmö, revealed that the smaller micro-place geography was better when studying the characteristics related to arson (Gerell, 2017). Smaller being 50-meter cells as compared to the larger small area markets statistics and the municipal part-areas. Arson is one of the studied outcomes in Study II, however named illegal fire setting. Furthermore, previous attempts at risk terrain modeling (RTM) in Malmö used a grid cell-size of 50-meter (Gerell, 2018a). Lastly in Study I, a cell-size of 50 meters rendered a 237 PAI-value when forecasting violent crime in 2017 using crime data from 2016. This compared with a PAI-value of 66.84 using a 100-meter cell size. Consequently, to reach a better forecast in Study II, a smaller area (smaller grid-cells) was used in Study II than in Study I. It is important to keep in mind that a too small study areas can lead to too few crime incidents for statistical analysis (see Lawton, 2018; Maltz, 2009), using smaller areas can however increase the variance between grid-cells and decrease the variance within grid-cells (Rengert & Lockwood, 2009).

3.2.3 The specific setting in Study III

In Study III, the 136 Malmö neighborhoods were used. Out of the 136 neighborhoods, 32 were excluded, see Figure 6. To be included in the study at least 200 people between the ages of 20 and 79 needed to be registered in the neighborhood (January 2015) and a minimum of 10 responses per neighborhood was required in each survey (2012 and 2015), to protect the integrity of the residents. Protecting the integrity meaning to keep the responses anonymous, respecting the privacy and confidentiality of the respondents. A minimum of 10 responses per neighborhood is quite low but has been seen in previous research as well (Steenbeek & Hipp, 2011). The aim in Study III was to assess perceived unsafety and fear in areas where people live and the excluded neighborhoods largely consisted largely of parks, harbors, and industrial areas (Guldåker & Hallin 2013; Ivert et al. 2013), where few people reside, see Figure 7. Hence, included in the current study were 104 neighborhoods with at least 200 residents and at least 10 respondents partaking in each survey (2012 and 2015). According to Malmö statistics, the mean number of residents (not only respondents) in the included neighborhoods was 3081 (SD = 2307) in 2015, ranging from 200 to 11,109 (Malmö stad, 2015).

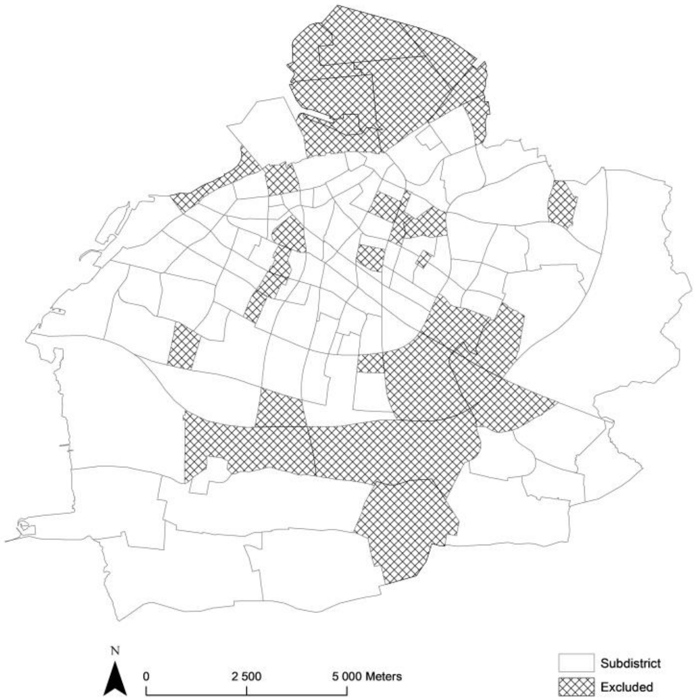

Figure 6. Included and excluded neighborhoods of Malmö, Sweden, that are used for Study II and III. Map maker Maria Camacho Doyle. Data source Malmö municipality.

Figure 7. Buildings in Malmö. Map maker Maria Camacho Doyle. Data source Malmö municipality.

3.3 Overview of study methods

The current dissertation was based on four data sets that are described separately. The first data set consisted of empirical data on crime incidents from the Swedish police (Studies I, II, III). The second data set consisted of empirical data on community structural-, and social characteristics, from the Swedish municipality (Studies II, III). The third data set consisted of empirical data, location of bus stops and amount of annual bus passengers, from the regional transportation company Skånetrafiken (Studies II, III). The fourth data set consisted of empirical data, regarding collective efficacy and perceived unsafety, from Malmö university (Studies II, III).

Table 1 Overview of study methods

Study	Overall Aim	Setting	Data	Outcome	Analysis
I	To compare the predictive accuracy of two methods using historical exposure to crime, and using different crime-time-periods, across different types of crimes.	Malmö divided into 100-meter grid-cells, N = 16,737	Reported crime	Violent- and Property crime types in 2017	KDE, SC in CrimeStat IV, and ArcGIS 10.3 PAI, RRI in Excel
II	To compare the predictive accuracy of prior crime, place attributes, ambient population, community structural-, and social characteristics, across different types of crimes.	Malmö divided into 50-meters grid cells, N = 65,588 (Level 1). And 104 administrative neighborhoods (level 2).	Reported crime, Place level crime generators, Community level spatial data, MCS	Violent- and Property crime types in 2017	Multilevel negative binomial regression in R 4.0.3 PAI, PEI* in Excel
III	To analyze the relationship between violent and property crime, community structural and social characteristics across different types of fear of crime.	Malmö administrative neighborhoods (N= 102)	Reported crime, Community level spatial data, MCS	Perceived unsafety, fear of crime, and avoidant behavior in 2015	Multiple regression in SPSS

Note. MCS: Malmö Community Survey; KDE: Kernel Density Estimation; SC: Simple Count; PAI: Predictive Accuracy Index; PEI*: Predictive Efficiency Index; RRI: Recapture Rate Index

3.4 Data and Measurements

Many different place-level and neighborhood-level characteristics can be relevant for forecasting unsafety, both crime and fear of crime. In the current dissertation the spatial risk factors considered in relation to unsafety are all based on the theories of crime pattern, concentrated disadvantage and collective efficacy (Brantingham & Brantingham, 1993; 1995; Sampson et al. 1997; Sampson 2012; Sampson & Groves, 1989) and previous research on characteristics related to crime (see e.g., Barnum et al., 2017; Caplan et al., 2015; Ceccato & Uittenbogard 2014; ; Haberman & Ratcliffe, 2015; Lee et al. 2020; Kennedy et al., 2016; Quick & Brunton-Smith, 2018; Weisburd et al. 2014ab; Wheeler, 2019; Wheeler & Steenbeek, 2021) and different aspects of perceived unsafety (Brunton-Smith et al., 2014; Brunton-Smith & Sturgis, 2011; Jakobi & Pòdör, 2020; Kuen et al., 2022; Ogneva-Himmelberger et al., 2019; Robinson et al. 2003). Lastly, though the terms prediction and forecast are used in the current dissertation, the variables included for analysis in Study I, II, III are correlates to crime, not causal mechanisms. Though the assumption is that they will forecast crime better than chance.

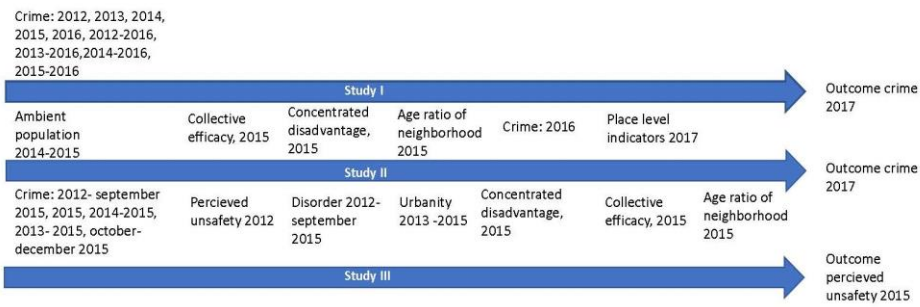

Figure 8. Quick overview of what year/years the included dependent and independent variables are from, for Study I, II, III

3.4.1 Crime variables

Crime in 2017, aggregated to grid-cells, was used as the outcome variable for studies I and II. Crime prior to 2017, aggregated to grid-cells, was used as predictors in studies I, II, and aggregated to neighborhoods for Study III. The crimes, point data that was subsequently aggregated, included public environment violent crime: assault, street robbery, as well as property crime: property damage (graffiti and vandalism), theft, vehicle theft (including bike theft) residential burglary, and illegal fire setting (e.g., arson or vandalism through fire). For Study I, both total violent crime and total property crime as well as all the under categories were used as the outcome. For Study II, only the different under categories was used as the outcome.

Based on the crime and fear generators of the crime pattern theory[1] as well as prior research (see e.g., Brunton-Smith et al., 2014; Brunton-Smith & Sturgis, 2011; Jackson, 2006; Wheeler & Steenbeek, 2021; Zhao et al., 2015). Police reported crimes were obtained from the Malmö police department from January 1st, 2012, through December 31st, 2017 (for Study I, II, III). Reported crimes in Sweden is similar to US crime incidents. Reported crimes are less extensive than calls for service. The crime data either came with geocodes to the specific address of the crime incident or was subsequently geocoded for spatial analysis. Geocoding and an interactive geocoding correction procedure was performed using ArcGIS online after all cases were geospatially anonymized, retaining only the X and Y coordinates along with an ID number.

[1] A location with previous crime can act as a crime attractor (Brantingham & Brantingham, 1993, 1995). The location itself can be known to be favorable for committing crimes or there can be a familiarity with the area. For example, the perception among potential offenders can be that criminal activities are tolerated, or they are less likely to be detected or reported in such an area. This perception may attract offenders to that area, leading to future criminal incidents. Knowing about crime in an area can also act as a fear generator.

Crime points were aggregated to 100-meter cells (Study I), 50-meter cells (Study II) and neighborhood level (Study III). All different crime types in 2017 are used as the outcome variables for Study I and Study II. Nine different combinations of past crime-time-periods (crime history) were used to forecast crime in 2017 in Study I. Crime history from the years 2016, 2015, 2014, 2013, 2012, were used and compared as well as the combinations 2016-2015, 2016-2014, 2016-2013, 2016-2012. Hence, in Study I, it was examined if a forecast was more accurate, if crime from the year 2016 was used in comparison to crime from the year 2015, forecasting crime in 2017. Or if a combination of crime from 2015 and 2016 was more accurate in forecasting crime in 2017, than using crime from 2016 only. Five different combinations of past crime-time-periods (crime history) were used to forecast perceived unsafety in 2015 in Study III. Crime history from the years 2015, 2014-2015, 2013-2015, were used and compared as well as crime from 2012 until September 2015 (until collection of survey data commenced) and crime during survey collection October through December 2015.

3.4.2 Perceived unsafety

The outcome variables for Study III were different measures of perceived unsafety. Two waves, the years 2012 and 2015 from a community mail survey in Malmö conducted by Malmö university, were used in the current dissertation (MCS). Three items measuring perceived unsafety, seven items measuring fear of crime and five items measuring avoidant behavior were included.

Perceived unsafety ($\alpha = .841$) was measured using three items: (1) Do you feel safe or unsafe if you walk alone late at night in your neighborhood? (2) Are there any people in your neighborhood that you are afraid of? (3) Has there been an instance when you have taken a different route to avoid an unpleasant place or person in your neighborhood? A fear of crime scale ($\alpha = .812$) consisted of seven items assessing worries about residential burglary, burglary in basement storage rooms, attic spaces, and/or garages, theft of vehicles (car, bike, or motorcycle), harassment, or assault in the respondent's area of residence. Worry about having a vehicle stolen was indexed (α

= .890). Then the worry about vehicle theft variable was indexed with the other four variables previously mentioned. An avoidance scale (α = .798) comprised five items that gauged whether respondents refrained from participating in activities such as movies/theater, restaurant/café/bar visits, sporting activities, club meetings/courses, or riding the bus/train due to perceived unsafety, fear of threats, assault, or violence. Cases with missing data were handled, and respondents with less than four fear-related items (out of five) and less than two perceived unsafety items (out of three) were excluded. Prior to indexing, all variables were aggregated at the neighborhood level and standardized as Z-scores. Both waves were used for analysis, 2015 as the outcome and 2012 as a robustness check.

The MCS contains nearly one hundred survey items including different aspects of fear of crime. Represented in the survey are Malmö neighborhoods with at least 100 residents between the ages of 18-85. From the smallest neighborhoods, 40 respondents were randomly selected to participate in the survey, and in the largest neighborhoods, 160 respondents were randomly selected to participate in the survey. In 2012 the sample was about 7,700 and in 2015 about 7,800. This corresponds to between three and four percent of the Malmö population. To ensure an acceptable representation of disadvantaged neighborhoods, an over-sampling of participants was conducted due to the anticipated low response rates in those areas (Ivert et al., 2013). Compared to the general population, the 2012 survey was answered by approximately 3 percent more females (54 percent in sample vs 51 percent in general population), 3 percent more Swedish-born (30 vs 27), 9 percent more employed (71 vs 62), 8 percent more homeowners as well as 8 percent more people aged 65–85 (25 vs 17) compared to the general population of the city. Only the age-difference was however significant, as reported by Ivert et al. (2013). The 2015 survey saw similar differences as compared to the general population (MCS, 2016). In 2012, there was a 50 percent response rate. In the year 2015, a 40 percent response rate. Because the response rate is quite low, the results should be interpreted with caution.

3.4.3 Collective efficacy for Study II and III

Based on the collective efficacy theory (Sampson et al. 1997; Sampson 2012) as well as prior research (see e.g., Gerell & Kronkvist, 2017; Kuen et al., 2022) data from the MCS, from the years 2015 was provided by Malmö university (MCS, 2016). Five Likert-type items measured cohesion and five measured informal control. These were aggregated to the neighborhood level, standardized as Z-scores, and indexed ($\alpha = .940$), to measure collective efficacy in studies II and III.

3.4.4 Neighborhood concentrated disadvantage for Study II and III

Based on the social disorganization theory (Sampson, 2012) as well as prior research (see e.g., Brunton-Smith et al., 2014; Brunton-Smith & Sturgis, 2011; Gerell & Kronkvist, 2017; Sampson et al., 1997; Quick & Brunton-Smith, 2018) data on median income, proportion of unemployment, proportion on public assistance, proportion of single parents, car ownership and proportion of foreign heritage were obtained from Malmö municipality (Study II, III). This census data was open-source data, and year 2015 was used unless otherwise stated in text. An index was created to reflect neighborhood concentrated disadvantage as has been done in previous research (Gerell & Kronkvist 2017; Sampson et al., 1997) using the six highly correlated variables mentioned ($\alpha = .925$). To capture the concept of living below the poverty line, the neighborhood median income data was used, reverse-coded, following the approach employed in previous studies (Gerell & Kronkvist 2017; Sampson et al., 1997). The proportion of unemployment was determined based on residents aged 20-64. The proportion of single-parent households was used to capture the concept of female-headed families, like previous studies (Gerell & Kronkvist, 2017). A single-parent household was defined as a household with a single adult living with at least one child who is biologically related. The proportion of foreign-born individuals (first and second generation) was employed as a measure to capture the concept of ethnicity. Additionally, a measure reflecting the proportion of car ownership was included and reversed in the index. The variables were standardized as Z-scores and included in the index for studies II and III. There is a strong correlation between ethnic-and economic segregation in the city of Malmö (Gerell & Kronkvist, 2017), making it impractical to examine separately in the same statistical model due to multicollinearity. Because of this proportion of foreign heritage was included in the concentrated disadvantage index (as in Gerell & Kronkvist, 2017) and not studied separately. Similarly, several of the included variables correlated highly, hence the index was used to deal with potential multicollinearity problems.

3.4.5 Age ratio of neighborhood for Study II and III

Based on the social disorganization theory (Sampson & Groves, 1989) and the relationship between crime and the ability to socially control unsupervised young people, as well earlier research (see e.g., Brunton-Smith et al., 2014; Brunton-Smith & Sturgis, 2011) data regarding the age structure of Malmö neighborhoods from 2015 was used to measure the impact of neighborhood age ratio (Study II, III). A higher adult-to-child ratio implied more adults, everybody 20 years and over, per young person, everybody 19 years and under.

3.4.6 Place level indicators for Study II

Based on the crime pattern theory (Brantingham & Brantingham, 1993, 1995) and earlier research (see e.g., Bernasco & Block 2011; Ceccato et al. 2015; Gerell, 2018a; Haberman & Ratcliffe 2015; Kubrin & Hipp 2016; Haberman et al. 2013; Kennedy et al. 2016; Marchment & Gill, 2021; Wheeler, 2019; Wheeler & Steenbeek, 2021), census data as well as point and polygon data regarding land use (place level indicators) were obtained from Malmö municipality (Study II). The following place-level crime generators were obtained, the location of restaurants, bars, ATM's, schools, preschools, bus stops, parks, town squares, sports fields, small house units with year-round housing, small house units with premises, apartment building units with mainly housing, apartment building units with housing and premises and vacation homes. Unfortunately, for information regarding these place-level indicators, only data from 2017 was available. This makes land use data concurrent with the time-period being forecasted.

KDEs with 50-meter grid cell size, 500-meter radius were used to assign cells a value for each risk factor of the point data (restaurants, bars, ATM's, schools, preschools, and bus stops). This was done in ArcMap 10.6.1. Processing extent was set to the municipal boundaries. The KDE values were then spatially joined using intersect to a fishnet grid with a total of 65,594 grid cells laid over the Malmö municipality area. The building and other landscaping (polygon) variables where spatially joined with intersect to the fishnet grid. Using the same data (2017 data) to both create a place level index and assess the index's accuracy will greatly overestimate the accuracy of the model. Although, the placement of some place variables such as apartment buildings, schools, preschools, town squares and parks are relatively stable over the years, some more so than others, schools, and apartment buildings more stable than bars and ATMs for example. Before analysis in R 4.0.3 all variables were standardized into Z-scores.

3.4.7 Ambient population for Study II

Based on the crime pattern theory (Brantingham & Brantingham, 1993, 1995) and earlier research (see e.g., Gerell, 2018a, 2021; Malleson & Andresen, 2016) information regarding the location of bus stops and the annual number of passengers boarding each stop (*N* = 40,157,943) between March 2014 and February 2015 was provided by the Malmö County public transport company (Skånetrafiken). The annual number of passengers per bus trip was used as a proxy for ambient population or flows of people in that general area (for Study II only). The data was geocoded in ArcGIS 10.6.1. Several of these bus trips had no place information and were excluded. Bus stops with fewer than 10,000 passengers were also excluded. This resulted in a final sample of 33,134,626 bus trips spread across a total of 586 bus stop locations. A KDE with 50-meter grid cell size, 500-meter radius populated by the total amount of passengers boarding each stop was used to assign all grid-cells a value. Before analysis in R 4.0.3. ambient population was standardized into Z-scores.

3.4.8 Urbanity for Study III

Based on the social disorganization theory (Sampson & Groves, 1989), as well earlier research (see e.g., Bruinsma et al., 2013; Gerell & Kronkvist, 2017; Sampson & Groves, 1989; Sutherland et al., 2013) an urbanity index was created (for Study III only). In the current dissertation, urbanity was based on the density of bars and the volume of people on the move. This was measured (as in Gerell & Kronkvist, 2017) by geocoded point data of local public bus stops and the annual number of passengers boarding each stop. Buffers of 100 and 200 meters around the point data were created and aggregated to the neighborhood level respectively. Density of alcohol outlets was used as a proxy for nightlife activity (as in Gerell & Kronkvist 2017). The data was geocoded in ArcGIS 10.6.1 and aggregated to the neighborhood level. Permits to serve alcohol after 1 am were used (N = 71) and calculated per 1,000 residents. The two urbanity variables were correlated (r = .531), and an urbanity index was created (α = .694).

3.4.9 Neighborhood level disorder for Study III

Based on parts of social disorganization theory (Sampson et al. 1997; Sampson 2012) and parts of crime pattern theory (Brantingham & Brantingham, 1993, 1995) as well as earlier research (see e.g., Box et al., 1988; Brunton-Smith & Sturgis, 2011; Ferraro, 1995; Hale et al., 1994; Jackson, 2004; O'Brien et al., 2019; Skogan, 1990; Wilson & Kelling, 1982) not only the structural characteristics of the neighborhood act as fear generators but also visible signs of neighborhood disorder (for Study III only). In the current dissertation police recorded accounts (point data) of property damage (graffiti and vandalism) and illegal fire setting aggregated to neighborhoods were used as a proxy for visible and independently measured neighborhood disorder. Property damage and illegal fire setting were calculated as crime rate per 1,000 residents in 2015. Crime history from January 2012 up until one month before the survey collection of the Malmö community survey, 2015 (MCS, 2016) was used, as more crime history equaled higher correlation to the outcome variables.

Property damage is often not reported to the police, and results should therefore be interpreted with caution.

3.5 Procedure and statistical analysis

Data management was performed using ArcGIS versions 10.3, 10.6.1, 10.8.2 and R 4.0.3. Analyses were performed in CrimeStat IV (Study I), R 4.0.3 (Study II) and SPSS (Study III). The significance level used in the studies was set to $p < .05$.

3.5.1 Study I, Study II

In Study I and Study II, prediction accuracy was compared. To compare different forecasting methods and combination of methods a common reference point was needed. In the current dissertation Predictive Accuracy Index (PAI), Studies I and II, Prediction Efficiency* (PEI*), Study II, and Recapture Rate Index (RRI) for Study I was calculated using the equations that can be found in the sections 3.5.1.1 – 3.5.1.3.

Table 2. Summary of symbols used.

Symbol	Definition
A	The total study area
a_1	The geographical area defined as a hotspot at time 1
a_2	The geographical area defined as a hotspot at time 2
N_1	The total number of crimes at time 1
N_2	The total number of crimes at time 2
n^1	The number of crimes at time 1 that are in the places defined as hotspots at time 1
n^2	The number of crimes at time 2 that are in places defined as hotspots at time 1
n^*	The most accurate forecast possible, by aggregating the highest number of crimes into areas of the same size as the defined hotspot area
$\text{PAI}_{\text{Measured}}$	PAI-value using data only from time 1
$\text{PAI}_{\text{Predictive}}$	PAI-value using data from time 1 to forecast crime at time 2.

3.5.1.1 The prediction accuracy index (PAI)

The prediction accuracy index (PAI) was the first crime index developed to specifically measure the accuracy of a crime hotspot model. With the PAI value you examine how accurate the method is in finding the hotspot, by comparing the hit rate: how much crime you predict in the hotspot compared to the total amount of crime in the study area, to the area of the hotspot and of the whole study area. The formula was originally proposed by Chainey et al., (2008). Simply put, the higher the PAI, the better the forecast. The n^1 represents the amount of crime incidents in the hotspot, the N_1 is the total amount of crime incidents in the study area. The a_1 is the area of the hotspot, and the A is the total study area.

$$\frac{\left(\frac{n^1}{N_1}\right)x100}{\left(\frac{a^1}{A}\right)x100} = \frac{HitRate}{AreaPercentage} = \textit{Prediction Accuracy Index}$$

Van Patten et al. (2009) extended the PAI formula, calling the former equation mentioned measured PAI, and the new equation predictive PAI. In predictive PAI, n^2 represents the predicted crime incidents (time two) in the base year hotspot (time one) and N_2 is the total amount of crime incidents in the study area (at time two). For example, violent crimes in 2017 as predicted crime incidents in the hotspots forecasted using 2016 violent crimes. The a_1 is the area of the hotspot at time one, and the A is the total study area.

$$\frac{\left(\frac{n^2}{N_2}\right)x100}{\left(\frac{a^1}{A}\right)x100} = \frac{HitRate}{AreaPercentage} = \textit{Prediction Accuracy Index}$$

As an example, from Study I, see the KDE predictive PAI calculation for violent crime 2016 predicting violent crime in 2017. The number 267 (n^2) represents violent crime incidents in 2017, in the hotspots that were predicted using data from 2016. The number 1,270 (N_2) is the total amount of violent crime incidents 2017, in the study area. The number 56 (a_1) are the top grid cells, hence the area defined as the hotspots, using crime 2016, and the number 16,737 (A) are all the grid cells in the total study area.

$$\frac{\left(\frac{267}{1270}\right)x100}{\left(\frac{56}{16737}\right)x100} = \frac{0.21023622}{0.00334588} = 62.83$$

3.5.1.2 The recapture rate index (RRI)

With the RRI value you can examine how precise the method is in finding the hotspot over time. The RRI precision values are based on the formula by Levine (2008). Based on the PAI from a base year ($PAI_{Measured}$) the RRI calculates at what ratio the prediction method, such as KDE, or RTM, recaptures the PAI in the prediction year ($PAI_{Predictive}$). The RRI hence measures the rate of change from one time-period (base/measured) to another time-period (prediction). Values close to one imply a precise forecast; the method is precise in finding the hotspot over time, also implying that the hotspots forecasted have not changed. Values below one means an under-prediction of where crime will be. More crimes are happening than were forecast. It could imply that the hotspots forecasted at time-one have become more intense at time two. Values above one is an indication of over-prediction. More crimes are forecasted to happen in the hotspots than are in fact happening. It could imply that the hotspots forecasted at time-one have become colder at time two.

The RRI-value in the current dissertation is based on Van Patten, et al., (2009) formulation as a macro-time perspective, that is one year or greater, is used in the current study. The assumption behind this equation is that hotspots are stable over time, they do not move. Other RRI-formulations exist. For example, Hunt (2016) assumes that hotspots can move between two time periods, hence stability is not likely, and a micro-time perspective might be more suitable. Van Patten et al. (2009)'s equation, it has been argued, can be used to see if hotspots at time-one are getting hotter or colder (see White et al., 2023).

$$\text{RRI} = \frac{PAI_{Predictive}}{PAI_{Measured}}$$

As an example, from Study I, see the KDE RRI calculation for violent crime 2016 predicting violent crime in 2017. The number 62.83 is the predictive PAI value and 86.95 is the measured PAI value.

$$\frac{62.83}{86.95} = 0.72$$

3.5.1.3 The prediction efficiency index (PEI)/(the PEI*)

Hunt (2016) proposed the PEI as a complementary measure to the PAI. PEI accounts for how well you did in your forecast, compared to how well you could have done. However, the original PEI allows the size of the forecasted area, amount of grid cells for example, to change from one time-period to the next. Hunt (2016) did also propose a constrained version of PEI to address this concern. It has been argued (White et al., 2023) that keeping the size of the area constant from time-to-time, for example the same number of grid-cells, might make PEI more operationally realistic. The constrained PEI* (Hunt, 2016) was first launched and used to help the judges judge all submissions to the 2017 National Institute of Justice (NIJ) Real-Time Crime Forecasting Challenge (National Institute of Justice, 2017). PEI* limits the PEI measure to having an equal sized hotspot area, across the different time-periods. Based on White et al., (2023) the equation is as follows, where n^2 is how many crime incidents that were forecasted in the hotspots and n* is how many crime incidents could have been forecasted in the same sized hotspots.

$$\text{PEI*} = \frac{n^2}{n*}$$

PEI* is easy to interpret. It measures how well a method does, as a percentage of how well it could do. Instead of saying a simple count of crime history is more/or less efficient or accurate than RTM, a percentage can be used. For example, from Study II, given the predetermined geographical area of the 50 top hotspots, crime history alone captured about 60 percent of the assault from the assault that could have been forecasted in the same sized hotspot. Or RMT captured around 14 percent of the assault that it could have done given the predetermined geographical area. Values of interest to calculate the three different crime indexes (PAI,RRI, PEI*) for Study II are presented in Table 3.

Table 3. Example from Study II of index calculations to evaluate different forecast methods for assault and theft. Total area 65,594 grid cells.

	T1	N_1	a_1	n^1	T2	N_2	a_2	n^2	n^*	PAI	RRI	PEI*
Assault RTM	2016	1053	50	34	2017	959	50	34	240	47	1.10	.14
Assault Crime	2016	1053	50	298	2017	959	50	143	240	196	0.53	.60
Assault Crime+RTM	2016	1053	50	289	2017	959	50	147	240	201	0.56	.61
Assault Crime+RTM+Nv	2016	1053	50	268	2017	959	50	1336	240	182	0.55	.55
Theft RTM	2016	3537	50	29	2017	959	50	34	826	47	0.57	.04
Theft Crime	2016	3537	50	709	2017	959	50	143	826	263	0.74	.86
Theft Crime+RTM	2016	3537	50	644	2017	959	50	147	826	239	0.69	.78
Theft Crime+RTM+AmbPop	2016	3537	50	658	2017	959	50	1336	826	244	0.70	.80

Note. Crime+RTM refers to crime history combined with RTM. Crime+RTM+Nv refers to crime history combined with RTM and significant neighborhood variables. Crime+RTM+AmbPop refers to crime history combined with RTM and ambient population.

3.5.2 Study I – KDE and SC

The aim was to compare the predictive accuracy of two methods using only historical exposure to crime (prior crime, crime history), across different time-periods. Dependent variables were all crime types:

- A violent crime umbrella and assault, robbery, in 2017
- A property crime umbrella and property damage, theft, vehicle theft, illegal fire setting and residential burglary in 2017

All aggregated into 100-meter grid cells. Crime history, aggregated to 100-meter grid cells, being the sole predictor to forecast crime in 2017. Different year combinations of crime history were used to forecast crime in 2017. Crime history from the years 2016, 2015, 2014, 2013, 2012, was used as well as the combinations 2016-2015, 2016-2014, 2016-2013, 2016-2012. PAI -, and RRI-values were calculated to compare the accuracy and precision of the two retrospective hotspot mapping techniques, Simple Count (SC) and Kernel Density Estimation (KDE).

3.5.2.1 Analysis

First, SC, the most basic form of analysis for a geographical area, was calculated in ArcGIS 10.3. A grid net, like a fishnet, was laid over the study area. In each grid cell of the fishnet, crimes from a certain year, like 2016, were counted and used to forecast crime in 2017. KDE was analyzed with the single kernel density interpolation technique in CrimeStat IV. A direct (Euclidean) type of distance measurement was used. For some analyses the indirect (Manhattan) type of distance measurement was also used and compared. One type of measurement (direct or indirect) did not produce consistently better results, which is why the direct type of distance measurement was chosen and used.

Within KDE certain parameters need to be set, method of interpolation, grid cell size and bandwidth. To find the best model possible for KDE to compare against SC, 18 analyses were run, (three interpolation methods times' six bandwidths). The best model was found by looking at the PAI and RRI averages. Quartic interpolation with a 100-meter cell size and a 100-meter bandwidth was chosen.

3.5.2.2 Determining the hotspots

For both SC and KDE, hotspots were considered the top grid cells that contained 30 percent of all crime incidents. Hence, the grid cells that captured approximately 30 percent of all crime in the years (for example the year 2016 or years 2014–2015) were used to forecast crime in 2017. For a simple and inexpensive way of finding the top hotspots a similar procedure to the greedy algorithm, also known as Kruskal's Algorithm (Kruskal, 1956), was used (see White & Hunt, 2022 for a mathematical description). Simply put, for the simple count method, the grid cells were first sorted from highest to lowest crime count in the attribute table of ArcMap. Then grid cells were assigned to hotspots until the stopping criteria of approximately 30 percent crime count was reached. See Figure 9. Then for the KDE method, the grid cells were also first sorted from highest to lowest crime density, then grid cells were assigned to hotspots until the stopping criteria of the same geographical size (that is, the same amount of grid cells) as the SC method was reached. See Figure 10.

The different types of violent and property crimes, including the violent and property crime umbrellas were counted separately and compared. Different number of years into the future was used and compared. For example, violence in 2016 or 2015 to forecast violence in 2017. Or residential burglary in 2016 or 2015 to forecast residential burglary in 2017. Also, years combined like violence in 2014-2016, 2015-2016 to forecast violence in 2017 was compared.

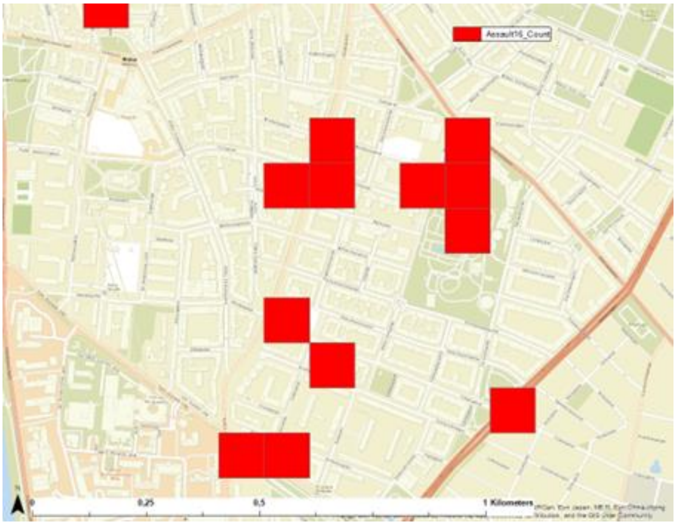

Figure 9. Example of the top forecasted grid-cells. Simple count, assault 2016, forecasting assault 2017. Map maker Maria Camacho Doyle. Data source the police authority.

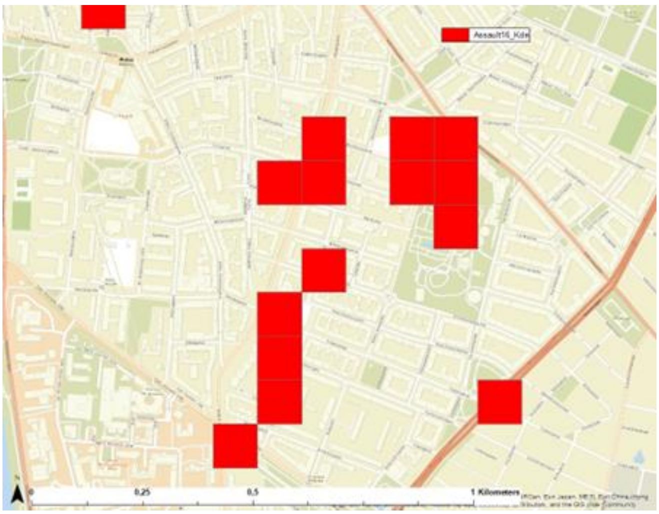

Figure 10. Example of the top forecasted grid-cells. KDE, assault 2016 forecasting assault 2017. Map maker Maria Camacho Doyle. Data source the police authority.

3.5.3 Study II Multilevel negative binomial regression

The aim was to compare the predictive accuracy of prior crime, place attributes, ambient population, and community structural-, and social characteristics, across different types of violent and property crimes. Dependent variables were:

- Assault and robbery in 2017
- Property damage, theft, vehicle theft, illegal fire setting and residential burglary in 2017

All aggregated to 50-meter grid cells. At level one in the models, the predictors were crime history, the same type of crime but from the year 2016, different place level indicators and ambient population. At level two in the models, the predictors were neighborhood level concentrated disadvantage, collective efficacy, and age ratio.

Negative binomial regressions were performed in R 4.0.3 using the MASS-package (Venables & Ripley, 2002). Multilevel negative binomial regressions were performed using the lme4-package (Bates et al., 2023). The multilevel models were used to analyze the contribution of micro-place, level one in the models, and neighborhood-level variables, level two in the models simultaneously, on grid-cells with crime in 2017. To be consistent with RTM, no cross-level, nor within-level interaction terms were included in the models.

3.5.3.1 Analysis

A very crude RTM was first performed for all crime types. The place variables were run separately with negative binomial regressions to get a combined place-level index for each crime type. Variables that revealed a positive and significant relationship with the respective crime type were weighted according to the regression coefficient and summed into an index. Then several more negative binomial regressions were run, for each crime type separately. In Model one, crime history (crime count in 2016) was run for each crime type respectively. In Model two the place-level index was added. In Model three, ambient population was added to the regression. In Model four, the neighborhood level variables (level two) collective efficacy, concentrated disadvantage and age ratio were added. For each crime type, indexes with significant results ($p < .05$) from Models two, three and four were created to get combined IRR-values as well as combined PAI, PEI*-values, similarly to a combined RTM score. This was done to see how the prediction accuracy increased or decreased with the adding of variables.

3.5.3.2 Determining the hotspots

For easy comparison of the different forecast methods, the hotspots were identified, again using the rather naïve method (like the greedy algorithm) of choosing the top grid cells predicted as hotspots (1, 10, 50, 100, 500 cells), up to 1 percent (about 656 cells) of the study area. Once again, the grid cells were first sorted from highest to lowest predicted areas in the attribute table of ArcMap. Then grid cells were assigned to hotspots until the stopping criteria of 1, 10, 50, 100, 500 656 cells was reached. In RTM (Kennedy et al., 2016) and earlier studies of KDE (Chainey et al., 2008; Drawve, 2016) the top hotspots are usually found by looking at two standard deviations above the mean for the prediction values. But for practical purposes the National Institute of Justice predictive policing challenge fixed the geographical thresholds to a certain proportion of the area under study instead (Lee, 2020; Mohler & Porter 2018). This fixed proportion area of finding hotspots was followed for Study II. See Figures 11-13 for examples of the top forecasted grid cells.

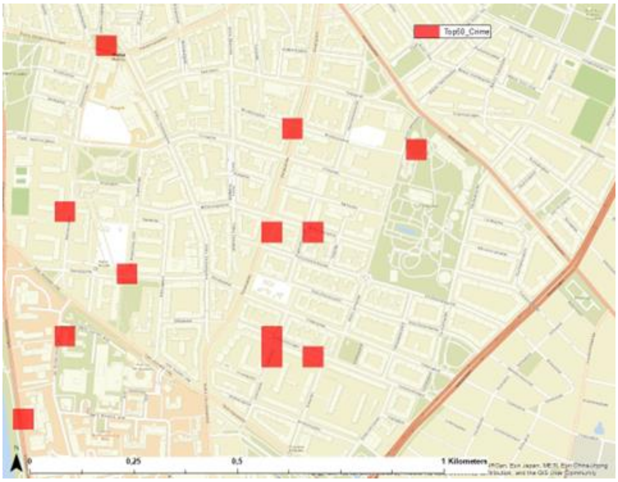

Figure 11. Assault 2016 forecasting assault 2017. Map maker Maria Camacho Doyle. Data source the police authority.

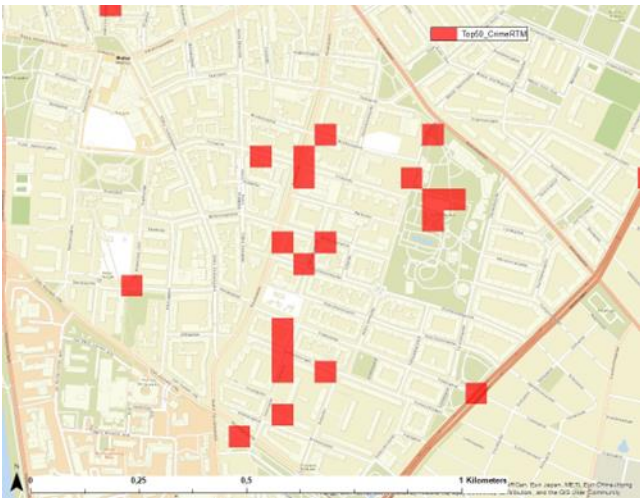

Figure 12. Assault 2016+RTM forecasting Assault 2017. Map maker Maria Camacho Doyle. Data source the police authority.

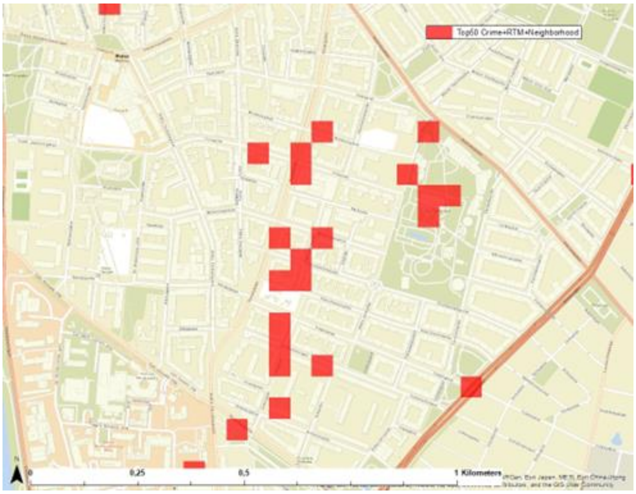

Figure 13. Assault 2016+RTM+Neighborhood variables forecasting Assault 2017. Map maker Maria Camacho Doyle. Data source the police authority.

3.5.3.3 Data/model fit

The dependent variables were crime counts, which as a norm contain a large number of zeros, most grid cells have a value of 0, and are over-dispersed that is, the variance is greater than the mean, (see Hilbe, 2011), therefore negative binomial regression models were estimated. To evaluate if the data fitted a negative binomial model or a Poisson model, a likelihood ratio was first tested with the lmtest package (Zeileis & Hothorn, 2002) in concurrence with chi^2. The boundary likelihood ratio test (Hilbe, 2001, p. 178) for over-dispersion that compares the fit of a negative binomial model to a Poisson model, were statistically significant see Table 4.

Table 4. The boundary likelihood ratio test for over-dispersion comparing the fit of a negative binomial model to a Poisson model for all included crime types.

Crime type	$\chi 2$ Value	p-Value
Assault	922.32	<.000
Robbery	13.62	<.000
Property Damage	11,995	<.000
Theft	7,638	<.000
Vehicle Theft	4,523.3	<.000
Residential Burglary	176.44	<.000
Illegal Fire Setting	114.92	<.000

These significant results suggested that the negative binomial model was more appropriate than a Poisson model for all crime types.

When comparing the fit of different models in the negative binomial regression *Pseudo-R*^{2}, The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) was used (see Hilbe, 2001, p. 68-71). Common Pseudo-R^2 described by Hilbe (2001) as:

$$R^2_p = 1 - \left(\frac{L_F}{L_1}\right)$$

L_F is the Log likelihood of the full model and L_1 the log-likelihood for the intercept only model. *Pseudo-R*^{2} gives a value between 0 and 1. The higher the value the more variation explained.

The Akaike Information Criterion (AIC) described by Hilbe (2001) as:

$$AIC = -2L + 2k = -2(L - k)$$

L is the Log likelihood of the full model and k the number of independent variables. The lower the AIC the better the model.

The Bayesian Information Criterion (BIC) described by Hilbe (2001) as:

$$BIC_L = -2L + k ln(n)$$

L is the Log likelihood of the full model and k the number of independent variables, including intercept, ln is the Logarithm, n represents the number of model observations in the model. The lower the BIC the better the model. When comparing the fit of different models in the multilevel negative binomial regression, Nakagawa r^2 was assessed using the performance-package (Lüdecke et al., 2021).

The Incidence Rate Ratio (IRR) of the negative binomial regression models were presented. The outcome variables (crimes 2017) are count variables so when you exponentiate the coefficients, they become a ratio of rates. Hence, the interpretation turns into a simpler gauge, compared to the coefficients, for assessing the strength and direction of the relationship between predictor variables and the outcome variable. IRR is a way to measure how one variable relates to the occurrence of crime hotspots compared to another variable. It helps us understand the relationship between these variables and the rate of crime. The IRR's can be interpreted as the change in the dependent variable, crime, in terms of a percentage increase or decrease for every unit increase in the independent variables, when holding the other variables constant. If the IRR is below one, it means a decrease of crime in that situation, if the IRR is above one, there is an increase in the crime count.

To avoid multicollinearity among independent variables, the Variance Inflation Factor (VIF) was tested for all independent variables. VIF was tested with the performance-package (Lüdecke et al., 2021). Bars and restaurants revealed a VIF of >5 and were therefore combined. After the combination of bars and restaurants VIF did not generate any values above five, hence highly correlated (concentrated disadvantage and collective efficacy = 3.15, 3.52, moderately correlated), therefore after bars and restaurants were combined all independent variables were used.

3.5.4 Study III – Multiple regression

The aim was to analyze the relationship between violent and property crime, community structural and social characteristics and different types of fear of crime. The dependent variables were:

- Perceived unsafety in 2015
- Fear of crime in 2015
- Avoidant behavior in 2015.

The independent variables were neighborhood level crime history, and measures of concentrated disadvantage, collective efficacy, disorder, urbanity, child-adult ratio, and prior neighborhood perceived unsafety, fear, and avoidant behavior (year 2012).

3.5.4.1 Analysis

In the main analysis, perceived unsafety, fear, and avoidance in 2015 were studied in relation to several types of crimes and in relation to variables measuring concentrated disadvantage, neighborhood collective efficacy, disorder, urbanity, child-adult ratio, and prior neighborhood perceived unsafety, fear, and avoidance (year 2012) to test the robustness of the results. This was done with multiple regressions in SPSS. The first model included different types of crime, calculated as crime rate per 1,000 residents in 2015. In the second model, concentrated disadvantage was added, to examine its role in relation to crime. The relationship between the different types of crime and perceived unsafety, fear, avoidance was observed. In the third model, collective efficacy was added to test whether this had an impact on the previously observed relationships. In the fourth model, disorder was added to test whether this had an impact on the previously observed relationships. In the fifth model, prior perceived unsafety, fear, and avoidance was added for robustness testing. For the main analyses, urbanity and age structure was not used, as it had lower correlations than .300 with the dependent variables.

3.5.4.2 Variable definition

Crime history was measured using crime data from January 2012 up until one month before survey collection, as more crime history equaled higher correlation with the outcome variables. Police recorded accounts (point data) of property damage and illegal fire setting (calculated as crime rate per 1,000 residents in 2015) aggregated to neighborhoods, was used as a proxy for visible neighborhood disorder. Property damage included graffiti and vandalism. The urbanity index ($\alpha = .694$) was created based on the density of bars and the ambient population measurement. Permits to serve alcohol after 1 am were used ($N = 71$) as the density of bars-measurement and calculated per 1,000 residents. The point data (bus stops) was aggregated to neighborhoods as a proxy for the quantity of people visiting the neighborhoods. To avoid a bias of bus stops ending up in only one neighborhood when they are located at major roads dividing the neighborhoods, buffers of 100 and 200 meters were used before aggregating. For each buffer, every neighborhood that intersected was assigned the value of the buffer divided by the number of intersecting neighborhoods.

3.5.5 Sensitivity analysis

Prior to any analyses with the crime data, Average Nearest Neighbor-tests (ANN) were run in ArcMap, to see if there were spatially significant crime clusters, hotspots, for all included crime types separately. ANN compares the actual average distance to the expected average distance under complete spatial randomness. The ANN results were significant and less than one for all crime types, which suggests clustering, meaning crime incidents were closer to each other than expected, for all crime types. It is important to keep in mind though that the size of the study area can influence the significance of the ANN test results.

In Study I, specific places in Malmö had more than a few missing geocodes for the reported crime types. If the places had more than 10 points of missing reported crime per year, then polygons were drawn in ArcGIS 10.3 and the amount of missing crime points were simulated by creating random points to represent the missing points (434 points in total). The information (such as date, time, and crime type) from the missing crime points was added to the randomly created points. Only property crime was affected by the missing points, with bike theft (part of vehicle theft) being the main crime affected. The PAI values did not increase much by creating random points for places with more than 10 crimes missing per year, which is why the decision was made not to create and include points for places with more than five crime points missing per year.

Within KDE certain parameters need to be set, method of interpolation, grid cell size and bandwidth. Because the interpolation method used, and bandwidth chosen can affect the outcome result (Hart & Zandbergen, 2014), a search for the "best KDE model" was completed. See appendix Study I for a more detailed account of the search for the "best KDE model". The cut-off for a hotspot in Study I was grid cells with 30 percent of all crimes. The KDE standard deviation method of selecting top hotspots was also calculated and compared to the SC method of selecting top hotspots for all crime types. The differences produced by these two different methods of calculating top hotspots was that the KDE standard deviation method generally produced lower PAI-values for comparison, due to the greater area rate used in this method. In other words, more 100-meter grid cells were generally needed to reach 30 percent of all crimes. The patterns were similar for both the SC and the KDE standard deviation cut-offs no matter crime type. Hence, it is unlikely that the method of locating the cut-offs (naïve method or standard deviation of KDE) substantially alters the main findings. Less-hot hotspots were furthermore examined, where 50 percent of all violent and property crime occurred and where 70–80 percent of all violent and property crime occurred. These 50 percent and 70–80 percent cut-offs also produced similar patterns when comparing KDE and SC predicting violent and property crime.

In Study II, separate 2016 crime history variables were created based on KDE with 50-meter grid cell size, 500-meter radius, with KDE-values assigned to each grid cell for comparison. A simple count of crime history gave better forecast values than KDE at every point. A separate unweighted place level indicator index was also created for sensitivity analysis. The results were like the weighted index, but weaker in strength. Poisson models were run for all models and compared to the negative binomial regression. AIC and BIC values showed negative binomial regression to be superior to the Poisson models for all crime types and all models.

In Study III, a separate concentrated disadvantage index without the public assistance and single parent household data respectively, was created and analyzed, with substantially the same results. This was done as public assistance data was from year 2016 (instead of 2015) and proportion of single-parent households presented a weaker association with the index than the other variables. A separate concentrated disadvantage index was also used that was adjusted according to factor loads, with substantially the same results in all models. Following the main analysis with multiple regression, logistic regressions with perceived unsafety, fear, and avoidance as dependents were also run, with similar results. Analyses were run on both the perceived unsafety scale (with two of three and three of three items) and the three separate items with similar results. Analyses were also run with different versions of the worry and avoidance scales (with two, three, four and five items of five) with similar results. Analyses were run on both dimensions of collective efficacy, cohesion and informal control, as separate indexes. The results were similar albeit informal control had a stronger correlation with both perceived unsafety and worry than cohesion. After the main analysis, analyses were also run with violent crime during survey collection ($N = 102$), with no substantial impact. A model 6 was run with urbanity (100m and 200m buffers) and age ratio added one at the time to the models. The only significant impact was the age ratio with fear (β=-.156 p= .047) in model 5. All models were also run with robbery and assault instead of violence, with substantially the same results. Crime during the survey collection, one year prior to the survey collection, two combined years and three combined years prior to the survey collection were also analyzed, no substantial difference. Residential burglary, theft, and vehicle theft were also analyzed separately, and results are presented in Study III.

3.6 Ethical approval and consideration

For Study I, II, and III, ethical approval was given by the Regional Ethical Review Board in Stockholm (2017/479).

First, it is important to reflect on one potential ethical problem when doing any type of geographical forecasting: the singling out of neighborhoods or smaller parts of neighborhoods as problematic. This discussion regards the ethical concerns of geographical forecasting in general as well as the current dissertation. There may be a risk of stigmatization of the areas (no matter what size) forecasted to be a hotspot of unsafety. Studies can make it clear that there is an increased frequency of crime with a potential for more crime, in certain areas. Residents or potential future residents in these potential hotspots of crime may react negatively. People with resources might move out of these areas, local businesses can leave the area, which can lead to a potential loss of job opportunities in the area. It can also affect homeowners, as the areas forecasted as potential hotspots may become less attractive. Mellgren (2011) did find that stigmatization might be a risk when mapping certain neighborhoods as unsafe or problematic.

If the preceding paragraph considered the risk of a geographical forecast, this paragraph concerns the benefit of such an endeavor. The results from geographical forecasting can be used for preventive measures, so that people who live in the areas concerned can avoid being exposed to crime and repeatedly exposed to crime. This should be seen as something positive. If the information is made available, homeowners or local stakeholders can use the information from geographical forecasting in general, to act preventively by, for example, reducing potential environmental risk factors, if these prove to be important for future crime in that location. In addition to this, the results from geographical forecasting may well be used to demonstrate that only certain stretches of so-called vulnerable areas are crime-prone, not the entire area as is often highlighted in media. Furthermore, perhaps using a micro-scale when forecasting unsafety will not have the same potential detrimental effect on a neighborhood level as only a small location in the greater neighborhood is shown to be problematic. This ethical discussion, however, of the potential detrimental effects of micro-level versus meso-level forecasts is open for debate.

Of importance for all reports and presentations of geographical crime forecasts and forecasts of unsafety in general is the information that forecasts regard an increased likelihood of future crime, not a deterministic cause-effect link. Nonetheless, the information emanating from geographical forecasting can be very valuable for future planning both when it comes to allocating police resources and for environmental prevention to reduce crime and increase safety.

3.6.1. Specific ethical considerations for the current dissertation

For all studies (I, II, III) reported crime with time and place with the geographical coordinates of crime incidents were used. No sensitive personal data related to reported crimes, as specified in Section 13 of the Personal Data Act (1998:204), such as: race, ethnic origin, political opinions, religious or philosophical beliefs, trade union membership, health, or sexual life, was collected. No direct personal data was collected, and no individual data of a sensitive nature was collected. Hence, data on reported crimes was collected, but the reported crimes were not directly linked to any individual data such as the identity of the perpetrator or the victim or the characteristics or features of these persons. However, the reported crimes all had addresses and/or geographical coordinates. Reported crimes that are indicated by address or geographical coordinates must be considered as the collection of data on crimes together with personal data, but indirect personal data in the sense that it is possible to find out who is registered at the address in question. It is possible to find out who lives at that location in relation to residential burglary.

In the current dissertation this problem will be dealt with by aggregating the crime points to grid-cells. No exact crime points will be displayed in the dissertation. It will not be possible to visualize the exact point of a crime. Residential burglary is however more sensitive to this problem, as one house can be in a 50-meter grid-cell, the cell-size in Study II. The other included crimes do not have this problem, as there is no clear victim, considering the address of residential burglary the victim. To ask all people registered at the current addresses of past residential burglary, about their consent to use the data, that is the location of past residential burglary, would be problematic. It is problematic as many of the crimes happened several years ago, people might have relocated, everyone registered at the current address in a high-rise apartment building for example, will not have been affected at all by the burglary in question. It could also bring back possible unpleasant memories. The assessment is that the legitimate societal interest with great benefits in safety promotion through a better forecast of unsafety outweighs the data subject's interest in protection against violation of personal integrity.

The empirical data collected from the Swedish municipality (Studies II, III) regarding concentrated disadvantage and neighborhood age ratio was all aggregated to neighborhood level, with a median population of about 2,500. No individual or place of residence was therefore able to be singled out in these specific data sets. Place variables such as locations of bars, restaurants and ATMs are environmental factors included in the analysis. They do not directly concern individual data, but the existence of businesses aggregated to 50-meter squares. The data set from the regional transportation company Skånetrafiken (Studies II, III) regards bus stops and annual passengers boarding this bus stop. No individual was therefore able to be singled out. The data set from Malmö university (Studies II, III) was a survey from residents in Malmö, MCS (MCS, 2016). In the current dissertation this data set was aggregated to neighborhood level before analysis, with a median population of about 2,500. No individual was therefore able to be singled out. The Malmö community survey was approved by the ethics board in Lund, 2014/826, prior to collecting the 2015 data wave and retroactively for using the 2012 data wave in research. Participants in MCS received information about the research project and informed consent was viewed as accomplished with the return of a completed survey (for more information see Ivert et al., 2013). This MCS dataset was however aggregated to neighborhood level prior to analysis in the current dissertation.

4 Results

The results presented in this chapter are the main findings from each study in the current dissertation.

Table 5. Overall aims and main results from Study I, II and III.

Study	Overall Aim	Results
I	To compare the predictive accuracy of two methods using historical exposure to crime, and using different crime-time-periods, across different types of violent and property crimes.	• No real difference between SC and KDE in forecast accuracy. • Counting crime, the year before worked well. • No added benefit of using more than one year crime history or KDE for most crime types.
II	To compare the predictive accuracy of prior crime, place attributes, ambient population, and community structural-, and social characteristics, across different types of violent and property crimes.	• Combining important place features renders fairly accurate forecasts for most crime types. • Only counting past crimes, however, still does a comparably good job.
III	To analyze the relationship between violent and property crime, community structural and social characteristics and different types of fear of crime.	• One-size-does-not-fit-all. • Collective efficacy and concentrated disadvantage were important for perceived unsafety. • Collective efficacy was important for overall fear of crime. • Avoidance needs to be investigated using other variables. • Fear of specific violent crimes was different from fear of specific property crimes.

4.1 Study I

When hotspots of violent crimes from 2016 were used to forecast violent crimes in 2017, 22 percent were accurately forecast. When randomly selecting locations from places with at least one past violent crime in 2016, eight percent of violent crimes in 2017 were accurately forecasted. When randomly selecting locations from any location in Malmö, 0.3 percent of violent crimes in 2017 were accurately forecasted. The take home message is to use last year's crime to forecast next year's crime, it is better than not using crime history at all.

However, the possibility of accurately forecasting crime differed substantially across crime types as can be seen in Tables 6 and 8. Some crime types were easier to forecast on a yearly basis. In Table 6, the best model for each crime type is presented, In Table 7 the average values for using different years forecasting crime in 2017 is presented. In Table 8 the average values for using Simple Count and KDE forecasting different types of crime in 2017 are presented.

Table 6. The best forecast model for crimes in 2017, across crime types from Study I

Crime type	Crimes forecasted	Area forecasted	Best model
Public environment assault	18 percent (156 assaults)	32 locations (0.2 percent of Malmö)	Assault in 2016, SC
Street robbery	13 percent (25 robberies)	33 locations (0.2 percent of Malmö.	Street robbery in 2016, SC
Theft	24 percent, (846 thefts)	52 locations (0.3 percent of Malmö).	Theft in 2016, SC
Vehicle thefts	23 percent (1006 vehicle thefts)	110 locations (0.7 percent of Malmö)	Vehicle theft in 2016, SC
Property damages	24 percent (869 property damages)	96 locations (0.6 percent of Malmö).	Property damages in 2016, SC
Illegal fire setting	12 percent (13 fire settings)	24 locations (0.1 percent of Malmö).	Illegal fire setting, in 2015-2016, KDE
Residential burglary	8 percent (56 residential burglaries)	101 locations (0.6 percent of Malmö).	Residential burglary in 2013, KDE

Note. In cases where there was not a five percent difference between the models, the simplest model is presented. For example, simple count based on the year 2016 is presented if there was no five percent difference between simple count based on 2016, 2015, and 2015-2016. Simple count is presented if there is no five percent difference between SC 2016 and KDE 2016.

Table 7. Average PAI and RRI values for using different years forecasting crime in 2017 from Study I

Year	KDE PAI	SC PAI	KDE RRI	SC RRI
2012	33.21^	33.09^	0.47*^	0.44*^
2013	35.10^	35.79^	0.53*^	0.49*^
2014	35.97^	36.71^	0.58^	0.56^
2015	38.47*^	42.89*^	0.57^	0.55^
2016	45.37*^	50.60*	0.63*^	0.59*^
2012-2016	39.08^	39.62^	0.77	0.74
2013-2016	39.42^	40.19^	0.76	0.73
2014-2016	41.35^	41.64^	0.77	0.73
2015-2016	47.91*	44.13*^	0.71*^	0.65*^
Total	39.54	40.52	0.65*	0.61*

Note. * denotes a >5 percent difference between the PAI and the RRI values of KDE and SC. ^ denotes a >5 percent difference between the PAI and the RRI values of the different years within each technique. Base years are KDE PAI: 2015-2016, SC PAI: 2016, KDE and SC RRI: 2012-2016.

Table 8. Average PAI and RRI values for different crime types forecasting crime in 2017 from Study I.

Crime type	KDE PAI	SC PAI	KDE RRI	SC RRI
Violent Crime	64.04	66.94	0.73	0.69
Assault	80.94	81.86	0.77*	0.70*
Robbery¤	37.09	35.93	0.35*	0.32*
Property Crime	20.16*	21.35*	0.85	0.84
Residential burglary¤	11.13*	9.79*	0.41*	0.34*
Theft	41.25*	43.64*	0.80	0.78
Vehicle Theft	29.69	29.58	0.87*	0.82*
Property damage	34.39*	38.78*	0.78	0.79
Arson¤	37.18	36.78	0.25*	0.19*
Total	39.54	40.52	0.65*	0.61*

Note. ¤ denotes the use of standard deviation in KDE rather than count in SC. * denotes a > 5 percent difference between the PAI and the RRI values of KDE and SC.

As seen in Table 6 and 8 simple count was similar to, or better than KDE for most crime types. Furthermore, also seen in table 6 and 7 using the year prior to 2017 usually rendered the highest forecast rate, across crime types. For ***public environment assault*** and ***theft*** prior crimes render good forecasts, with 18 and 24 percent of assaults and thefts forecasted respectively in an area as small as 0.3 percent of the municipality. ***Vehicle theft*** and ***property damage*** were more spread out geographically and hence harder to forecast than theft and assault. However, 23 and 24 percent of vehicle thefts and property damages in 2017 were forecasted respectively in an area smaller than one percent of the municipality simply by counting last year's crime incidents. Thirteen percent of ***street robberies*** were forecast in 0.2 percent of the municipality. The analysis was less useful for ***residential burglary*** however, as the analysis fluctuated and only eight percent of residential burglaries in 0.6 percent of the municipality were forecasted with the best model. For ***illegal fire setting***, the geographical area where crimes occurred were stably quite small, about 0.1 percent of the municipality, that is 24 grid cells. However, using two or more years to inform the forecast with KDE, the best model for illegal fire setting, only about 12 percent, that is 13 incidents of illegal fire setting were forecast.

So how do the two different methods, simple count, and KDE, based on historical crime data, impact the predictive accuracy in forecasting various types of violent and property crimes? The answer is they are both similar in their accuracy across crime types. Additionally, to what extent does the amount of crime history influence prediction accuracy, regardless of the method used? As hypothesized, longer periods of crime history generally do not increase the accuracy level, regardless of method used. The general take home message is, use a simple count of last year's crime to forecast next year's crime. You do not have to make it harder than that. This message does not work for residential burglary nor perhaps illegal fire setting, however. In consensus with the prediction hypothesis there was no added benefit to smooth out the effect of the crime points to nearby areas or to collect several years of crime data. Keep it simple.

4.2 Study II

In short, where there had been crime in the past, the risk for future crime was higher, even after controlling for all other variables. Where characteristics conducive for crime congregated, the risk for crime was higher, even after controlling for all other variables. Community social-, and structural characteristics and ambient population were important for some crime types. Lower levels of ambient population were related to higher levels of robberies, thefts, vehicle thefts and residential burglaries after other variables were controlled for. High concentrated disadvantage was related to higher levels of public assaults. Low neighborhood level collective efficacy was related to higher levels of assaults, robberies, property damages, vehicle thefts and residential burglaries. Finally, areas with more adults per young person were related to higher levels of assaults and vehicle thefts, all other things considered.

In Table 9 the best models for three different hotspot thresholds are presented. In Figures 14-27, presented below Table 9, the proportion area for assault and property damage on the horizontal axis, is the area percentage from one grid cell up until one percent of the total area. The grid cells on the horizontal axis, for all other crime types, indicate the number of grid cells. Crime + RTM means the results of crime history and RTM combined. Crime + RTM + AmbPop means crime history, RTM and ambient population combined. Crime +RTM+NV means crime history, RTM, and significant neighborhood level variables combined.

Table 9. The best model for 3 different hotspot thresholds

Crime type	Best model top 10 hotspots	Best model top 50 hotspots	Best model top 100 hotspots
Public environment assault	Assault history, RTM, and neighborhood variables combined	Assault history alone	Assault history alone
Street robbery	Street robbery history alone	Street robbery history alone	Street robbery history alone
Theft	Theft history alone	Theft history alone	Theft history alone
Vehicle thefts	Vehicle theft history, RTM, ambient population, and neighborhood variables combined	Vehicle theft history alone	Vehicle theft history alone
Property damages	Property damages and RTM combined	Property damage history alone	Property damage history alone
Illegal fire setting	Illegal fire setting history alone	Illegal fire setting history alone	Illegal fire setting history and RTM combined
Residential burglary	Residential burglary history alone	Residential burglary history alone	Residential burglary history alone

Note. In cases where different models rendered the exact same PAI and PEI* values, the simplest model is presented in the Table. For example, crime history alone is presented, if crime history alone and crime history combined with RTM renders the exact same PAI and PEI* values. This was the case with, for example, robbery. Hence, the prediction values were not increased with added data collection, therefore the simplest one is presented.

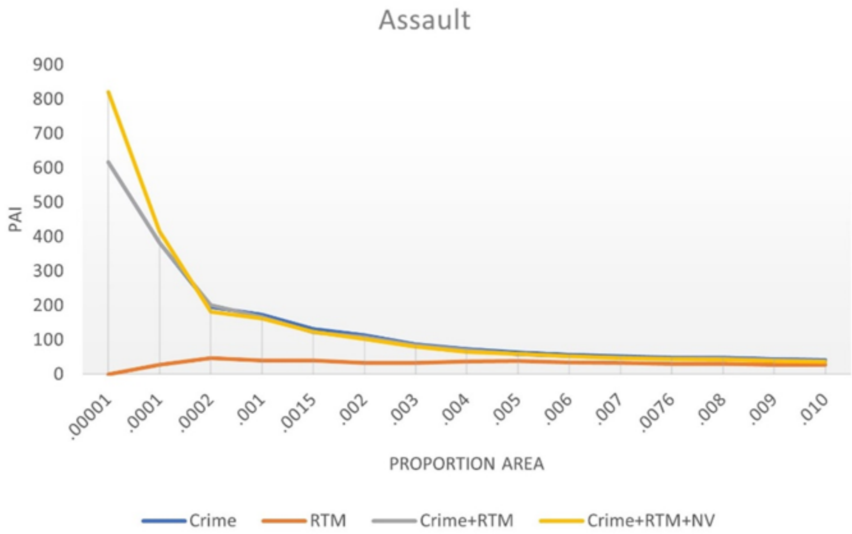

Figure 14. Predictive accuracy index for each of the different forecast models for assault. Across multiple thresholds, from one grid cell up to one percent of the study area.

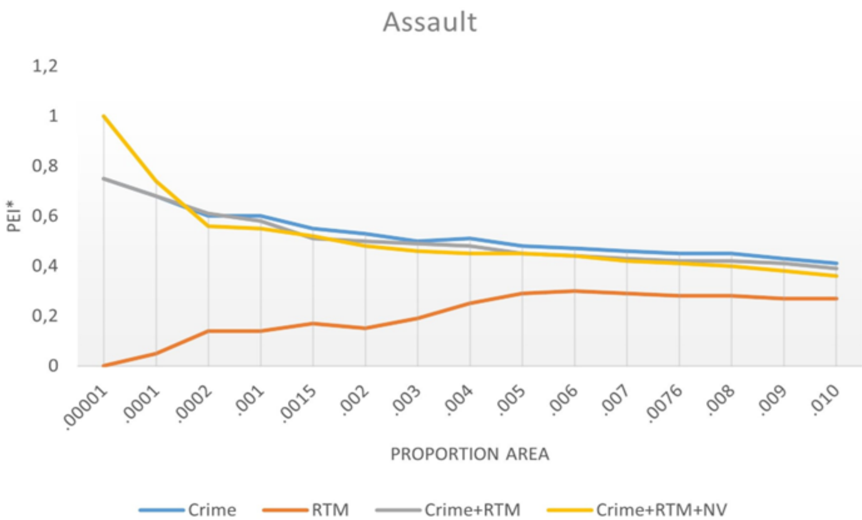

Figure 15. Predictive efficiency index for each of the different forecast models for assault. Across multiple thresholds, from one grid cell up to one percent of the study area.

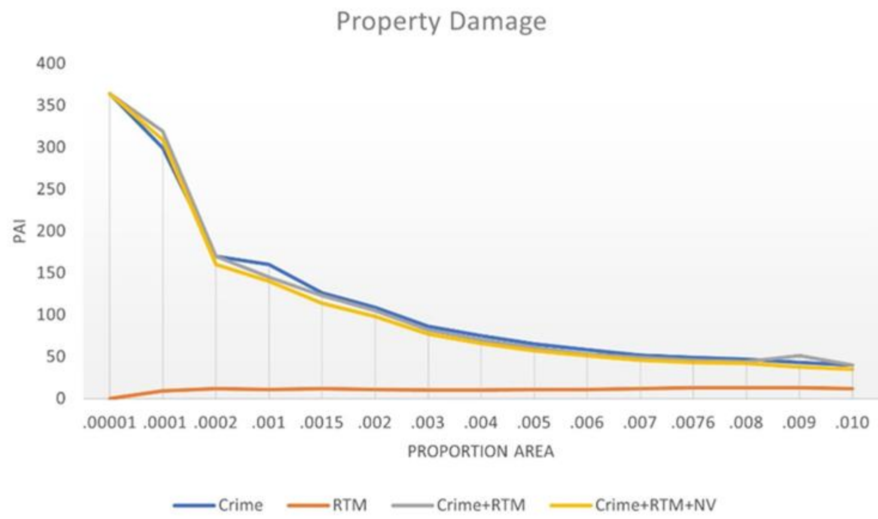

Figure 16. Predictive accuracy index for each of the different forecast models for property damage. Across multiple thresholds, from one grid cell up to one percent of the study area.

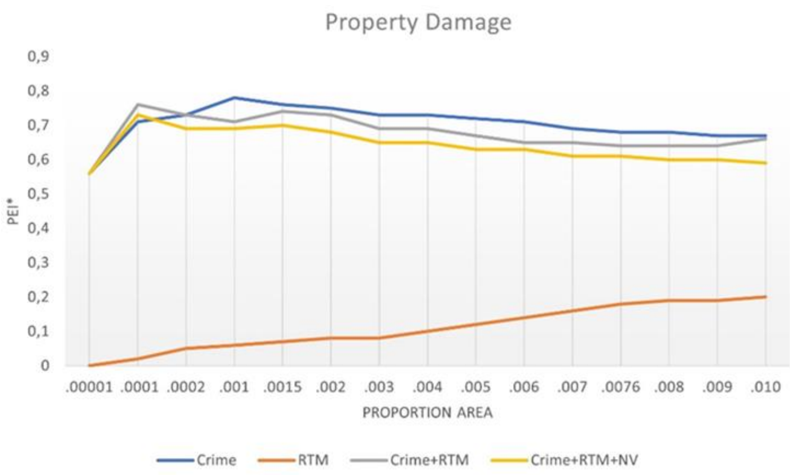

Figure 17. Predictive efficiency index for each of the different forecast models for property damage. Across multiple thresholds, from one grid cell up to one percent of the study area.

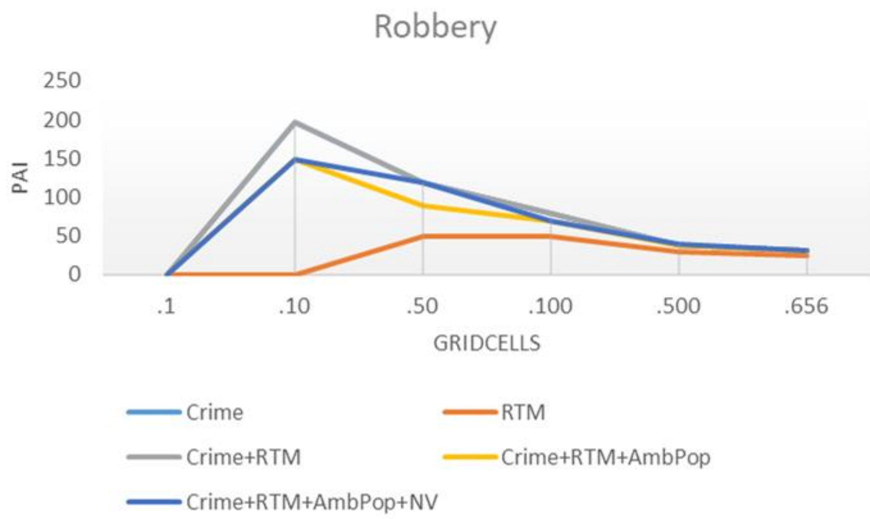

Figure 18. Predictive accuracy index for each of the different forecast models for robbery. Across six thresholds, from one grid cell up to one percent of the study area (656 grid cells).

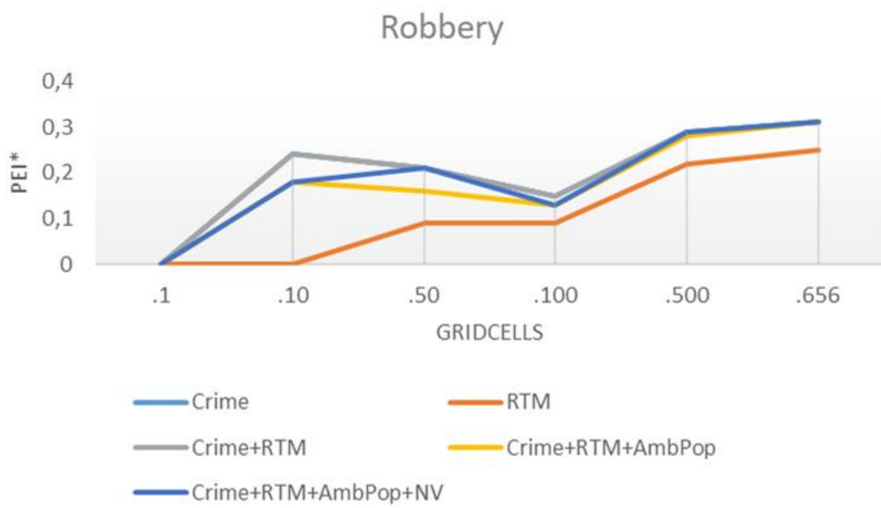

Figure 19. Predictive efficiency index for each of the different forecast models for robbery. Across six thresholds, from one grid cell up to one percent of the study area (656 grid cells).

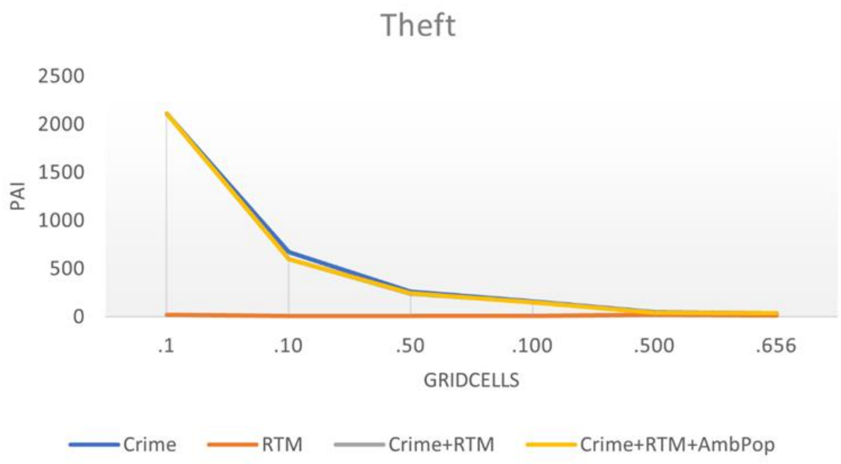

Figure 20. Predictive accuracy index for each of the different forecast models for theft. Across six thresholds, from one grid cell up to one percent of the study area (656 grid cells).

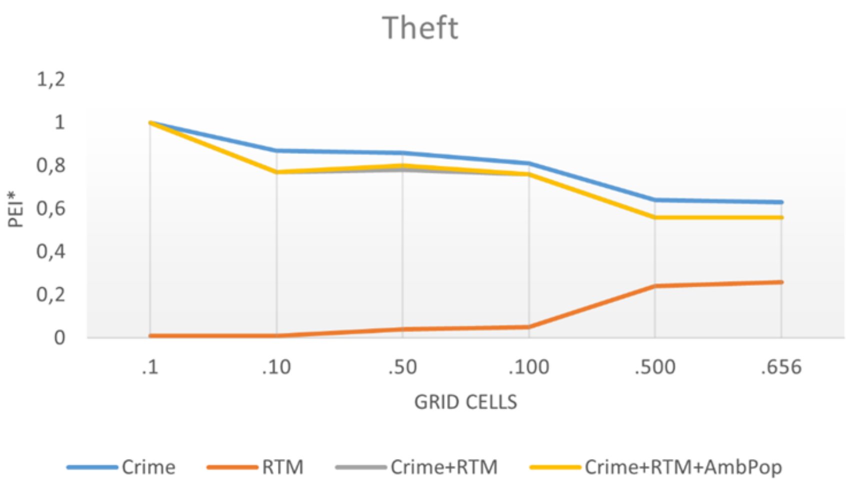

Figure 21. Predictive efficiency index for each of the different forecast models for theft. Across six thresholds, from one grid cell up to one percent of the study area (656 grid cells).

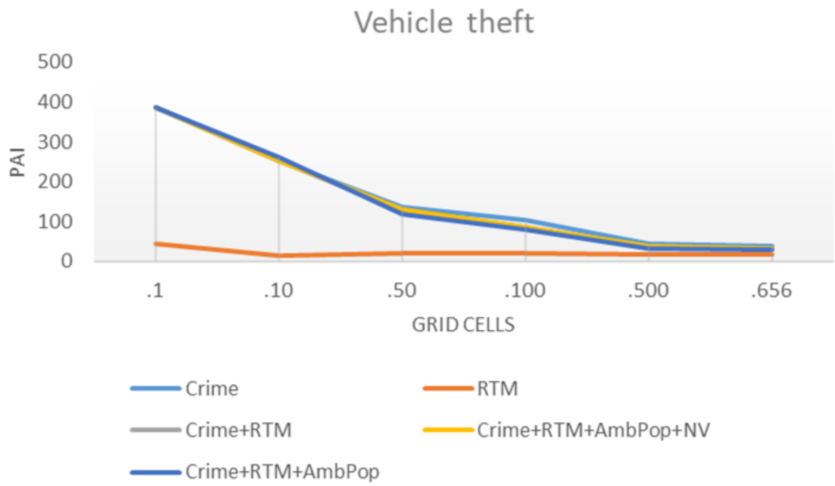

Figure 22. Predictive accuracy index for each of the different forecast models for vehicle theft. Across six thresholds, from one grid cell up to one percent of the study area (656 grid cells).

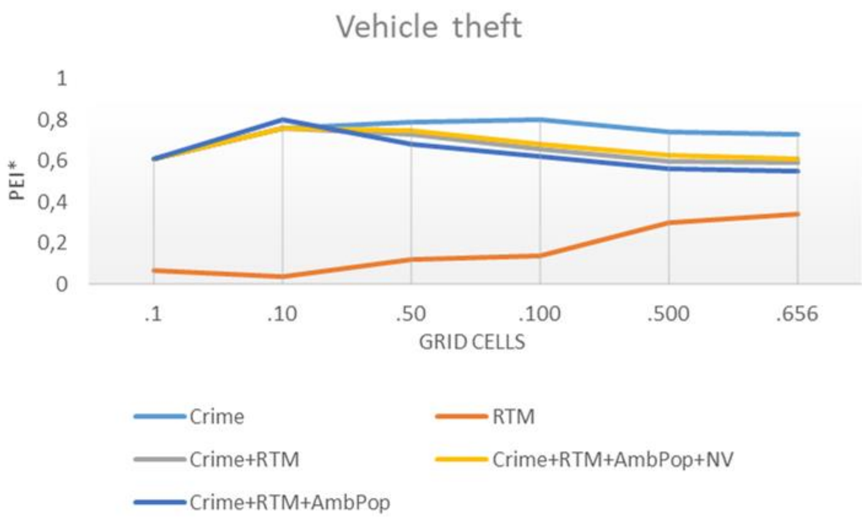

Figure 23. Predictive efficiency index for each of the different forecast models for vehicle theft. Across six thresholds, from one grid cell up to one percent of the study area (656 grid cells).

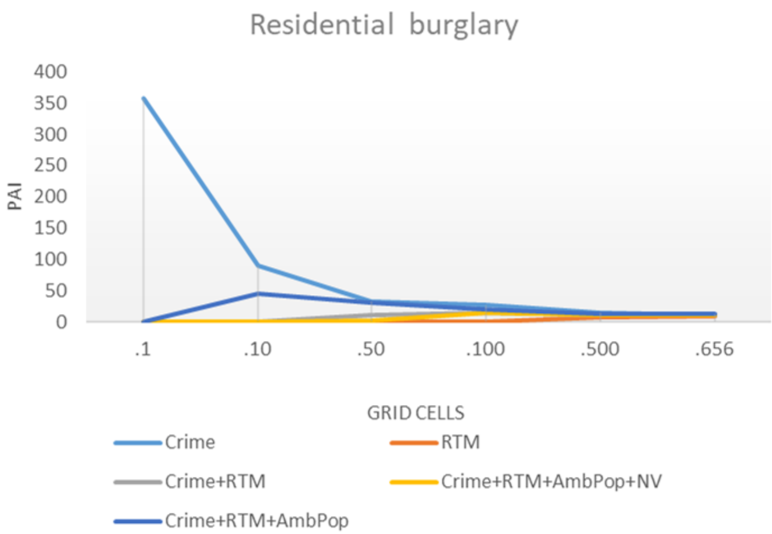

Figure 24. Predictive accuracy index for each of the different forecast models for residential burglary. Across six thresholds, from one grid cell up to one percent of the study area (656 grid cells).

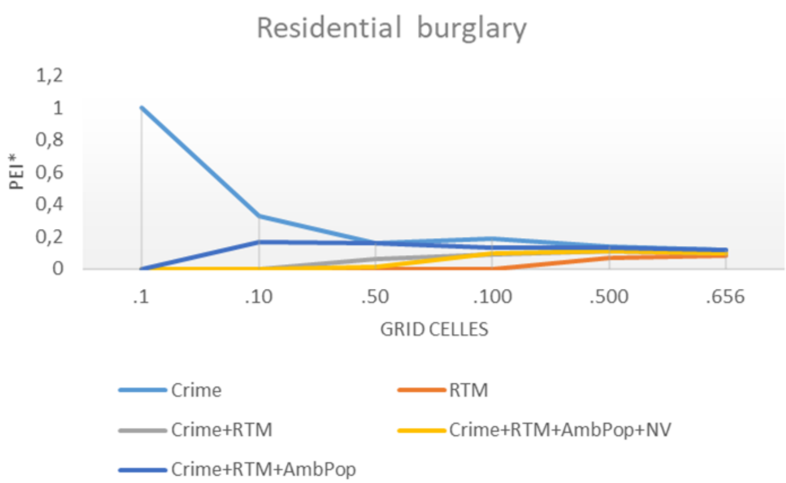

Figure 25. Predictive efficiency index for each of the different forecast models for residential burglary. Across six thresholds, from one grid cell up to one percent of the study area (656 grid cells).

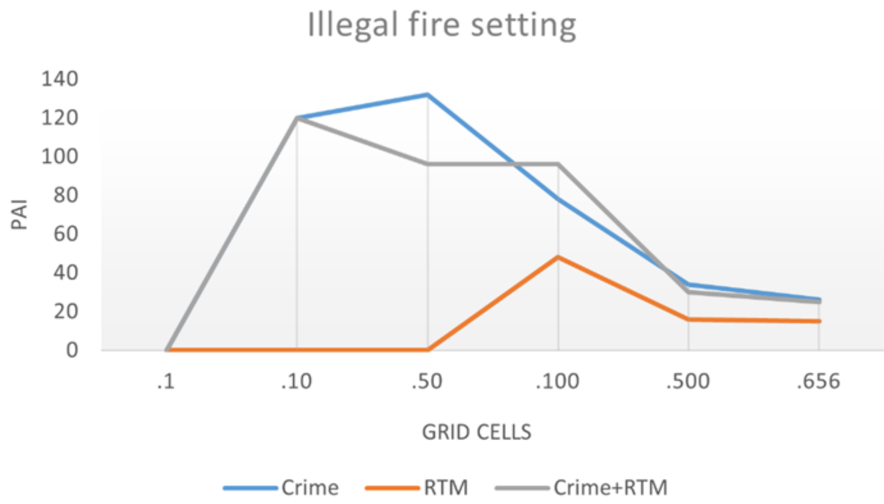

Figure 26. Predictive accuracy index for each of the different forecast models for illegal fire setting. Across six thresholds, from one grid cell up to one percent of the study area (656 grid cells).

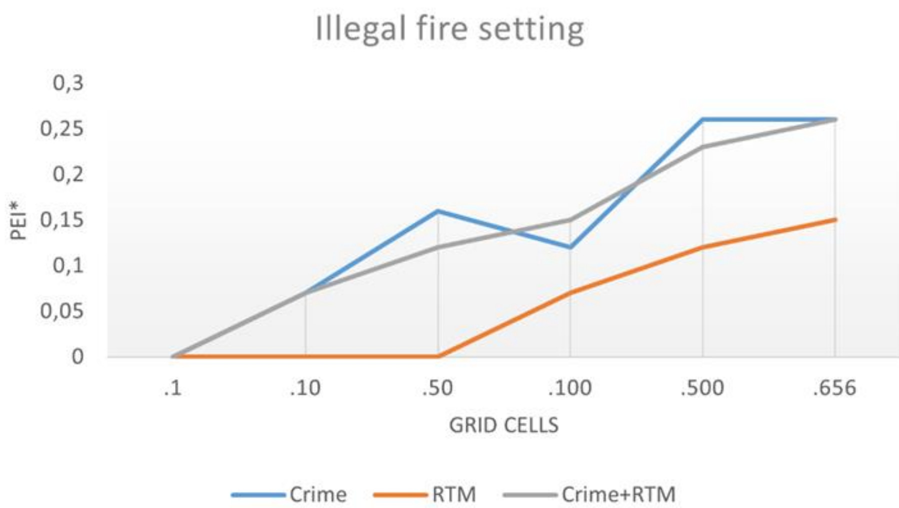

Figure 27. Predictive efficiency index for each of the different forecast models for illegal fire setting. Across six thresholds, from one grid cell up to one percent of the study area (656 grid cells).

When taking the size of the geographical area into account see Figures 14-27, the crude RTM alone performed the worst out of all models when it came to prediction accuracy and efficiency (PAI and PEI*) for all crime types. However, when combined with crime history, RTM performed quite well. Generally, combining more data to forecast all different types of crime performed well, but it did not outperform simply using prior crime counts as the forecast. Looking at the PAI/PEI*-values (Figures 14-27), for ***robbery***, most models (except for RTM alone) rendered similar prediction accuracy with some fluctuation. For ***residential burglary*** and ***theft*** using prior crime alone reached the highest prediction accuracy. For residential burglary, however, the prediction efficiency values were quite low across models, in comparison to the other crime types. Looking at the top ten hotspots for ***vehicle theft***, the prediction efficiency was higher for the full model, but as more hotspot locations were included crime history alone reached the highest prediction accuracy. For ***illegal fire setting***, the results fluctuated across geographical area, that is amount of included hotspot locations, crime history alone generally reached higher prediction accuracy and efficiency than the other models. For the top ten hotspots for ***assault*** and top 50 hotspots for ***property damage***, a combination of all significant coefficients and a combination of crime history and RTM alone reached the highest prediction accuracy, respectively. For all other cut-offs, including more hotspot locations, crime history alone generally reached the highest prediction accuracy. The prediction accuracy decreases as the included area gets larger and the highest accuracy is reached within the top hotspots.

So, how does the predictive accuracy differ when using individual factors (e.g., prior crime, place attributes, ambient population, community structural and social characteristics), in isolation and when combined in forecasting various types of violent and property crimes? In short, a combination of crime history, place-, and neighborhood level attributes can all be important when trying to accurately forecast crime, long-term at the micro-place. The variables in combination aid in increasing the prediction accuracy (not for theft nor residential burglary however). Only counting past crimes, however, still does a really good job. Crime history alone generally renders equal, or higher, prediction accuracy as the model that includes all data. In consensus with the prediction hypothesis there was no added benefit to collecting more data if the only goal is long-term crime forecasting at the micro-place. Keep it simple. Also, in consensus with the prevention hypothesis the inclusion of a broader set of variables, such as place attributes, ambient population, and community structural and social characteristics, do yield predictions of similar accuracy to historical crime data alone, except for theft. Be informed to prevent. Residential burglary, however, might need to be assessed with different variables than done in the current study.

4.3 Study III

Key findings were that collective efficacy was the strongest correlate of both perceived unsafety and overall fear of crime. In addition, and importantly it was not possible to relate avoidant behavior with the neighborhood variables as measured in the current study. Finally, fear of specific violent crimes was different from fear of specific property crimes and should hence be examined separately.

The results from the multiple regression of perceived unsafety, fear of crime and avoidance are as follows. **Model 1** showed a significant relationship between **violent crime** and

- ***perceived unsafety***, $R_2 = .143$, $\beta = .389$, $p = .000$.
- ***fear of crime*** $R_2 = .117$, $\beta = .354$, $p = .000$.
- but not for ***avoidance*** $R_2 = .017$, $\beta = .165$, $p = .099$.

In **Model 5**, where concentrated disadvantage, collective efficacy, disorder, and prior perceived unsafety measures were all added, the results revealed a major impact on the relationship between violent crime and

- ***perceived unsafety*** $R_2 = .822$,

  crime $\beta = .051$, $p = .387$,

  concentrated disadvantage $\beta = .239$, $p = .004$,

  collective efficacy $\beta = -.480$, $p = .000$, disorder $\beta = -.058$, $p = .331$,

prior perceived unsafety $\beta = .268$, $p = .000$.

- ***fear of crime*** $R_2 = .690$,

  crime $\beta = .080$, $p = .309$,

  concentrated disadvantage $\beta = -.160$, $p = .160$,

  collective efficacy $\beta = -.581$, $p = .000$,

  disorder $\beta = -.081$, $p = .303$,

  prior fear of crime $\beta = .487$, $p = .000$.

- ***avoidance*** no variable was significant in Model 5, not even prior avoidant behavior. $R_2 = .111$

Prior perceived unsafety reduced the coefficients for concentrated disadvantage and collective efficacy a little, but other than that the relationships remain for perceived unsafety. Prior fear of crime reduces the coefficients for collective efficacy a little, but collective efficacy still has the strongest association with fear of crime.

The results also revealed that if you want to analyze the relationship between different fear of crime aspects and crime (both total and specific crimes), longer crime rate history as supposed to shorter intervals will likely provide stronger relationships. Crime that occurred during survey collection did not relate to either measured outcome. While violent and property crime rates did not correlate with the multiple-item measures of fear of crime nor fear of violent crime after controlling for other neighborhood variables, property crime did correlate with fear of specific property crimes when examined separately. Hence, neighborhood crime levels were important for fear of property crimes, but not for fear of violent crimes. Neighborhood-level fear of being assaulted or threatened was related to low collective efficacy and high concentrated disadvantage in the neighborhood, not the rate of violent or property crime or disorder. For residential burglary conversely, the crime that sticks out as a bit different compared to the other measured crime types in the current dissertation, the relationship was reversed. Previous accounts of residential burglary increased fear of future victimization of residential burglary at the neighborhood level, lack of social integration did not add anything extra. In addition, neighborhood-level fear of having your vehicle stolen was related to the neighborhood rate of vehicle theft as well as a low collective efficacy in the neighborhood.

So, what is the nature of the relationship between violent and property crime, community structural and social characteristics, and different types of fear of crime (e.g., perceived unsafety, general and specific fear of crime, avoidant behavior)? At the neighborhood level neither crime nor disorder are as important as being socially integrated for being fearful of crime and perceiving unsafety. In conflict with the prediction hypothesis, crime history alone does not serve as a reliable predictor all other things considered, except for fear of residential burglary and fear of having your vehicle stolen. Also, in somewhat conflict with the prevention hypothesis collecting more data and specifically data on collective efficacy renders *better* prediction accuracy than crime history alone. The more the better. Avoidant behavior needs to be assessed using different variables altogether. The take home message is, first know what you want to forecast as different aspects of fear are distinct. Second, in general, collective efficacy seems important.

5 Discussion

5.1 Main finding

The overall aim of the current dissertation was to examine the relationship between historical crime data, environmental factors, and neighborhood characteristics in the context of forecasting unsafety, both crime and fear of crime. It was hypothesized (Occam's Razor), that basic forecasting methods, such as using past crime data, which is easy, clear, and feasible, could achieve similar accuracy in forecasts as more complex methods like RTM. RTM requires extensive data collection. Or methods like KDE that smooth out past crime patterns geographically, which is a bit more advanced. Additionally, while also considering the neighborhood context and different crime-time perspectives. It was also hypothesized (Variable Inclusion), that including more variables would yield similar prediction accuracy to historical crime data alone. The overall aim was pursued through three empirical studies that address specific questions tied to the overall goal.

The general conclusion is: Rather simple things can get you quite far when it comes to crime forecasting. If your only goal is to forecast crime long-term at the micro-place, counting last year's crime, no more crime needed, render similar accuracy as methods that smooth out the effect of past crime geographically and the inclusion of different place, and neighborhood variables. This held true for both violent and property crimes. A bit more is needed however when it comes to forecasting overall safety, both crime and fear of crime, at the neighborhood level. First, you need to know what you aim to forecast, crime, perceived unsafety, general or specific fear of crime or avoidant behavior, as different aspects of perceived unsafety and crime are differently related to crime and other neighborhood factors. In general, collective efficacy, not crime, should be considered at the neighborhood level when forecasting perceived safety.

The current dissertation simultaneously adds to the research that argues that if the goal is merely to forecast crime, simple methods of crime forecasting can be enough for practical purposes. As well as adding to the research that argues that crime history might not be the only thing needed for accurate forecasting of unsafety when perceived unsafety and related measures are the outcome, at least at the neighborhood level. Consequently, one-size-does-not-fit-all. It is pertinent to first establish what goal you are attempting and what geographic scale you will be using, prior to forecasting unsafety. Two related but separate strands of reasoning will be considered in the following discussion. On the one side there are research oriented and policy making arguments to be made and on the other side there is the argument of practice with practical feasibility and application.

5.2 Forecasting unsafety (crime and fear of crime)

Based on previous studies (Brunton-Smith & Sturgis, 2011; Doran & Burgess, 2012; Hale, 1996; May & Dunaway, 2000; Rader et al., 2012; Schafer et al., 2006; Wilcox -Rountree 1998; Wilcox -Rountree & Land 1996a, 1996b; Zhao et al., 2015), and the crime/fear generators of the CPT (Brantingham et al., 1995), the original hypothesis of the current dissertation was that historical crime data, when considered on its own, would serve as a reliable predictor for general unsafety, both crime and fear of crime. Following this logic using crime as a predictor for both future crime and perceived unsafety might have been viable. For research oriented and policy making arguments however, and in discord with the prediction hypothesis (Occam's razor), the results of the current dissertation show that one-size-does-not-fit-all, concerning overall unsafety at the neighborhood level. Estimating fear of crime and perceived unsafety (Study III), at the neighborhood level, showed that crime rates and visible disorder appeared important for perceived unsafety only when not considering collective efficacy at the same time. Being socially integrated was more important than neighborhood level crime and disorder for perceived safety and the levels of fear. Avoiding going to the movies and or using the bus/train due to a fear of being threatened, assaulted, or subjected to violence (Study III) was not related to any of the included neighborhood level fear generators, hence other variables, such as earlier victimization (May et al., 2010) might need to be assessed.

Likewise, the inclusion of more crime generators from different levels of geography, micro-place, and meso-neighborhood (Study II) was also beneficial for pretty much all crime types but theft, in the most intense hotspots. That the predictive accuracy increased slightly, also when including more place-level crime generators in the top hotspots, reverberates other research on RTM, that crime generators at the place level, proximity to bus stations, bars, and ATM's and such joint with crime history render a better forecast than place level indicators alone (see e.g., Caplan et al., 2013a; Caplan et al., 2020).

In concordance with the prevention hypothesis (variable inclusion), crime history, environmental and neighborhood characteristics all relate to unsafety both crime and fear of crime, to some extent. Hence, following these results and related research for both crime (see e.g., Boessen & Hipp 2018; Hipp & Kim, 2017; Hipp et al., 2017; Hipp & Williams, 2020; Jones & Pridemore, 2019) and perceived unsafety (Barton et al., 2017; Franklin et al., 2008; May et al., 2010; Scarborough et al., 2010; Wyant, 2008), a more holistic approach to data collection and analysis might be required for forecasting a more general measure of unsafety, including both crime and fear. Not just prior crime incidents.

5.2.1 Understanding the results aided by theory

That crime history, environmental and neighborhood characteristics all relate to unsafety to some extent, do reverberate the theoretical spatial-contextual approach of the current dissertation. Crimes, and likely future crimes, take place in a context that includes both the immediate- and the greater environment. Different types of micro-places do not produce crime in the same way in different neighborhood contexts. Instead, (see also Tillyer et al., 2021) there are higher levels of crime at places in neighborhoods with rich criminal opportunities, while there is less crime at places in neighborhoods with fewer opportunities for crime. The top hotspots for public assault (Study II) for example could be found at locations, the place level, with a history of assaults and a higher concentration of town squares, bars, restaurants, ATMs, bus stops, schools, and rental apartments in areas, the neighborhood level, with a higher concentrated disadvantage, lower collective efficacy, and more adults per young people. Looking at property damages they were more likely to occur at locations, the place level, with a history of property damage and a higher concentration of town squares, ATMs, bus stops, schools, preschools, industrial areas, rental apartments, and owner-occupied houses in areas, the neighborhood level, with lower collective efficacy. Both the micro-place level and meso-neighborhood level hence added to the forecast accuracy, as the spatial-contextual approach suggests.

The results (Study II, III) do also echo the theory of collective efficacy, for both crime and perceived unsafety. Places with low neighborhood collective efficacy through low social cohesion and informal control are perceived as more unsafe (see also Markowitz et al., 2001; Scarborough et al., 2010; Sampson et al., 1997) and places with high collective efficacy through strong ties between neighbors (see also Swatt et al., 2013) are perceived as safer. This argument is also similar to other research that include measures of social integration, such as collective efficacy, and perceived unsafety (and related measures) showing that a level of social integration is important (see e.g., Abdullah et al. 2015; Brunton-Smith et al., 2014; Brunton-Smith & Sturgis 2011; Hinkle 2015; Markowitz et al. 2001; Swatt et al. 2013).

For crime we see that perhaps the neighborhood level collective efficacy acts as a type of capable neighborhood guardianship providing a deterrent effect on the crime-prone people to not act on the opportunities presented at these specific locations. Whilst the specific place-level crime generators such as closeness to bars, restaurants and bus stops are important places that can provide opportunities for crime. The results (Study II) did show that places with a high concentration of place level indicators and a low neighborhood collective efficacy generally had more crime at the forecasted time. Places with the same concentration of place level indicators but a high neighborhood collective efficacy had less crime at the forecasted time in comparison.

According to CPT (Brantingham & Brantingham, 1993, 1995, 2013) a sheer concentration of people and potential goods generate crime. More people, more crime. Contrary to this we found that more people moving about equaled less crime. If two places had the same concentration of place level indicators and same level of neighborhood collective efficacy but one place had more people present, there would be 13 percent less robberies there, which makes sense due to the nature of the crime (see Ceccato et al., 2020a). A certain amount of anonymity and poor surveillance might be important for robbery. But there were also seven percent less residential burglaries, and five percent less vehicle theft, at that spot. If two places had the same concentration of place level indicators but one place had more people present, there would also be six percent less theft. Perhaps the effect of bars, restaurants, and prior crime captures the fact that these places have more people and more potential offenders. Whilst adding more people to the place could generate more capable guardians (Cohen & Felson, 1979).

Looking through the lens of geography, the results from the current dissertation also showed that different combinations of absolute, relative, and relational space were important to understand and forecast different types of unsafety. The absolute place with the built environment, and relational space with neighborhood level collective efficacy aided in forecasting crime and relational space was generally important for the different types of perceived unsafety. Relative space through proximity to concentrated disadvantage aided in forecasting assault and different types of perceived unsafety. Regardless of the criminological or geographical definition chosen to describe the places of interest, a combination of different levels aid in the forecast of unsafety to different degrees.

5.2.2 Where do we go from here?

In sum, based on theory and the results from the current dissertation, that crime history, environmental and neighborhood characteristics all relate to unsafety both crime and fear of crime, to some extent: a more holistic approach to data collection and analysis is needed when forecasting general unsafety, than only counting past crimes. This expanded set of variables will also provide valuable insights for crime prevention strategies and interventions.

The more holistic approach of looking at crime/fear generators at different levels, both from a contextual and a spatial perspective, to forecast crime and perceived unsafety, would speak in favor of using more advanced statistical methods than the ones used in the current dissertation in the future, at least as research and prevention is concerned. Because although there are theories aimed at explaining hotspots of unsafety at different levels, specific location, and neighborhood, it is not always clear how the specified theoretical variables affect the crime and fear levels. There are some issues with combining theory and methodology in spatial-contextual criminology. For example, a potential crime generator according to CPT, can be the presence of a bar. The presence of a bar can be important for assault through both the distance to the nearest bar (proximity) but also through the number of nearby bars (density). Using the crime generator, bar, to measure the effect on public environment violence (see Gerell & Kronkvist, 2017) might seem simple enough. But should the presence of a bar be measured through the distance to the nearest bar (proximity) alone, or as the number of bars as well as distance of nearby bars in a location (density) (Caplan et al., 2011; Deryol et al. 2016)? There is also the choice of letting the crime generators (the bar) affect crime with a decaying effect, hence have less power the further away the generator is and include a break point (Ratcliffe, 2012). It is not clear from the theoretical aspect how the potential variables relate to crime.

Using more advanced statistical methods, than the ones used here, to understand the holistic perspective of hotspots of unsafety, might also be preferred as explanations at the different levels interact with each other (see also e.g., Brantingham & Brantingham, 1993, 1999; Taylor, 1998, Tillyer, 2015; Tillyer et al, 2021; Wilcox et al., 2013). Although no interaction effects were studied in the current dissertation, variables from different levels did add to the forecast for the most part. There might have been significant interactions between and within the extensive list of crime generators used at the different levels. A single address with a lot of crime, for example a bar (single address hotspot named either hotdot or risky facility) can be in a hotspot, in a high crime neighborhood. The effects of the risky facility can radiate out onto the streets surrounding it (see e.g., Bowers, 2014). This should be considered in combination with the fact that even in the most disadvantaged, high-crime neighborhoods, most places have little to no crime (Weisburd et al., 2012). The complex patterns of interrelations given by prior theories and research, between different crime generators and crime generators at different levels of explanation are not easy to study (see Haberman & Ratcliffe, 2015). It is not easy to study because there are numerous modelling choices, different spatial operationalizations and potential interaction effects between and within levels, with extensive lists of crime generators.

Many more advanced forecasting algorithms such as random forest and neural network are now being used in the field of criminology as well as in other fields such as sociology, geography, and computer science (see Butt et al., 2020; Kounadi et al., 2020; Lee et al., 2020). This machine learning development in forecasting unsafety is encouraging, as these techniques can account for the vast amount of crime generators, interactions between crime generators at different spatial scales, non-linearity, and different spatial methodological decisions when forecasting crime (see Hipp et al. 2017; Mohler & Porter 2018; Wheeler & Steenbeek, 2021). As interactions, between and within level, and intricate non-linear effects can be detected and deciphered in the more advanced machine learning methods of analysis, this can help us further test the spatial-contextual theoretical approach, both place and context combined. This development can hence further the development of the theoretical perspectives on the criminology of place.

These machine learning techniques might furthermore aid in decreasing bias, due to less decisions being based on researcher assumptions. Random forest, or neural networks, do rely on fewer assumptions and decisions made by researchers at the onset, compared to traditional regression models and RTM, with the tool RTMDx. There is hence the chance of decreased bias using machine learning techniques, as there are no predefined set of linear relationships that need to be specified. Running an RTM, the RTMDx decides how far away the crime generator will affect crime depending on pre-decided distance thresholds that are put into the model. The results from the current dissertation also came from kernel densities and regression models with pre-decided distance thresholds. The machine learning models do at least make these methodological decisions more independent of researcher involvement and perhaps bias.

It is important to keep in mind, however, that machine learning models do rely on training data sets to learn patterns and make forecasts. If the training data used to develop the crime forecasting model is biased or incomplete, the model can continue or even amplify existing biases (see e.g., Mayson, 2019; Navarro et al., 2021; Van Giffen et al., 2022). Biases can arise from factors such as biased police practices, historical patterns of crime reporting, or socioeconomic disparities. As a result, the model may produce unfair or discriminatory forecasts, disproportionately targeting specific communities or demographics. What is put in, is what comes out. Furthermore, as promising as the machine learning techniques are, they do also have a black-box problem, as RTM with the tool RTMDx also have. Black-box problem meaning that the underlying mechanisms and algorithms are not clearly transparent. How the inputs, crime generators, are related to the outcome; crime, is not clear. It is apparent where future crime might take place, but it is not apparent why this is. This lack of interpretability poses challenges for understanding how the model arrives at its forecasts. The inability to explain the reasoning behind a forecast can lead to concerns about accountability and transparency, especially in contexts where the decisions made by the model, where to increase police presence for example, may have significant real-world implications (see e.g., Collins, 2018; Ferguson, 2012; Rieland, 2018). There are attempts of making complex machine learning models interpretable for practitioners in progress (see Wheeler & Steenbeek, 2021), but these attempts are not fully disseminated in practice yet.

Identifying/forecasting hotspots of unsafety is not the same as understanding them. Prevention, built on a more holistic perspective of these hotspots of unsafety is something different from predictive analysis. Then finding these interactions of context and place can aid in developing localized problem-oriented strategies to address the crime and perceived unsafety in these hotspots. Depending on the geographical level of the identified hotspot, prevention will differ. The results from the current dissertation showed that variables from different levels did add to the explanation for the most part and hence might add in prevention efforts as well. Interventions tailored to the specific need of the place in a problem-oriented way might have a greater success (see Braga et al., 2019) than simply adding police officers to that location. Working with the community at place and together solve the root cause of the crime problem to alleviate future crime problems at places with enduring crime risk. Here place-level variables can be of great use to understand the problem and prevent the problem. For risky facilities, place management is important (see e.g., Eck, 2015). The difference between bars with a lot of crime compared to bars with less crime could for example be place managers choosing to enforce the rules or not. At the micro-geographic level of streets, it might be more about how opportunities present themselves with a high concentration of people, offenders, and victims alike, in the absence of capable guardians on certain streets with certain place-level indicators as compared to other streets (see also Braga et al. 2019; Weisburd & Majmundar, 2018). Working with decreasing the potential opportunities and increasing the capable guardians on certain streets might be proper here. At the even greater neighborhood level it might be relevant to look at collective efficacy, and concentrations of potential crime targets (see also Burchfield & Silver, 2013; Browning et al., 2004; Mazerolle et al., 2010; Morenoff et al., 2001; Sampson et al., 1997; Sampson & Raudenbush, 1999; Sampson & Wikström, 2008; Wikström et al., 2012). The results from the current dissertation did show that working with increasing levels of cohesion and informal social control, collective efficacy, in said neighborhoods might increase perceived safety and decrease a general fear of crime as well as decrease crime levels. Perhaps the best prevention and intertwined forecasts would be aimed at different levels simultaneously.

5.3 Forecasting unsafety (crime and fear of crime) for practice

The current dissertation does however also show that sometimes simple-is-enough for crime forecasting (see Lee et al., 2020). The aim of the current dissertation was to explore the relationship between different characteristics to render the best possible accuracy of forecasting unsafety, whilst also having a functional mindset for practice. In line with the prediction hypothesis (Occam's razor) the inclusion of more crime generators (Study II) and a slightly more complicated method of analysis (Study I) did not greatly increase the accuracy of the crime forecasts. In fact, when the size of the geographical area was considered, a simple count of past crimes rendered similar, or better, forecasts to methods that required more data collection. Looking at the top 50 hotspots (Study II) the best model to use for crime forecasting was crime history alone for assault, theft, vehicle theft, residential burglary, and illegal fire setting. For robbery and property damage crime history alone and crime history with RTM rendered the same accuracy, so for practicality the question is if it is worth collecting the extra data when the forecast accuracy does not increase. There generally was no added benefit of using more than one year of crime history (Study I), nor of using a simple KDE for any of the included crime types.

Looking at the more intense hotspots (Study II), the top ten hotspots and *the* top hotspot, crime history stayed the best predictor for theft and residential burglary, for the other crime types adding more data did increase the forecasts slightly or rendered the same results. In Study I, the results generally showed simple count to be as accurate as KDE, if not more so, across all different model specifications. The accuracy did not increase greatly with the more extensive data collection at the more intense hotspots, however. When looking at the top ten hotspots, ten squares the size of 50 by 50 meters, including all variables contribute to a slightly better forecast. For instance, 6.4 percent of assaults forecast versus 5.8 percent using crime history alone. For assaults this means that considering a higher concentration of town squares, bars, restaurants, ATMs, bus stops, schools, and rental apartments in areas with a higher concentrated disadvantage, lower collective efficacy, more adults per young person and a history of assaults implies 0.6 percent better forecast than using crime history alone. This is a ten percent improvement.

Other past studies have likewise shown that adding more spatial data than crime history does not vastly improve the forecast (se e.g., Drawve, 2016; Drawve et al., 2016; Rummens & Hardyns, 2020; Wheeler & Steenbeek, 2021, albeit see Caplan et al., 2011; Kennedy et al., 2011; Ohyama & Amemiya, 2018). If the accuracy of the forecast is not superior to one year of crime history, can one justify the time, effort, and finances spent on collecting more data if the goal is tactical deployment of police officers. In general, reasonably simple methods do render good results, albeit not the best (see also Lee et al., 2020).

Looking through the spectacles of the CPT and a spatial-contextual perspective, persistent long-term hotspots make sense. Crime is not randomly distributed across space and time. There are highly situational opportunities provided in the context of the specific location that affects crime (Brantingham & Brantingham, 1981; Cohen & Felson, 1979). If these opportunities remain consistent over time, offenders can develop habits and routines based on their past criminal experiences at these places. Offenders' choices are influenced by both specific micro-level place variables and the broader contextual factors in which these variables are situated. Consequently, previous criminal behavior at places can create future crime opportunities at the same locations. Crime attractors according to CPT are environments and situations where it is known to be conducive to commit crime. These are places and times where motivated offenders are drawn due to the known opportunity to commit crime. Hence crime begets crime. There is a historical persistence of crime at micro-place hotspots (Andresen et al., 2017; Curman et al. 2014; Weisburd et al. 2004; Wheeler et al. 2016) making crime history viable in forecasting crime. Using a simple count of crime history works with only one variable, crime with time and place.

The question then becomes, is it worth the added time, hassle, and cost to collect more data than local crime history, and analyze the data with more advanced methods, when the goal is crime forecasting for the practical purpose of police deployment. Making forecasts with a large amount of spatial data is very time-consuming. The data must first be collected and then processed. Using vast amounts of spatial data also introduces a lot of decisions that need to be made by the crime analysist. These decisions should probably not be made without thorough examination, for each location specifically. As previously mentioned, there is an extensive list of potential crime/fear generators, at different geographical levels (spatial scales) that needs to be considered. Then there are likely interaction effects to consider (see e.g., Brantingham & Brantingham, 1993, 1999; Taylor, 1998, Tillyer, 2015; Tillyer et al, 2021; Wilcox et al., 2013), for all included potential crime/fear generators, at the different geographical levels (different spatial scales). There are also other methodological decisions to be made for each included variable (see e.g., Wheeler & Steenbeek, 2021), for example the distance to the nearest bar, the number of nearby bars, how far can the bar affect the outcome, as well as accounting for possible non-linearity and spatial autocorrelation, regarding all the included crime/fear generators.

Simply obtaining certain data can be challenging and using it may raise ethical or privacy concerns (see e.g., Gstrein et al., 2019; Schlehahn et al., 2015). Obtaining data can be a hassle, and crime analysists working practically usually work with certain time constraints. To find data on for example cul-de-sac turnarounds, one first needs to find who has that data, collect the data, clean the data. Is it up to date? That might be one of many interesting place level indicators. Stationary street food trucks could also be of interest, there is a need to locate permits for these and pinpoint them correctly on the map. Bars/restaurants are of interest, however, should all bars be given the same weight in the analysis, or should the problematic ones receive a greater weight, whilst bars/restaurants with place managers that work proactively receive another. Broken lights that need to be fixed in the area, and the timing for how long they were broken before they were fixed might be of interest for both actual and perceived unsafety. For all place level indicators there is a process of finding the right vendors of information and then cleaning the data and then separating specific crime/fear generators (bars e.g.,) that are problematic from others.

Looking at the methodological decisions to be made, not data collection, but decisions regarding in what way the data might influence the outcome, development in research regarding automatic or semi-automatic aids in crime analysis such as the Oxrisk risk calculators (Oxrisk, 2023) are promising. In the future development of these automatic or semi-automatic tools, transparency is an important issue to keep in mind. Advanced methods, such as machine learning algorithms, as previously stated, often produce complex models that can be challenging to interpret and understand. Lack of transparency in the decision-making process can raise concerns about accountability and make it difficult for stakeholders, such as law enforcement but also the public, to evaluate the validity, fairness, and impartialness of the forecasts. More advanced models are harder to interpret, which compromises their transparency. Furthermore, many of the proprietary techniques today (see e.g., PredPol, RTMDx) also require expensive contracts with private vendors and do although semi-automated still require some hands-on expertise with specifically allocated time.

Regardless of new models for analysis of spatial data being developed in the future, the overall results from the current dissertation in relation to prior research and the theoretical foundation showed that the end-goal of forecasts should be at the forefront of the decision-making process. The main goal is important, as one-size-does-not-fit-all. Is the goal to deploy police officers to stop an imminent threat, stop crimes from happening tomorrow or the next day, or work with fear of crime right after a recent shooting then perhaps one type of forecast is needed. Is the goal to work with places where crime and fear of crime seem to cluster already, that is crime/fear hotspots, and stop crimes in the not-too-distant future, then perhaps another type of forecast is needed. Or is the goal to work with areas that have been problematic for a longer period and to understand the underlying causes, and for the police to collaborate with other stakeholders, to change the root causes of crime and perceived unsafety/fear of crime at the place, then perhaps a third type of forecast is needed. For perceived unsafety, it is also important to ask the question what the end-goal of the forecast is: reducing fear of crime, increasing perceived safety, or reducing avoidant behavior. While the method used in Study III prohibits me from making any assumptions beyond establishing a relationship, in general, it seems that different fear generators and characteristics are needed to forecast different aspects of perceived unsafety.

It might be pertinent to use different methods of forecasting for different forecast goals. For instance, identifying a repeat chain of crimes or an imminent threat of crime, and perhaps residential burglary in general based on the current dissertation, it may be most effectively accomplished by assessing recent exposure to crime. This involves considering crime incidents that have occurred recently. It is well established that there is an elevated risk of additional crime after a first crime incident (see e.g., Bernasco, 2008; Hoppe & Gerell 2019; Johnson et al., 2007; Johnson, 2013; Short et al., 2009; Townsley et al., 2003; Wells et al., 2012). Furthermore, this elevated risk decays after a certain amount of time, such as weeks and/or months (see Bowers & Johnson, 2005; Farrell & Pease, 1993; Hoppe & Gerell 2019; Lee et al., 2020; Johnson, 2008; Pease, 1998; Short et al., 2009; Tseloni & Pease, 2003). The elevated risk for residential burglary in Malmö specifically is perhaps strongest within a few weeks, and within a few hundred meters (Hoppe & Gerell, 2019). Near repeat patterns have been observed, not only for burglaries (Bernasco, 2008; Johnson, 2013; Short et al., 2009; Townsley et al., 2003), but also for crimes such as street robbery (Haberman & Ratcliffe, 2012; Youstin et al., 2011), and retaliatory gun violence (Ratcliffe & Rengert, 2008; Wells et al., 2012) to name a few crime types. For perceived unsafety and related outcomes, the current dissertation cannot answer whether this would be an effective tool. Conducting repeat and near-repeat analyses is a quick, efficient, and cost-effective way of forecasting crime, as it only requires crime incidents with time and place, and an ability to map the exposure.

On the other hand, to work with crimes in the not-too-distant future, examining past crime history and identifying crimes in specific areas is perhaps suitable. Prior studies have highlighted the historical persistence of crime at micro-place hotspots (Andresen et al., 2017; Curman et al. 2014; Weisburd et al. 2004; Wheeler et al. 2016). A straightforward, efficient, and cost-effective option here is to simply count past crimes (see Groff & La Vigne, 2002; Wheeler & Steenbeek, 2021). Once again, based on the results of the current dissertation, the only requirement is crime history from the least year with geocodes, and an ability to map the persistence of the hotspots.

To address the persistent crime and perceived unsafety in certain locations despite the implementation of hotspot policing methods and fear reducing strategies, a diagnostic assessment might be necessary to uncover the underlying causes and roots of the problem (see e.g., Caplan et al 2013a, b; Caplan et al., 2015). This assessment can be improved by using various place-level indicators and neighborhood-level characteristics. By examining these factors, law enforcement agencies can develop a deeper understanding of the dynamics contributing to the enduring local crime and/or fear of crime. This, in turn, enables the development of targeted strategies and interventions to address the underlying issues, in collaboration with other stakeholders.

5.4 Understanding the results through the lens of methodology

There are several methodological considerations related to this dissertation that are worth discussing. With spatial data there are several problems related to data quality that can arise. It is important to remember that what is put into the analysis is what will come out. No matter what spatial data is used, incomplete or inaccurate data can introduce errors and biases into crime forecasts, limiting their reliability and effectiveness.

5.4.1 Crime data and other variables

Crime data can be incomplete. Underreporting of crimes in certain areas, influenced by public willingness to report the crime, trust in law enforcement, community engagement, and cultural norms, can result in an inaccurate representation of the true crime rates in the area. Likewise, crimes involving interpersonal conflicts within marginalized communities might be less likely to be reported due to concerns about retaliation or negative consequences. Underreporting of crimes might vary depending on crime type, property damage suffering more from this problem than perhaps assault or residential burglary. This will influence the forecasts made and comparisons between crime types. Relying solely on reported crime data from the police may hence introduce limitations to the validity of the forecast. Unreported crimes were not captured in the current dataset, potentially leading to an incomplete or biased representation of crime patterns and forecasts. These biases can lead to skewed forecasts, mislead prevention efforts, and exacerbate existing inequalities in the criminal justice system. No arrest data or event reports, affected by over-policing in specific areas, was used in the current dissertation alleviating some bias, however reported crimes can still suffer from reporting biases and bias due to policing practices.

There can also be problems with the geographical reliability of reported crimes. Prior research from Malmö found police data for torched cars showed a median error of 83 meters (Gerell, 2018b). This will likely affect Study II more than Study I and III, as the spatial scale was smaller in Study II and more likely affected of potential discrepancies in the police data. There is also the chance that crimes are reported at intersections or the middle of a street segment instead of at the appropriate address where the crime occurred, that is the issue of incorrect placement of geocodes. As seen in Study I, there was a slush-coordinate point used for several crimes (1459, about 1.7 percent) these were either geocoded online if possible (85 about 0.001 percent) or discarded (1374 about 1.6 percent). Attempting to validate the crime data points (used for all Studies), the accuracy of the crime data points was assessed by drawing a random number of geocoded crimes for every year (2012–2017) and checking if the crime incidents were placed in the correct position according to address, coordinates, and information regarding the crime. No placement problem of crime points was apparent in the observed data, this does not exclude however that there still might a problem.

Furthermore, only within-crime-type was used as the independent variable, prior crime, for both Study I and Study II. This is rather naïve, as it is likely that different crime types interact and influence each other. A more thorough analysis of the interplay between various crime types is warranted to gain a deeper understanding of their connected dynamics and their shared influence on future crime.

Lastly, what is important to keep in mind when forecasting any type of crime geographically, or otherwise, is that time and other variables most likely will affect the outcome of the forecast. Crime is not a static phenomenon. Changes in the landscape, demographics, economic conditions, social factors, and law enforcement strategies can all impact the patterns and trends in crime. For example, when law enforcement agencies allocate resources to known crime hotspots, it can have a deterrent effect and lead to a temporary decline in crime in that area, some crime can also displace to nearby areas. This creates a feedback loop where successful policing in one area affects future crime patterns and consequently leads to a decline in predictive accuracy. If policing strategies change, forecasts should be updated accordingly. Maintaining and updating these models with the most recent data and accounting for the factors listed above can help improve their accuracy over time. Additionally, forecast models should be regularly validated and refined to ensure their reliability in real-world scenarios. The predictor variables in Study II were from different years, they did not give a snapshot of what the environment and context looked like in the year 2016, to predict crime in 2017. All neighborhood level variables were from 2015, the RTM based on data from 2017 and ambient population based on data from March 2014-March 2015. The fact that the data used for analyses came from different years and that there was a period of high immigration in Malmö in the year 2015 needs to be considered when reflecting on the results. Perhaps the results will not generalize well to periods with different immigration trends. The specific temporal and contextual factors in Malmö at the specific time when the data was collected might affect the applicability to different time periods and/or settings. The results do however align with the theoretical framework of the current dissertation, as well as research from other contexts and time-periods as previously stated. This might give support to the idea that the relationships identified are not limited to a specific time or place.

5.4.2 What is a good forecast?

When considering what a good forecast is, it is important to keep in mind the differences between a group-based forecast and the forecast of risk for individuals. The current dissertation concerns the former. For comparison, a meta-analysis of population-based studies on early home visitation to prevent physical child abuse and neglect showed an effect size attributable to early home visitation of 3.72 percent (Guterman, 1999). This might seem like a small effect size however, as with the crime problem, it is important to consider the baseline rates of the problem being addressed. The study mentions that about four percent of children in the United States were reported for abuse or neglect to child protective services systems at the time. A 3.72 percent effect size to a baseline of four percent, can represent a substantial reduction in the incidence of reported abuse or neglect. Even small changes in outcomes can have significant real-world impacts. Small changes can also accumulate and lead to more significant improvements. In practice the chance that practitioners work with limited resources is quite high. Achieving a 3.72 percent improvement without significantly increasing resources may therefore be seen as a practical and efficient use of available resources.

For comparison, in another study the ETAS algorithm (PredPol) was used to predict the total crime rate (burglary, criminal damage, car theft, and theft from vehicle in different constellations) in 20 grid cells of 150 meters (Mohler et al., 2015). The ETAS algorithm forecasted 9.8 percent of total crime in 0.11 percent of the area. 6.8 percent of total crime in 0.12 percent of the area and 4.7 percent of total crime in 1.37 percent of the area in different parts of LA, USA and Kent, UK.

Defining what makes a good forecast is something that the field of spatial crime analysis, regardless of one's research field, whether it be criminology, sociology, geography, or computer science, needs to establish a consensus on. The absence of standardized terminology, standardized evaluation criteria, and consistent reporting of initial parameters likely affects the lack of consensus of what a good hotspot forecast is (Kounadi et al. 2020). To be able to agree on what a good forecast is, standardized terminology, standardized evaluation criteria, and consistent reporting of initial parameters needs to be used across fields. See White and Hunt (2022) and White et al., 2023 for attempts to do so.

5.4.3 MAUP

Then there is the issue of MAUP, the zonation and scale problems concerning all the data, as MAUP is an inherit spatial data problem. The choice of crime hotspot boundaries, a raster-based approach of grid-cells in a fishnet, may not align with the actual spatial patterns of crime. This potential mismatch between data aggregation and the actual spatial distribution of crime can affect the accuracy of the forecasts made. Perhaps another spatial unit, such as a street segment could produce better forecasts (see Rosser et al., 2017)? Street segments and intersections are popular spatial scales at the micro-place level (Andresen et al., 2017; Braga et al., 2010; Steenbeek & Weisburd, 2016; Weisburd et al., 2004; Wheeler et al., 2016). There might furthermore be more similarities than differences over the drawn (grid-cells) borders. We did not consider the impact of crimes in neighboring grid-cells on the forecasted grid-cell (no spatial lag effect). The goal was to keep the forecasting models simple and straightforward for practical purposes, and a simple count and RTM do not consider spatial autocorrelation, ignoring spatial autocorrelation could therefore be seen as justified for that specific goal. These assumptions/justifications are, however, simplistic, so we recommend that future studies incorporate spatial autocorrelation into their forecasting algorithms. KDEs were however produced for all crime types when used as predictors. The KDEs were employed to smooth out the effect of the crime variables, as for instance assault likely affects not just the exact location where it is, but also nearby locations. The KDE's produced less accurate forecasts for every crime type in comparison to a simple count of crime history in Paper II. It was similar to or less accurate than a simple count of crime history in Paper I.

Results might differ depending on the scale of the location put into the analysis. In the current dissertation the spatial scales of analysis were 100-meter grid-cells (Study I), 50-meter grid-cells (Study II) and neighborhood level (Study III). No correction for this has been made in the current dissertation. There have been prior studies from the same setting showing 'the smaller is better' notion is accurate at least for some crime types (Gerell, 2017). But it should be noted that smaller areas might also be vulnerable to the MAUP (see Grubesic, 2006).

The issues of MAUP are likely important for measures of perceived safety, perceptions of disorder and collective efficacy as well. The scale of geography used in the analysis (Study III), was the neighborhood level. In a prior study (Kuen et al., 2022), crime at the street-level (micro unit) increased residents' fear of crime, while the greater spatial unit of the community did not. Other related research (see e.g., Kronkvist 2022), also shows crime to be important for fear when measured at the micro-level. It might be that people who live near a particular area are more likely to notice crimes happening there compared to incidents that occur a few blocks away in the same community (see Weisburd et al., 2011a; Weisburd et al., 2012; Zhao et al., 2015). CPT is also inherently an environmental theory of crime with crime and fear generators at the micro-level. Perceived unsafety and related measures might perhaps be better examined, and forecasted, at a micro-level.

Perhaps MAUP is one of the reasons why findings from prior studies (Brunton-Smith & Sturgis, 2011; Franklin et al., 2008; Wyant, 2008; Zhao et al., 2015) are mixed when examining the crime and fear relationship. A direction for future research is to use a multilevel analysis to untangle the variations within and between neighborhoods, that might occur on the different fear outcomes. To analyze the data at smaller spatial units such as street segments while taking the spatial autocorrelation of neighboring neighborhoods or streets into account (see Barton et al. 2017; Breetzke & Pearson 2014; Weisburd et al., 2012).

5.4.4 Analysis

When there are more places than crimes in the analysis, as in Studies I and II with smaller units of analysis, there is a risk of falsely confirming the law of crime concentration at places (Bernasco & Steenbeek, 2017; Chalfin et al., 2021; Mohler et al., 2019). This introduces the potential risk of incorrect prevention methods being used, based on the forecasted crime hotspots, that do not exist. A direction for the future research on crime concentration at places is to use the generalized versions of the Lorenz curve and the Gini coefficient (Bernasco & Steenbeek, 2017) or the marginal crime concentration (Chalfin et al., 2021), which might be easier to interpret than the Lorenz curve and the Gini coefficient. No correction for 'more crimes than places' has been made in the current dissertation, perhaps leading to the conclusion that crime was highly concentrated when it in fact was not, which in turn can lead to flawed forecasts. Although ANN was run prior to all analysis in the current dissertation, and significant clusters were found, ANN is sensitive to the scale of the area as previously mentioned. For example, the fact that there were a small number of places accounting for most, if not all the robberies they might appear to be concentrated (see also Hipp & Kim, 2017), when they perhaps were not. There were few robbery incidents in the analysis. Making us draw conclusions on potential hotspots when there were none and forecasting non-existent robbery hotspots.

No corrections for multiple testing were made for the negative binomial regressions in Study II or the multiple regressions in Study III. Although corrections are essential for avoiding Type I errors, they can potentially increase the risk of Type II errors. There is an ongoing scientific debate about when and how to apply these corrections, with different opinions on the most appropriate method (Althouse, 2016; Bender & Lange, 2001; Gelman et al., 2012; Rothman, 1990; Rothman, 2014; Streiner & Norman, 2011). By reporting uncorrected p-values, others can apply the correction method they find appropriate (Althouse, 2016).

Another weakness was the a-temporal analyses made. Year data was used (Study I and II). Meaning that no shorter crime-time-periods than a year was used in the analysis. Perhaps crime would have been even stronger related to the outcome if they were closer in time to the forecast. Especially for residential burglary, as prior research has shown the risk of future crime increases due to previous, and more recent crime (see e.g., (Hoppe & Gerell, 2019; Johnson, 2008; Johnson & Bowers, 2004ab; Short et al., 2009). Shorter time frames might have rendered more accurate forecasts. For Study III this was not an issue as crime was measured at different time-points, even during survey collection only. The results in Study III showed that a long historical picture of crime in the neighborhood mattered most for the different perceived unsafety measurements.

For Study II, it would have been preferable to use a training dataset and a separate test set for the (RTM) place variable index. This approach would have reduced the risk of overestimating the accuracy of the model. It is worth noting that the placement of place variables, such as apartment buildings, schools, preschools, town squares, and parks, tends to be relatively stable over the years, although the degree of stability may vary. Schools and apartment buildings may be more stable compared to bars and ATMs, for example.

5.5 Future research

Based on the findings of the current dissertation, for fear of crime, it would be both fruitful and interesting to continue to disentangle the within and between neighborhood differences that might occur in all the different independent variables on the different fear outcomes. A three-level analysis, individuals nested in micro-places, nested in neighborhoods could aid in this endeavor. Perhaps the effect of crime and disorder would relate stronger to levels of fear of crime at a micro-level whilst controlling for individual differences. Is it possible that variables at the micro-level affect avoidant behavior or is it at the individual level only that avoidant behavior is shaped.

Another interesting avenue for future research would be to add a longer time perspective for different place level indicators. Having several years of data regarding land use variables and other such information could perhaps provide important information on how different variables affect crime in a place. For example, if they build a new housing complex, move a bus station, if a school or a bar closes how does this affect crime and future crime levels in the area. If there is a problem with street lighting for a while at certain stretches how does this affect perceived unsafety, fear of crime, avoidant behavior, and crime too for that matter.

For continued research, using more advanced analyses methods, such as a random forest or neural network will most likely aid in future understanding of what affects crime in a location. Not only investigating the linear effect of different variables on crime and fear, but also adding cross- interactions of different crime types, between, and within level interactions of independent variables. Furthermore, to add a recent exposure of crime whilst keeping the history of crime as a predictor. A three-level analysis might be interesting here as well. Recent exposure to crime, nested in micro-levels, nested in neighborhoods.

The results of the current dissertation indicate that, in line with the prediction hypothesis, the law of parsimony, also known as Occam's razor, should always be kept in mind. Until otherwise proven the simplest explanation, hypotheses and models are usually the most plausible or preferable. There will be situations where more complex explanations and methods are necessary or justified, and this should continually be rigorously tested. Nonetheless, as the use of more and more sophisticated models continues to develop in the future, the results from this dissertation still suggest keeping the law of parsimony in mind. Simple explanations might still be precedent. Sophisticated methods might not always be superior, in all situations, with all goals. As such, it is pertinent to continue to add a comparison of a simple count of past crime to the more advanced models. Hence, after all the data collection is done, and all the analyses with whatever sophisticated machine learning model are made, one should compare the end result of the more advanced methods to a simple count of crime history. Comparing the simple count and the more advanced methods as regards the predictive accuracy, for short-term risk (days weeks), intermediate risk (months) and long-term risk (years). How much, if any, did the more advanced method increase in accuracy over simply counting past crimes. Just because something is fancy or requires a lot of data or a lot of researcher competence, it does not necessarily mean that it is automatically better than the simpler option.

6 Conclusions

Properly forecasting unsafe locations in a functional way is important. Only after identifying potentially risky places, can we work with making them safer. Proper strategies can be put into place to increase the perception of safety, reduce violence as well as property crime types. The overall goal of the current dissertation was therefore to explore the relationship between crime history, environmental and neighborhood characteristics as regards forecasting unsafety, both crime and fear of crime. The collective results of the included studies suggest that one-size-does-not-fit-all, but that simpler methods generally are almost as good as more complicated ones when forecasting crime long term at the micro-level. At the neighborhood level social integration is important for levels of perceived unsafety and fear of crime. The work presented in the current dissertation more specifically suggest that residential burglary and avoidant behavior be examined with somewhat other variables for example recent exposure to crime and individual and micro-place level variables respectively.

Furthermore, in combination with prior research (see e.g., Chainey, 2020) and the contextual-spatial theoretical perspective the results imply that different forecasting methods, with varying levels of data inclusion, may be necessary for different crime and fear hotspots. To identify near repeat crime chains and residential burglary, it may be appropriate to examine recent exposure to nearby crimes at the micro-level, aiding reactive law enforcement responses. For forecasting crime risk in the not-too-distant future, analyzing past crime patterns at specific micro-locations could be more suitable, informing strategic problem-oriented hotspot policing strategies. To assess persistent risk and perceived unsafety at specific locations, models like RTM (with RTMDx) or similar approaches can be used to identify contributing factors. These models can provide a foundation for collaborative efforts among law enforcement agencies, landowners, place managers, and the municipality for example to address the underlying issues.

In closing, as we delve into the fascinating realm of forecasting crime and understanding the perception of unsafety, one thing becomes abundantly clear: the forecast is not always peachy but can be helpful. There is an undeniable chance of feeling, and being, unsafe in our ever-changing urban landscape. However, armed with proper knowledge we can embrace the challenge, to shape a safer and more secure future for all. It is like looking at the weather report and seeing "Forecast: crime with a chance of feeling unsafe" and preparing for it.

7 Populärvetenskaplig sammanfattning

7.1 Introduktion

Kan brott och otrygghet förutses, eller är det bara science fiction? Svaret är att det faktiskt går att förutse brott och otrygghet, åtminstone delvis. Det är således också delvis möjligt att förhindra att folk blir misshandlade eller rånade när de är ute på stan en kväll och att öka tryggheten i ett grannskap.

I Sverige rapporteras det cirka 1,5 miljoner brott till polisen varje år (NCCP, 2022). Mängdbrott som stölder, skadegörelse, bostadsinbrott och misshandel utgör omkring tre fjärdedelar av dessa brott (Polismyndigheten, 2022). I Sverige tror också 80 procent av befolkningen (16–84 år) att brottsligheten har ökat de senaste tre åren och 45 procent oroar sig för brott i samhället (NCCP, 2021). Tjugoåtta procent känner sig otrygga, och 35 procent oroar sig för att en släkting eller vän ska bli offer.

Det finns många olika vetenskapliga metoder som syftar till att förutse brott och otrygghet geografiskt och de varierar i komplexitet. Det går tillexempel att använda brottsstatistik på lite olika sätt för att försöka förutse brott och otrygghet. Det går också att samla in data om egenskaper både på den specifika platsen och i det större grannskapet. För att avgöra vilka metoder som är mest praktiska och tillämpliga måste vi jämföra enkla, transparenta och funktionella metoder med mer komplicerade tekniker som kräver mer datainsamling.

Syftet med föreliggande avhandling var därför att se hur mycket data om de olika geografiska platserna som behövs för att förutse både brott och otrygghet vid olika platser.

7.2 Metod

- Avhandlingen baserades på tre vetenskapliga studier. Dessa inkluderade:

  1. Två studier med förutsägelser av brott på små platser (mindre än 100x100 meter) innefattande våldsbrott som misshandel i

offentlig miljö och rån och egendomsbrott som skadegörelse, stöld, stöld från fordon, inbrott i bostad, och allmänfarlig vårdslöshet - vållande av brand (ej mordbrand).

2. En studie med förutsägelser av olika typer av otrygghet i grannskapet, inklusive generell otrygghet, generell rädsla för brott, rädsla för olika typer av brott, och undvikande beteende på grund av rädsla för brott.

- För att förutse både brott och otrygghet på dessa platser samlades följande data in:
    - Historisk brottsstatistik (samma brottstyper som tidigare nämnts).
    - Egenskaper på platsen, såsom närhet till busshållplatser, barer, restauranger, skolor, hyreshus, torg, och parker, med mera.
    - Egenskaper i grannskapet, inklusive fattigdom, arbetslöshet, och kollektiv förmåga, med mera.
    - Undersökning av antalet människor som rörde sig i området.
- I studie ett och två jämfördes olika metoder för att förutsäga brott och olika mängder data användes i analyserna.
- I studie tre undersöktes det hur mycket av otryggheten som kunde förklaras med hjälp av olika mycket data.

7.3 Resultat

Resultat visade att det inte finns en universallösning för att förutse övergripande trygghet, och olika faktorer spelar en roll beroende på om man fokuserar på brott eller olika typer av otrygghet.

När man förutser brott på lång sikt (ett år framåt) på en plats som inte är större än 100 gånger 100 meter var brottshistorik en bra variabel att använda. Att helt enkelt räkna antalet brott från föregående år på den specifika platsen var lika effektivt som mer komplexa metoder som analyserar brottens geografiska fördelning och metoder som kräver mer data. Detta gäller för alla undersökta brottstyper, förutom inbrott och vållande av brand (ej mordbrand).

Men när det gäller att förutse övergripande trygghet, särskilt på platser som är så stora som ett grannskap, blir det mer komplicerat. Här spelar sociala faktorer en avgörande roll. För generell otrygghet, generell rädsla och rädsla för olika typer av våldsbrott så var kollektiv förmåga den viktigaste aspekten.

För rädsla för inbrott var brottshistorik den viktigaste faktorn. Rädsla för att få ett fordon stulet påverkades både av brottshistorik som kollektiv förmåga i grannskapet. Undvikande beteende på grund av rädsla för brott kunde inte förutses med någon av de inkluderade variablerna, utan behöver undersökas/förutses på annat sätt.

7.4 Praktiska implikationer

Dessa resultat har flera viktiga praktiska implikationer för de personer som i sitt arbete jobbar med att förebygga brott och skapa trygghet. Beroende på vad man har för mål, minska brott eller skapa trygghet så kan man tänka lite annorlunda. Olika sätt att förutse brott och otrygghet kan vara passande beroende på vad man vill förutse/arbeta med.

7.4.1 Förutse brott imorgon eller nästa vecka

Om man vill förhindra brott som kan inträffa imorgon eller dagen efter, eller förutse inbrott och andra brott som har en ”smittorisk”, det vill säga en risk att sprida sig relativt snabbt, bör man kanske titta på brottslighet som skett nyligen. De senaste två-tre veckorna. ”Smittorisk” innebär att efter ett hus har fått inbrott, (blivit förkyld) så ökar risken för att andra hus i närheten blir utsatta för inbrott (förkylning) under en viss tid med minskande risk över tid. Precis som ett virus sprids till närliggande mottagare och den risken minskar också med tid. Här kan man göra något som heter near-repeat analyser som är ett snabbt, effektivt och kostnadseffektivt sätt att förutse brott. Den enda information man behöver är brottshändelser med tid för brottet och geokoder. Sen behöver man också en möjlighet att kartlägga brotten.

7.4.2 Förutse brott nästa år

Vill man däremot arbeta med områden som man redan vet har en problematik med brott går det baserat på resultaten av den aktuella avhandlingen att bara använda brott från förra året och kartlägga dessa för att få en bra inblick i vart brott sannolikt kommer att ske nästa år. Den enda information man behöver här är brottshändelser från förra året med geokoder. Sen behöver man också en möjlighet att kartlägga brotten.

7.4.3 Förutse brott och otrygghet på platser med ihållande problematik

För att hantera ihållande brottslighet eller ihållande upplevd otryggheten på vissa platser där man redan satt in insatser som polispatrullering tillexempel, kan en diagnostisk bedömning vara nödvändig för att avslöja de underliggande orsakerna och rötterna till de ihållande problemen. Denna bedömning kan förbättras genom att använda olika egenskaper på den specifika platsen och egenskaper på grannskapsnivå tillexempel genom en metod som kallas RTMDx (eller liknande). Genom att undersöka dessa faktorer kan polismyndigheter utveckla en djupare förståelse för den dynamik som bidrar till den ihållande lokala brottsligheten och/eller rädslan för brott. Detta möjliggör i sin tur utvecklingen av riktade strategier och insatser för att hantera de underliggande problemen, i samarbete med andra intressenter.

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