Comparing and Evaluating the Forecasting of Reported Crimes in Hot Spot and Not Hot Spot Areas Using Two Different Retrospective Methods

by

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Science Pledge

By my signature below, I certify that my thesis is entirely the result of my own work. I have cited all sources I have used in my theses and I have always indicated their origin.

Villach, 15.06.2016

(Lukas Oswald)

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Zusammenfassung

Das Hauptziel dieser wissenschaftlichen Forschungsarbeit liegt im Vergleichen und Testen einer neu entwickelten Vorhersageanalysemethode in der Kriminalstatistik, die auf Grundlage des „Near Repeat" (NR) Konzeptes aufbaut. Dieses „Crime Predictive Analytics" (CriPA) Projekt wurde im Jahr 2012 vom österreichischen Förderprogramm für Sicherheitsforschung (KIRAS) ins Leben gerufen und beschäftigt sich seither mit der Entwicklung von Methoden und Softwarekomponenten um zukünftige Kriminalitätsentwicklungen vorherzusagen oder das Risiko für Straftaten anhand von neuen Methoden der Kriminalstatistik abzuschätzen zu können. Diese Forschungsarbeit soll die Methoden der entwickelten Software (CriPA Demonstrator), mit bereits gängigen Vorhersageanalysen in der Kriminalitätsstatistik, wie den Hot Spot Analysen, vergleichen. Die zwei genannten Methoden finden in den Vereinigten Staaten von Amerika bereits regelmäßig Anwendung in aktuellen Studien. Für österreichische Studien gibt es noch kaum Erfahrungswerte. Für die Gegenüberstellung der beiden Vorhersagemethoden werden jeweils die gleichen Daten sowie das gleiche Untersuchungsgebiet gewählt. Die Daten beziehungsweise das Untersuchungsgebiete beschränken sich auf die Stadt Wien. Die relevanten Daten stammen von dem Sicherheitsmonitor (SIMO) des Bundeskriminalamtes (BK). Der Zeitraum der Daten beschränkt sich die Jahre 2009 bis 2015 und beinhaltet Wohnungs-, Auto-, Wohnhaus- und Firmeneinbrüche. Auch die Art der Begehung, jene Art, mit der sich der/die TäterIn Zutritt verschafft hat, wird in der Analyse berücksichtigt. Die daraus resultierenden Ergebnisse können vor allem bei der Frage nach SerientäterInnen genutzt werden. Zeitliche und räumliche Unterschiede sind vor allem für die Genauigkeit der Ergebnisse der zu untersuchenden Analysemethoden wichtig. Für die Anwendung des CriPA Demonstrators wird der PyScripter verwendet. Zur Identifizierung von Hot Spots werden CrimeStat, der Near Repeat Calculator und der Spatial Analyst von ArcGIS verwendet. Die Ergebnisse werden mittels aussagekräftigen statistischen Indexe wie zum Beispiel der Hit Rate (HR) evaluiert. Zusätzlich wird auch eine visuelle Interpretation der Ergebnisse ausgeführt. Es wird erwartet, dass die durchgeführten Evaluierungen für zukünftige Projekte, von zum Beispiel KIRAS, genutzt werden können und die Kriminalitätsvorhersage verbessert werden kann, was zukünftige Prognosen zuverlässiger macht und zur strategischen Bekämpfung von Kriminalität beiträgt.

Abstract

The main goal of this research is to compare and evaluate two different retrospective crime forecasting analysis methods to both Hot Spot and not Hot Spot areas. On the one hand, the project will forecast crime events in time and space by using the Crime Predictive Analytics (CriPA) Demonstrator, which is based on the Near Repeat (NR) concept. On the other hand, different Hot Spot methods, such as the Kernel Density Estimation, methods will be applied to predict crime. A second goal is to evaluate the forecasting performance of different crime types (apartment burglaries, house, burglaries, car burglaries, car thefts, etc.). A third goal is to identify the best parameter setting for each forecasting method in terms of forecasting quality. The Near Repeat Analysis is a recently developed approach, which has not yet been comprehensively tested in Austria. The study area for this research is the city of Vienna, Austria. The Austrian Federal Criminal Police Office (BK) provides the necessary crime data. The data include auto thefts, burglaries in apartments -and houses, and robberies. The data are from the Security Monitor (SIMO) - database. All reported crimes are recorded in all Austria on a daily basis in this database. Using the example of the city of Vienna, predictions are made for the four different crime events for a seven-year period. In addition, results are evaluated and compared for each year. In order to compare these results with each other, different software tools are used. CrimeStat, the Near Repeat Calculator, ArcGIS including its extension, the Spatial Analyst module of ArcGIS, are used to identify Hot Spots. The PyScripter Software executes the CriPA Demonstrator. To evaluate the forecasting quality between Hot Spot and Cold Spot districts and alternatively defined regions, three different statistical indexes are used. These three statistical indexes are the Hit Rate Percentage (HR), the Prediction Accuracy Index (PAI), and the Recapture Rate Index (RRI). After the statistical evaluation, there will also be a visual interpretation of results. This evaluation will help to determine the accuracy of the predictive analysis of this research. Furthermore, results will also provide law enforcement with valuable information for adequately and efficiently distributing their resources and possibly leading to a decrease in crime.

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List of Abbreviations

BK	*Austrian Federal Criminal Police Office*
CMRC	*Crime Mapping Research Center*
CriPA	*Crime Predictive Analytics*
CSV	*Comma Separated Values*
CUAS	*Carinthia University of Applied Sciences*
GIS	*Geographic Information System*
HR	*Hit Rate*
KDE	*Kernel Density Estimation*
LA	*Louisiana*
LSU	*Louisiana State University*
MS	*Microsoft*
NNHC	*Nearest Neighbor Hierarchical Cluster*
NR	*Near Repeat*
PAI	*Prediction Accuracy Index*
RRI	*Recapture Rate Index*
RTM	*Risk Terrain Modelling*
SIMO	*Security Monitor*
TX	*Texas*
USA	*United States of America*

1. Introduction

This chapter includes a brief statement about the motivation, the problem definition, the methods of solutions and the expected results. The last point in chapter one describes the workflow or the structure of this thesis.

1.1. Motivation

In a recently concluded KIRAS – Security Research study on Crime Predictive Analytics (CriPA) project, one of the main findings was that the success of forecasting burglaries was about ten times higher in a burglary Hot Spot district of Vienna (5th District Margarethen) compared to a burglary in a Cold Spot district (19th District Döbling). This finding was a result from the so-called CriPA Demonstrator, which uses methods from the Near Repeat concept (Ratcliffe & Rengert 2008). Crime data in the mentioned study were reported apartment burglaries in both districts from October 1 2012 to September 30 2014. Motivated by that, it seemed very interesting whether the result of this KIRAS research study can be generalized to other districts of Vienna, other Hot and Cold Spot regions of Vienna that are not defined by administrative-statistical boundaries, other crime types than apartment burglaries, and other forecasting methods than the one's based on the Near Repeat concept. To the best knowledge of this author, an evaluation of crime forecasting between Hot Spots and Cold Spots has never been carried out in Austria before. While for example Hot Spot mapping is a widely available method used by the Austrian Federal Criminal Police Office, called Bundeskriminalamt (BK) in German, the Near Repeat Calculation is a more recent approach. In the USA, on the other hand, the concept of the Near Repeat victimisation is already well tested. For that reason, the main research was done in the USA at the Louisiana State University (LSU) in Baton Rouge, Louisiana. In the end, the main motivation for this work is to provide law enforcement with valuable information for adequately and efficiently distributing their resources and possibly leading to a decrease in crime.

1.2. Problem Definition

According to several annual reports by the Austrian Federal Criminal Police Office since 2006, the number of crime events in Vienna increased by 4.57% from 2006 to 2009. Crime events rose from a total of 218,497 crime events in 2006 to 228,486 crime events in 2009. Since 2009 the number of crime events in Vienna decreased by 17.11% until 2015 (195,096). Similarly, in 2010 the Austrian Federal Criminal Police Office in Vienna started to focus on the utility of Hot Spot mapping for predicting spatial patterns of crime. For this purpose, a series of Hot Spot mapping methods have been proposed in the past few years for Vienna, for example the Crime Predictive Analytics Demonstrator. The aim of these methods is to predict where and when a crime will happen, but each method has its strengths and weaknesses. The reasons why the predictive accuracy of Hot Spot methods varies can depend on several parameters, for example, the particular study area, the crime type, or the parameter settings of each method (Fan 2014). In general, geospatial technology has been used to support crime analysis by the Austrian Federal Police since 2004 and since the past few years these types of new techniques achieved a significant success. For instance, in the annual comparison from 2014 to 2015 the number of reported apartment and house burglaries in Vienna decreased from 8,907 to 7,069 which means a decline of 20.6 percent. In addition, the crime clearance rate for apartment and house burglaries increased from 6.2% to 7.6% during the same time-frame. The collection of all reported criminal offences by the Federal Police in one database, named SIMO, maid the useful appliance of Hot Spot mapping possible.

1.3. Methods of Solutions

There are two main retrospective forecasting methods which are used in this research. These two methods are on the one hand the Hot Spot Analysis and on the other hand the concept of the Near Repeat Calculation. The reason why these two methods are used is that they are very popular with police and that they have been tested many times before. Spatial clusters or Hot Spot areas are places with a higher concentration of crime than what would be expected by chance. Hot Spots can be street addresses, blocks, neighbourhoods, districts, or towns and cities. In the Hot Spot analysis, it is determined whether spatial patterns are statistically significant and if a clustering in the data occurs (Kennedy et al. 2011). In addition, random patterns display a certain clustering, but those clusters would not be classified as being statistically significant. In other words, when interpreting crime Hot Spots, it is often difficult to say whether the results have been caused by spatial processes or purely by coincidence. The second retrospective forecasting method is based on the Near Repeat concept by using the most recently developed CriPA Demonstrator. The discovered phenomenon of the Near Repeat concept says that if your apartment/house has been burgled, you are at a heightened risk of being burgled again. This means, that you are not definitely being burgled again, but the risk is increased. This heightened risk rapidly decays with time. The highest period of risk is within a few days of the initial incident. Repeat victimization is most common in high crime areas. In high crime areas, like in some districts of Vienna, crime is so concentrated among repeat victims that recurring offenses can create Hot Spots, which are relatively small geographic areas in which victims are clustered. One well-known software for forecasting crime events is the Near Repeat Calculator developed by Jerry Ratcliffe at the Temple University, Philadelphia (Ratcliffe 2009). While other crime analysis programs are able to tell you where clusters of crime events take place, part of the predictive power of the Near Repeat hypothesis is that knowing the space and time of Near Repeats helps to put spatial and temporal boundaries on proactive crime prevention measures. It may be that in some parts of a jurisdiction the risk of Near Repeats is much greater than in other areas, irrespective of the actual distribution of the general crime pattern. This function can help to identify the high-count originator events. The Near Repeat phenomenon is observed for different crime types in the study area of Vienna.

Moreover, the needed tools and software for this research are CrimeStat, the CriPA demonstrator, the Near Repeat Calculator and ArcGIS. CrimeStat is an open source software (Levine 2015) and the CriPA demonstrator is provided free of charge by the external supervisor of this Bachelor Theses, Michael Leitner. The results are presented in tables and graphs. For the visualization and creation of maps, ArcGIS is used. Finally, the Austrian Federal Criminal Police Office provided the necessary crime data. These datasets come from the Security Monitor (in German: Sicherheitsmonitor – SIMO) database. This is a database in which all reported criminal cases in Austria are recorded (Kampitsch et al. 2008).

1.4. Expected Results

It is expected that, in general, the success of the forecasting of crime is higher in Hot Spot compared to Cold Spot areas, independent of how these areas are being defined (Pleschberger 2015). It is further expected that the forecasting quality differs between different crime types and retrospective forecasting methods (Kocher 2014). Finally, it is expected that an "ideal" set of parameters for each forecasting method is found that results in the highest forecasting quality for each method.

1.5. Structure of the Thesis

Before the analysis of the above-mentioned problems can start, this thesis will provide a review of the important literature to get an overview about all necessary forecasting methods, including the Hot Spot Analysis, the concept of the Near Repeat Victimization and the Risk Terrain Modelling (see Chapter 2). The theoretical part is followed by the implementation sector, where all steps from the data processing until the final result tables are described. Chapter four provides the results and the interpretation. In chapter five the used methods are discussed and the work is reflected critically. The last chapter, chapter six, shows a final conclusion and a future outlook. At the end the references, the list of figures and the list of tables are given.

2. Theoretical background

This chapter provides an overview and documentation about the relevant theoretical concepts, literature, and best-practice projects. This covers scientific text books, and publications in scientific journals. In detail, the theoretical background is about the assumptions behind criminogenic factors as well as three different crime prediction analysis. In the end of chapter two the used evaluation methods are described.

2.1. The Geography of Crime

Crime has an inherent geographical quality because in general, when a crime occurs, it happens at a place with a geographical location. Furthermore, for someone to have committed a crime this person must have also come from a place, for example, a workplace or a home (Chainey & Ratcliffe 2005). This place could be the same location where the crime was committed or is often close to where the crime was perpetrated (Wiles & Costello 2000). The mentioned 'Place' plays a significant role in the understanding of a crime and how a crime can be tackled. Since the late 1970s the spatial dimension of crime began to be more fully explored. The police, for example, has recognised the inherent geographical component of crime by sticking pins into maps, which are displayed on walls. This method deals with the same principle like computer based GIS applications, where each pin or point represents a crime event. From that time on, a series of new techniques emerged. Including techniques that identify patterns and concentrations of crime or the exploration of relationships between crime and the environment and even techniques to assess the effectiveness of policing and crime reduction programmes. The most recent example for such programmes is the Crime Predictive Analytics Demonstrator, developed by Austrian crime researcher in cooperation with the Austrian Federal Police. To sum up in the words of Spencer Chainey and Jerry Ratcliffe (2005): "What has materialised from this emergence of academic and practitioner activity is the field of crime mapping - a progressive blend of practical criminal justice issues with the research field of Geographical Information System" (p.2).

2.1.1. Legal Definition of a Criminal Offence

In general, crime includes many different activities such as theft, fraud, robbery, corruption, assault, rape, and murder. This particular research discusses crime types like apartment, house, or company burglaries and car robberies or car thefts. Nevertheless, the legal definition for such crimes can be very difficult and comprehensive. The simplest way of defining crime is that it is an act that contravenes the criminal law. Some might simply define crime as 'the doing of wrong' and it is a commonly used approach related to notions of morality. Yet not all actions or activities that might be considered immoral are considered crimes (Burke 2014). Legal definitions can also change over time and vary across culture. Moreover, definitions of crime and thus criminality are also closely linked to socio-political factors and how we view the nature of society. In 2014 Roger Hopkins Burke noted that "crime happens when the four elements of a law, an offender, a target and a place concur" (p.279), which is a more scientific definition. These mentioned elements play a significant role in the understanding of crime analysis and crime prevention. According to this definition a crime has four main elements or also known as dimensions. There is the law dimension, an offender dimension, the target dimension and the place or spatial dimension. Every GIS works with the spatial dimension of a crime offence. As already mentioned in Sub Chapter 2.1., the place of the offence plays a significant role in understanding crime and how crime can be tackled. Every crime event has a geospatial relation. This relation can be an address or particular coordinates.

2.1.2. Brief History of GIS and Crime Mapping

From the 1960s onwards, GIS has emerged as a discipline in its own right. The use of GIS started in land use applications. Nowadays, GIS is an all-pervasive technology used in applications as diverse as in-car navigation, retail store site location, customer targeting, risk management, construction, weather forecasting, utilities management and military planning, GIS has become ubiquitous in modern life (Chainey & Ratcliffe 2005). One of the most significant role in the development of GIS has played the imagery of the earth from satellites. This research field has started through the military. It is uncontested, that the military is responsible for the first uniform system of measuring location, driven by the need for accurately targeting missiles. In addition, it is important to mention, that the military is also initially responsible for the development of the Global Positioning System (GPS). In the 1980s, when the price for a personal computer became affordable, the development of the GIS software industry started. According to Spencer Chainey and Jerry Ratcliffe (2005), "these reductions in the cost of computer hardware were complemented by improved operating systems, electronic storage media and developments in computer software, and have had a wide and significant impact in introducing GIS technologies to new areas, such as policing and crime reduction" (p. 2). On the one hand the computerisation of police records has come with a realisation that this material can be used for crime and intelligence analysis (Ratcliffe 2004) and in turn used to better recognise patterns of crime that can be targeted for action, patterns that evidence suggests police officers are not necessarily aware of (Ratcliffe & McCullagh 2001). On the other hand, the use of GIS for mapping crime was often held back by organisational and management problems. For example, problems with sharing information, or technical issues like software failures and geocoding problems. Nowadays, many of these problems have not simply gone away, and several ones have emerged. Crime mapping is becoming central to policing and crime reduction in the 21st century, and this book aims to make a contribution to its continued growth. As Clarke (2004) notes, "Quite soon, crime mapping will become as much an essential tool of criminological research as statistical analysis is at present" (p.60).

2.1.3. Using GIS in Policing and to Prevent Crime

The first country which started to use GIS in policing and crime prevention was the USA, where much of the innovation in crime mapping was driven. The so called National Institute of Justice's Crime Mapping Research Center (CMRC) was one main US government initiative which worked and researched on new GIS analytical methodologies for crime prevention. From time to time crime mapping was used in many other countries, including the United Kingdom, Australia, South Africa and across South America. But how does the use of GIS in policing work? First of all, it is important to say that crime mapping consist of several steps and processes, which can all play an important role in the policing and crime reduction process. These steps can be from the first stage of data collection through to the monitoring and evaluation of any targeted response. Examples for main activities of GIS in policing can be:

- Recording and mapping police activity, crime reduction projects, calls for service, and crime incidents;
- Supporting the briefing of operational police officers by identifying crimes that have recently occurred and predicting where crime may occur in the future;
- Identifying crime Hot Spots for targeting, deploying, and allocating suitable crime reduction responses;
- Helping to effectively understand crime distribution, and to explore the mechanisms, dynamics, and generators to criminal activity, through pattern analysis with other local data;
- Monitoring the impact of crime reduction initiatives, and using maps as a medium to communicate to the public crime statistics for their area and the initiatives that are being implemented to tackle crime problems (Chainey & Ratcliffe 2005).

2.1.3.1. The Crime Predictive Analytics Demonstrator

The Crime Predictive Analytics (short: CriPA) Demonstrator is a program which includes a set of Near Repeat approaches to predict where and when crime will most likely happen in the future based on crime data from the past. This program is a predictive policing tool, which has been applied to mostly in Vienna and Graz, Austria, so far. Predictive policing uses crime data based on the past (time and location) to provide where and at what times police should patrol or maintain a presence in order to make the best use of resources or to have the greatest chance of deterring or preventing future crime events. This research deals with the short-term and large-scale predication of the CriPA software. This software tool is based on the Near Repeat Concept. This concept allows the early identification of space-time related patterns and can help the police form prevention measures in the future. The CriPA project team has started to test the application with the prediction of apartment burglaries in Vienna in 2014. To understand the input and output of the program the user should have experience with python scripting because the demonstrator is still in a prototype stage and principles and parameters for the analysis are declared by python scripting. Therefore, the functionality is based entirely on the user's definition and not predefined as in similar programs, for example CrimeStat. The output file of this particular program is in a csv format. Furthermore, each trial result is a table using an excel sheet. In the future, this demonstrator should be one full-fledged software application which for example can find the right parameter settings automatically. The overall goal is to possibly integrate the final CriPA software into the dashboard of the Austrian law enforcement management. Moreover, the CriPA demonstrator should be able to make long-term, large-scale predictions about developments in crime and trend models such as generalized additive models.

2.2. Spatial Statistics for Crime Prediction Analysis

The applications of spatial statistics in crime analysis (often called: crime mapping) are numerous. Spatial statistics can identify crime patterns, crime problems, and even Hot Spots. Moreover, it can provide a visual aid to the analysis of patterns and problems. One main advantage of spatial statistic is to show the relationship between crime and other spatial factors, for example when looking at the movement in crime patterns or to query data by location. Other main application fields for spatial statistics in crime analysis can be:

- Creating and modifying patrol districts,
- tracking changes in crime, and
- making maps for police

The literature and training in the field of crime mapping has generally focused on these tasks, on the mechanics of matching database records to geographic locations (geocoding), making thematic maps, conducting queries on attributes and geography, and creating map layouts that are functional and attractive (Bruce & Smith 2011).

2.2.1. Hot Spot Analysis

Based on the previous subchapter, producing a map is only the first part in the crime analysis process. Questions like: "Where are the Hot Spots be consistent in spelling Hot Spots for this type of crime?" or "Where might a serial offender strike next?" are not able to answer with visual interpretation of regular statistics. And this is where the Hot Spot analysis comes in. Hot Spot Analysis is used to analyse spatial patterns that can visualize the potential of spatial clustering in the study area. This potential is carried out with GIS spatial data analysis applications. Then, the existence of spatial clustering is used to examine data more rigorously as a way of generating new hypotheses from the data (Eck et al. 2005). Moreover, Hot Spot Analyses evaluates the degree of spatial randomness in the data. Most of the already available Hot Spot analysis tools provide different ways of determining, if the investigated pattern is uniform over space, or if significant clusters or other spatial patterns exist. Clusters are not compatible with spatial randomness. If clusters are detected, simple mapping techniques can now be supplemented with new methods and applications to show meaningful associations. The result can be presented in maps. Moreover, the found clusters, that are often called Hot Spots, and associations between each cluster can be further investigated, for example with other hypotheses tests.

2.2.2. What is a Hot Spot?

To understand the meaning of Hot Spots it has to be said that in general, geodata are not spread evenly across areas. A good example for that phenomenon is the distribution of crime data, because they clump in some areas and are absent in others. And when this crime activity clumps together a Hot Spot occurs. There is no single definition for a Hot Spot, because the term Hot Spot has a number of meanings. Researchers and police use the term in many different ways. Crime Hot Spots, for example, are areas of concentrated crime. Crime researchers or crime analysts look for concentrations of individual events that might indicate a series of related crimes. Police use this understanding every day. Sometimes also small areas with a high number of crime or disorder are investigated. It can be said that a crime Hot Spot is a specific location (e.g. district) with an above average amount of crime. It is important to mention is, that a Hot Spot does not have a specific size. Hot Spots are found at any size. According to that it can be a Hot Spot place or a Hot Spot region. But something, they all have in common, is the concentration of activity (e.g. crime). In this research, Hot Spots are mostly referred to as Hot Spot regions (districts) in Vienna. To sum up, it can be said that Hot Spots or particular crime Hot Spots are places where crime events are relatively densely distributed. Moreover, crime Hot Spots are referred to as areas where crimes concentrate spatially (Eck et al. 2005).

2.2.2.1. Relevant Types of Hot Spot Methods

To analyse the forecast accuracy of the CriPA demonstrator different cluster and Hot Spot methods will be applied in this study. Cluster analysis, in general, are based on the assumption that future crimes will also be located in past crime Hot Spots. In this research, the appropriate units of analysis are districts or smaller inner city centers. One of the most often applied Hot Spot Methods is the Kernel Density Estimation (KDE) (Perry et al. 2013). The KDE is a statistical method to estimate the probability distribution of interpolated spatial point patterns. To interpolate the point pattern, the user can select between five different types of KDE functions in the CrimeStat software (Levine 2015). This includes the triangular, quartic, uniform, normal, and negative exponential KDE function. Each of these individual functions describes the shape of the curves, e.g. the distance of influence of each crime event. The function type can be selected in the parameter setting in CrimeStat IV. Another important parameter relates to the bandwidth of each kernel function. The bandwidth can be either fixed or adaptive (recommended). Depending on the size of the point pattern, the size of the output cell is defined (Levine 2015).

One other important cluster technique is called the Nearest Neighbor Hierarchical Cluster Method (NNHC). CrimeStat IV has developed a special algorithm which is used for the NNHC method. It is a risk-based technique. It identifies groups of incidents that are locally close. Then, points with the same attribute or criteria are clustered together. This process is repeated until all points are grouped into a single cluster (see Sub Chapter 3.5.1.). A detailed description of the analysis process with the NNHC technique is provided in the implementation chapter (see Sub Chapter 3.5.)

2.2.3. The Near Repeat Concept

The previously mentioned Hot Spot Methods are based on the distribution of events in a spatial point pattern. But also random patterns can display a certain clustering, but those Hot Spots would not be classified as being statistically significant. In other words, when using cluster analyses the found Hot Spot results can have been caused by coincidence. This problem can sometimes make a crime prediction difficult. In contrast, the discovered phenomenon of the Near Repeat concept, which says that if someone has been burgled, you are at a heightened risk of being burgled again, focuses more on predictions of future criminal activities than on the concentration of crime patterns. This phenomenon does not say that someone is definitely being burgled again, but the risk is increased. This heightened risk rapidly decays with time and distance. The highest period of risk is within a few days of the initial incident. Repeat victimization is most common in Hot Spot areas, however the CriPA demonstrator can also be applied to Cold Spot areas or cities with less crime activity. But in some high crime areas, like in a few districts of Vienna, crime is so spatially concentrated among repeat victims that recurring offenses can create those Hot Spots, which are then used for the CriPA analysis (see Sub Chapter 3.2). The assumption that, where previously a crime has occurred, the probability of a future crime to occur is increased, has already been proven for various types of crime in some urban areas in the USA and especially for burglaries. This approach also considers the temporal component between the crimes (Ratcliffe & Rengert 2008) (Patten et al. 2009). One recently developed software that this phenomenon is based upon and which is related to the CriPA demonstrator is the Near Repeat Calculator developed by Jerry Ratcliffe at the Temple University, Philadelphia (Ratcliffe 2009). The Near Repeat Calculator compares the actual pattern of spatial-temporal relationships between all points (called the observed pattern) with the pattern one would expect if there were no Near Repeat process taking place (called the expected pattern). The expected pattern is derived from a redistribution of date values randomly reallocated to the spatial points. For this process to be statistically valid, this random reallocation has to be performed many times. Within social sciences, the standard minimum threshold for statistical significance is $p = 0.05$. This can be achieved with 20 reallocations, called iterations (Levine 2015).

2.3. Evaluation of Crime Forecasting

Testing the predictive validity of the results is a main goal in this study. The evaluation has a simple principle: A predictive model (e.g. predicted offence) is implemented and then it is tested how many crimes indeed happened in the predicted time frame and location. Through the evaluation process it can be shown which model result achieves the highest overall score (Chainey et al. 2008). It is also possible to find out, which time period or which parameters are most suitable for the prediction.

To evaluate the predictive analytic success of these two forecasting methods, three different evaluation methods are applied:

- Hit Score Percentage
- Prediction Accuracy Index
- Recapture Rate Index

The Hit Rate Percentage (HR) is defined as the percentage of crimes that are hitting the calculated retrospective period. The Hit Rate Percentage is calculated as,

$$HR = (n / N) \times 100 \qquad \text{Formula 1}$$

where n is the number of crimes in the forecast that are hitting the calculated retrospective period and N is the number of all crimes in the forecast period (Hart et al. 2012).

The Prediction Accuracy Index (PAI) is calculated as the ratio of the hit rate to the proportion of the study area that are Hot Spots. It is computed as,

$$PAI = [(n / N) \times 100] / [(a / A) \times 100] \quad \text{Formula 2}$$

where n is the number of crimes in the forecast, that are hitting the calculated retrospective period and N is the number of all crimes in the forecast period. “a” is the size of all retrospective Hot Spots together and A is the size of the study area. (Hart et al. 2012)

Finally, the Recapture Rate Index (RRI) determines the quality of Hot Spot prediction (Levine 2008) and is based on the ratio of hotspot density. It is calculated as

$$RRI = [(n1 / n2) / (N1 / N2)] \quad \text{Formula 3}$$

where n1 is the number of crimes that are hitting the calculated retrospective period and n2 is the number of crimes in the forecast that are hitting the calculated retrospective period. N1 is the number of all crimes in the retrospective period and N2 is the number of all crimes in the calculated forecast period (Hart et al. 2012).

3. Methodology

This chapter presents the methodology of the thesis. A detailed problem definition and the method of solution are described in the following two subchapters, followed by comments on the project area and the required data. Then, the implementation section, which describes how the data are implemented, is discussed. The last section summarizes this chapter.

3.1. Problem Definition

The main task of this bachelor project is to evaluate the accuracy of the recently developed Criminal Predictive Analytics Demonstrator (CriPA). This evaluation is done by comparing the results of the demonstrator with other crime prediction analysis methods, such as Hot Spot methods. The main problem or difference between the CriPA demonstrator and alternative Hot Spot methods is that the CriPA demonstrator is based on the phenomenon of the Near Repeat concept, while the Hot Spot analysis deal with spatial statistically analysis that is not built on the Near Repeat concept. Moreover, in the Hot Spot analysis it is often determined whether spatial patterns are statistically significant and if a spatial clustering in the data occurs (Kennedy et al. 2011). Also random patterns can display a certain clustering, but those clusters would not be classified as being statistically significant. In other words, when interpreting crime Hot Spots, it is often difficult to say whether the results have been caused by spatial processes or purely by coincidence. This problem can sometimes make a crime prediction only based on Hot Spot methods difficult. On the other side, the discovered phenomenon of the Near Repeat concept, which says that if you have been burgled once, you are at a heightened risk of being burgled again, focuses more on predictions of future criminal activity than on the statistically significant concentration of crime patterns. The Near Repeat concept does not say that you are definitely being burgled again, but the risk is increased. This heightened risk rapidly decays with time and distance. The highest period of risk is within a few days of the initial incident. Repeat victimization is more common in high crime areas and less likely in Cold Spot areas or cities with lower crime activity. But in some high crime areas, including a few districts of Vienna, crime is so concentrated among repeat victims that recurring offenses can create those Hot Spots, which are then used for the CriPA analysis.

3.2. Methods of Solutions

The overall goal of this implementation is to find out how accurately future crimes can be predicted from past crime data. Can crime be prevented by using crime prediction methods?

After the discussion of the technical background in Chapter 2, this Sub Chapter gives an overview about each step of the analysis. The implementation for the analysis is broken down into the following steps for this research project:

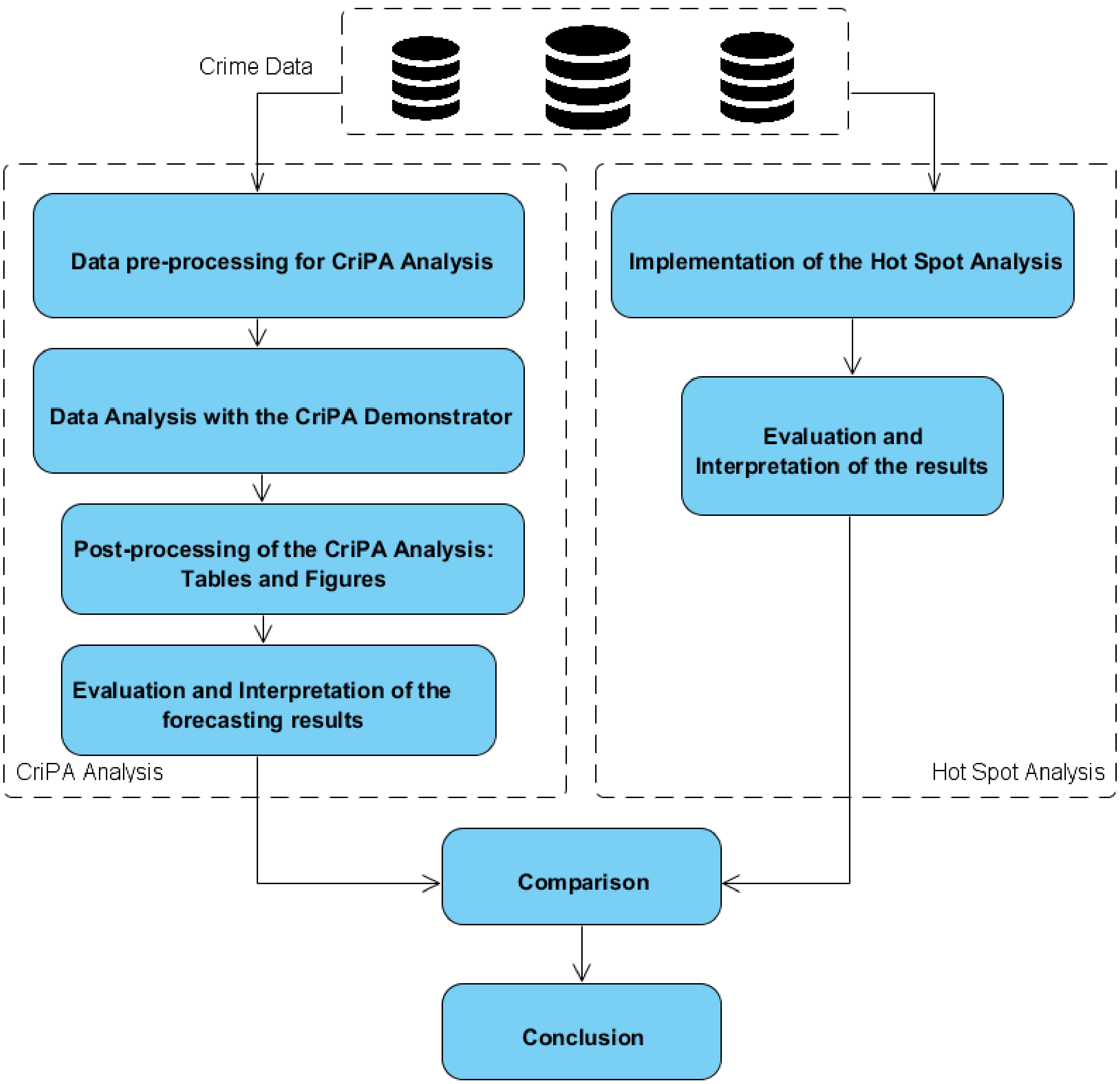

Figure 1: Workflow of the Implementation Process

Figure 1 shows each step from the data pre-processing until the result comparison and conclusion. The first step is data pre-processing, where the datasets are checked for errors and inconsistencies. This step focuses on different parameters, which are described in detail in Sub Chapter 3.4.2. After the data preparation the data analysis can be done with the CriPA Demonstrator. The analysis with the CriPA demonstrator is entirely different from the Hot Spot analysis. This is because the demonstrator is a prototype and the principles and parameters for the analysis are declared by python scripting. Therefore, the functionality is based entirely on the user's definition. In addition to a lot of pre-processing work, there is also a lot of post-processing work, which has to be done. The result of the CriPA analysis is presented in a csv format file. After the post-processing the final CriPA results can be shown in Figures and Tables. The detail post-processing workflow is described in Sub Chapter 3.5.2.1. At the same time of the CriPA analysis, a Hot Spot analysis is performed. A selected set of Hot Spot methods are used because they are very common in crime analysis and their results are easy to interpret. The most appropriate parameters for the selected Hot Spot methods must be found in this step. Then, the results are displayed and edited in ArcGIS. Finally, for both the CriPA and the Hot Spot analysis, there will be an individual evaluation and interpretation for each result. The analysis workflow ends with a short conclusion.

3.3. Project Area

The study area for this research is the city of Vienna, Austria. With a population of 1,797,337 inhabitants and an area of 414.87 square kilometers, Vienna is the largest city and also the capital city of Austria (Lukacsy & Fendt 2015). Vienna is located in the north east of Austria and is divided into 23 districts. The distribution of the 23 districts are shown in the upper left window in Figure 2. The reason for choosing this area is because Vienna has the highest concentration of population and crime of all Austrian cities. The high crime rate in some districts of Vienna is ideal for the CriPA analysis, because the near repeat phenomenon is most common in high crime areas and less common in Cold Spot areas or cities with less crime activity. But in some high crime areas, like in a few districts of Vienna, crime is so concentrated among repeat victims that recurring offenses can create those Hot Spots, which are then used for the CriPA analysis.

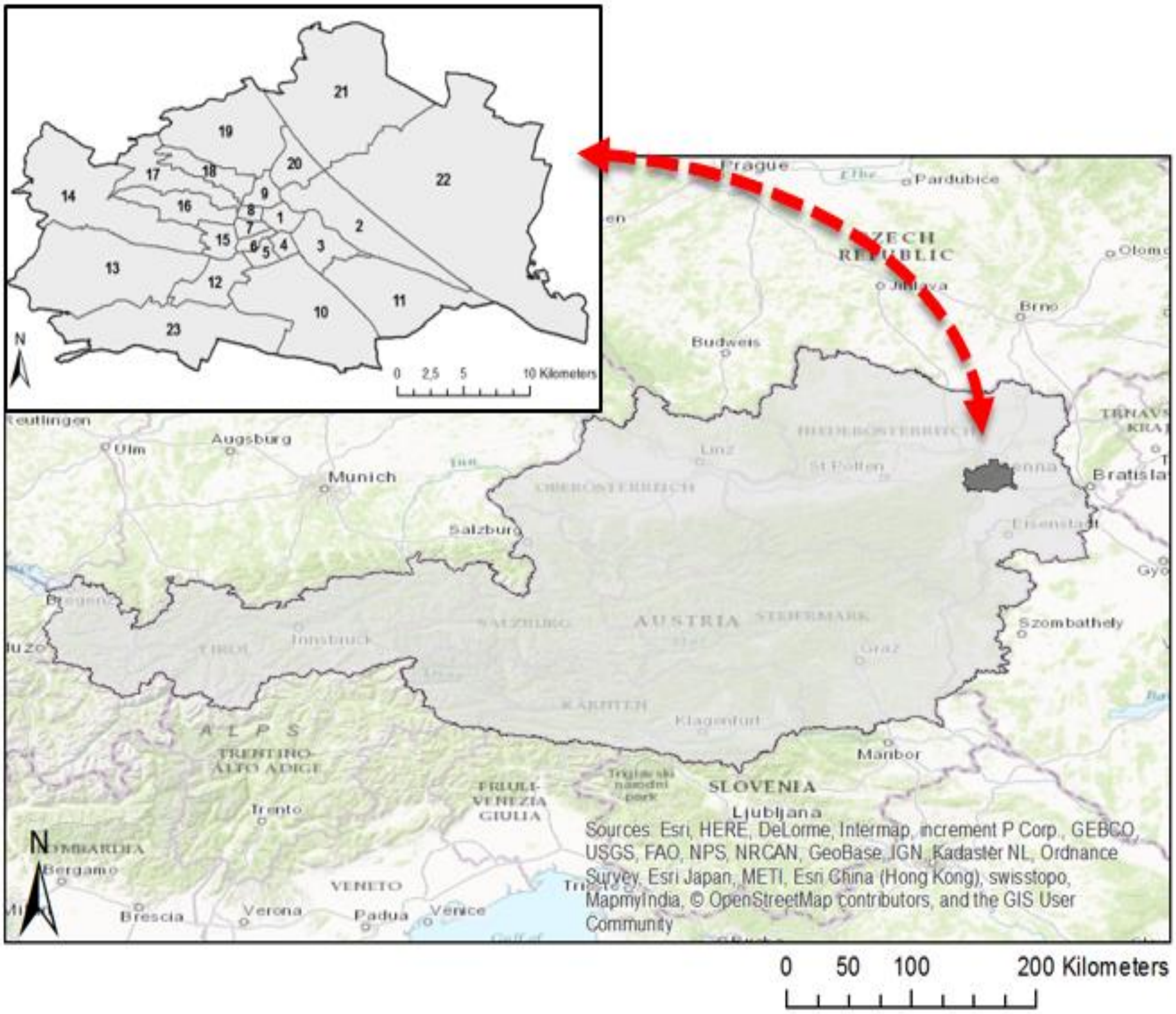

Figure 2: The Study Area of the City of Vienna, located in Austria

Table 1 provides a list of all 23 districts of Vienna, for which crime data were collected. In addition to the zip code and the district name, the size of each district in square kilometers are shown. The zip code is consisting of the district number (1-23) and the unique zip code for Vienna (1000). The zip code for Margareten is 1050, for example.

Zip Code	District Name	Size (km²)	Zip Code	District Name	Size (km²)
	Vienna	95,50	1120	12. Meidling	8,10
1010	1. Innere Stadt	2,87	1130	13. Hietzing	37,71
1020	2. Leopoldstadt	19,24	1140	14. Penzing	33,76
1030	3. Landstraße	7,40	1150	15. Rudolfsheim	3,92
1040	4. Wieden	1,78	1160	16. Ottakring	8,67
1050	5. Margareten	2,01	1170	17. Hernals	11,39
1060	6. Mariahilf	1,46	1180	18. Währing	6,35
1070	7. Neubau	1,61	1190	19. Döbling	24,94
1080	8. Josefstadt	1,09	1200	20. Brigittenau	5,71
1090	9. Alsergrund	2,97	1210	21. Floridsdorf	44,44
1100	10. Favoriten	31,83	1220	22. Donaustadt	102,30
1110	11. Simmering	23,26	1230	23. Liesing	32,06

Table 1: A List of all 23 Districts of Vienna

As is shown in Table 1, the size of each district varies considerably. District 22 for example is 100 times larger than the 8th district close to the city center. The size of each district plays an important role in the analysis and interpretation of the CriPA demonstrator.

3.4. Geodata: Crime Data of Vienna

Chapter 3.4. provides an overview about the necessary crime data and all steps that were completed before and after using the CriPA demonstrator.

3.4.1. Data Overview

The Austrian Federal Criminal Police Office, in German “Bundeskriminalamt” (BK), provides the necessary crime data for the city of Vienna. These data come from the Security Monitor (SIMO) database. This is a database, in which all reported criminal cases in Austria are recorded and persons outside of law enforcement cannot access the data analysis (Kampitsch et al. 2008). The SIMO is used for preventing, tracking, and predicting criminal activities.

The received data are stored in one Microsoft (MS) Excel table. The Excel table includes 210,812 different offences during the past seven years (2009-2015). Furthermore, the data include nine different types of crime and each crime is documented in 27 columns. The nine different crime types include bank offence (e.g.

bank robbery), car theft, car burglary, apartment burglary, house burglary, handbag robbery, mobile phone theft, business robbery, and company burglary. The distribution of the different crime types is shown in Table 2. In the 27 different columns there is information stored such as the beginning time of the crime offence, the end time of crime offence, district name, district number, street name, crime type number, crime type, case status, way of entering a building (e.g. through the door), x-coordinate and y-coordinate of the crime location, or stolen good.

id	tatzeit_von	tatzeit_bis	bdl	bezirk	plz	ort	delikt	schlagwort	geklaert	versuch
4705388	13.04.2011 19:00	14.04.2011 14:00	Wien	Simmering	1110	Wien	129	KFZ-ED	Nein	Nein
4705412	08.04.2011 22:00	10.04.2011 09:00	Wien	Leopoldstadt	1020	Wien	129	FirmenED	Nein	Nein
4705428	26.08.2011 20:00	27.08.2011 08:15	Wien	Donaustadt	1220	Wien	129	KFZ-Entfremdung	Nein	Nein
4705435	26.08.2011 15:00	26.08.2011 18:00	Wien	Donaustadt	1220	Wien	129	KFZ-Entfremdung	Nein	Nein
4925744	26.08.2011 21:30	27.08.2011 13:00	Wien	Landstraße	1030	Wien	129	KFZ-ED	Ja	Nein
4926480	26.08.2011 18:00	27.08.2011 13:00	Wien	Simmering	1110	Wien	129	KFZ-ED	Nein	Nein
4926624	20.08.2011 14:00	27.08.2011 14:00	Wien	Hietzing	1130	Wien	129	WohnungsED	Nein	Ja
4926798	27.08.2011 14:10	27.08.2011 17:15	Wien	Favoriten	1100	Wien	129	KFZ-ED	Nein	Nein

Table 2: An Example of Reported Crimes from the Original SIMO Database

As is shown in Table 2, each data already has a unique ID (see column 1). It is also assumed that addresses of the crime locations were geocoded correctly. The x and y coordinate values are based on the WGS84 spatial reference system (EPSG:4326).

The second and third columns show in which time period the crime was committed. The column "bezirk" names the district in which the crime event took place. The crime types are listed in the column "schlagwort". The shown data are only randomly generated data as an example for the original data from the security monitor. Addresses are deleted on purpose from Table 2 due to privacy concerns.

Table 3 gives an overview about the distribution of all crime types and the number of offences. The overall sum is listed at the lower right. At first glance it seems that the crime activity declined during the last seven years starting with a total of 41,151 crime events for all nine crime types in 2009 and ending with 23,800 crimes in 2015. The crime type with the most offences is the car burglary followed by apartment burglary. These two types account for more than 60% of all crime events in this study. Based on this fact, this research emphasis car burglaries, apartment burglaries, and house burglaries.

year	bank robbery	company burglary	company robbery	handbag theft	phone theft	car burglary	car theft	house burglary	apartment burglary	Sum
2009	56	7026	404	490	434	16141	3772	1987	5472	36882
2010	44	6570	354	481	448	12518	2953	1662	6772	32913
2011	47	5295	251	401	454	9888	2747	1629	7635	29587
2012	39	5600	329	388	474	8134	2643	1677	6449	27133
2013	29	5707	260	395	423	8990	2232	1347	7368	28353
2014	30	5009	219	310	501	8884	1966	1623	7896	28060
2015	21	4373	161	277	348	8244	1742	1633	9795	28144
	266	39580	1978	2742	3082	72799	18055	11558	51387	**211072**

Table 3: An Overview about the Distribution of each Crime Type over the Years

3.4.2. Data Preparation

The data preparation is divided into 4 steps (see Table 4).

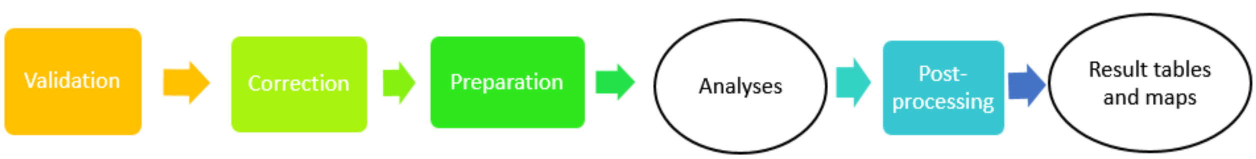

Table 4: Workflow of the Data Processing

The first part of the data preparation was to delete all crime events with errors in the original SIMO data received from the BK. Therefore, the first step was to verify the completeness of each crime event. In this step 9,512 errors were found. The highest number of errors included crime events which had no crime type (9,369). Another set of crime events (141) had no street name in their respective attribute column. 82 more crime offences are located outside of Vienna. In total, the number of data errors amounted to 9,592 (Table 5), which is 4.55% of all data. All crime events with these described errors were deleted and not included in further analysis.

Error Type	Number of Events	% of Total
Located outside of Vienna	82	0,04%
Missing crime type	9369	4,44%
Missing street name	141	0,07%
	9592	4,55%

Table 5: List of Most Common Errors of SIMO Crime Data

The next step of the pre-processing task was data correction. In this step, the data were first displayed in ArcMap. Then, a selection by attribute was carried out to test the correctness of the data. For example, all data which have the district name "Margareten" where selected. Normally, all selected data have to be located in the 9th district called Margareten, but instead, there were some points which are located in other districts. The number of incorrectly located offences by district name was between five to ten events in each district. These data were corrected manually and kept in the dataset.

After the data validation and the data correction, the data had to be prepared for the CriPA analysis. The main goal in this step is to prepare the Excel table so that the analysis with the CriPA software can be done. This step can also be done during the analysis by recoding the python script, in other words adapting the demonstrator to the particular data. Based on the fact that one aim of this study was to evaluate and compare the demonstrator with alternative prediction methods, the program was not modified. Instead, it was decided to adapt the data instead of the demonstrator. Therefore, some additional columns were added to the original Excel table. The most important missing feature for the CriPA analysis was the value for time/date difference for each criminal event. Each offence has a start time and an end time. The start time is that time, for example, when the thief entered the house and the end time would be that time, when the thief has left the house. Normally this happens within an hour. But sometimes it is not known when the thief has entered and left the house. Therefore, the victim has to guess the earliest time when it could have been possible for the thief to enter (start time) and the time, when the victim realized that he/she was robbed (end time). This time length can be several hours or also several days. This information is very important for the following CriPA analysis, which is described in Sub Chapter 3.5.2.1. Furthermore, a column called "type of enter" was created. In the original SIMO dataset, all "types of enter" were associated with a specific code.

The demonstrator cannot work with these codes in the parameters, so the codes had to be changed into the associated names. As a result, a new column which could be read by the demonstrator was added. After some minor final edits in the MS Excel file, for example, renaming the column headings for a better understanding and replacing some “exotic” letters into machine-readable letters, the Excel table could be imported into ArcMap. In the final step the modified datasets were added and displayed in ArcMap. The used tool for this operation was the “excel to table” tool. As a result of that step, feature classes for each crime type could be created so that they are ready for the analysis part. The post-processing part is described in Sub Chapter 3.5.2.1. as a part of the CriPA Analysis.

3.5. Implementation

The implementation shows how the different analysis parts are used and how they work. In the beginning, the software and tools are named. The analysis chapter provides a step by step documentation for each analysis and is divided into two subchapters. On the one hand the CriPA analyses are discussed and on the other hand the implementation of the Hot Spot analysis is shown. The analysis part includes the procedure of the applied analysis, the post-processing, and the evaluation and visualization of the results.

3.5.1. Software and Tools

All analyses are done with different programs and individual software tools. First of all, the used programs for the implementation are CrimeStat IV, CriPA demonstrator, ArcGIS 10.3, and MS Excel 2016. CrimeStat IV is used for the Hot Spot analysis. The results of the Hot Spot analysis will be displayed in ArcMap. Therefore, a software extension named Spatial Analyst (Eck et al. 2005) for ArcGIS is needed. ArcGIS is only available for commercial use but there is a 30-days trail version available without any additional software packages like the Spatial Analyst. CrimeStat IV however, is an open source software (Levine 2015) and the CriPA demonstrator is provided free of charge, too. The CriPA software is provided by the external supervisor, Prof. Michael Leitner, and its use is supervised by its developers. Last but not least, Microsoft Excel is used, on the one hand, to prepare the received data and, on the other hand, to visualize the output of the CriPA demonstrator in resulting tables. As mentioned before, the results are presented in tables and graphs and for the visualization and creation of maps, ArcGIS is used.

3.5.2. Analysis

The analysis chapter lists a step by step documentation for each analysis. This part is divided into two subchapters which is, on the one hand, the CriPA analysis and, on the other hand, the Hot Spot analysis. The analysis section includes the procedure of the applied analysis, the post-processing, the evaluation, and the visualization of the results.

3.5.2.1. CriPA Analysis

First of all, it is important to mention that the analysis with the CriPA demonstrator is very different compared to the Hot Spot analysis. This is because the demonstrator is in a prototype status and the principles and parameters for the analysis are declared by python scripting. Therefore, the functionality is based entirely on the user's definition. In addition to a lot of previous mentioned pre-processing work, there is a lot of post-processing work, too. Results of the CriPA analysis are presented in a csv format file. After the post-processing the final CriPA results can be shown in Figures and Tables. For obtaining the best forecasting results from the CriPA demonstrator a lot of trials and test runs have to be completed in order to understand the principle of the software. Various attributes are considered individually in the first set of trials. Then, a combination of these attributes are included in trials in the next test phase. After a precise and successful test run, the procedure can be repeated for all crime data.

Before using the CriPA demonstrator the parameter setting should be checked. The following parameter settings can be changed in the software: Observation period (1-5 days), prognoses period (1-3 days), way of enter, examining district, forecast radius (200-400 meters), radius type, offence duration (0-72 hours), and analysis timeframe (up to 7 years). The observation period can be set to 1, 3, or 5 days. This setting allows the user to change the timeframe to investigate and analyse previous crime events in the specific area. As a result of test runs and to the best knowledge of the developer, it is proven that the more days are included in the observation period, the more hits are shown in the forecast (Bowers & Johnson 2004). Therefore, after the first test trails with a variation of parameter settings, the final analysis is carried out with a five-day observation period. The prognoses period can change between 1, 2, and 3 days. Like the observation period, also the prognoses period is more precise, if the time frame is longer, because the forecasted Near Repeats have a higher chance to be hit in a 3-day time frame than in a 1-day time frame. This phenomenon is shown in the result chapter. The "way of enter" parameter allows the researcher to define certain types for the way a burglar enters an apartment or a house, for example. In this study five different parameters are defined. These parameters are: Crashing a window, breaking a door, drilling, unlocking, bolt cutting. These five parameters are most common in apartment, business, and house burglaries. In general, all five different parameters are selected for the analysis. The next parameter is the observation area. Normally, two different districts are selected for one run and one study. It is possible to select the whole city of Vienna, too. The parameter called "forecasting radius" is significant for the prediction accuracy. The choice of a 200, 300, or 400-meter radius can show a variation in the hit rate of the predicted events, therefore all three different radius values are selected in each analysis. The next parameter setting allows the user to define the type for the prediction radius. There are three kinds of radii. The difference between each radius type is shown in Figure 3. Each point in Figure 3 represents a criminal activity. The blue box represents the first offence, followed by the red circle, and the yellow star. The first two events are falling into the observation period of the forecast. The last event (yellow star) is in the prediction time period. The radius on the left side (Figure 3A) is formed around the first and the investigated crime event. The middle circle is drawn around the second and the last investigated offence in the observation period of the analysis (Figure 3B). The third solution and type of radius is shown on the right. This is a merged circle which is drawn around both, the first and the second offence (Figure 3C). The size of the merged area is bigger than one single circle. It is assumed that the forecast accuracy improves, when the size of the forecast area is larger. Also, in the given example (Figure 3) the produced forecast area hit the crime offence. To prove this assumption, all three types of radii are selected for every analysis.

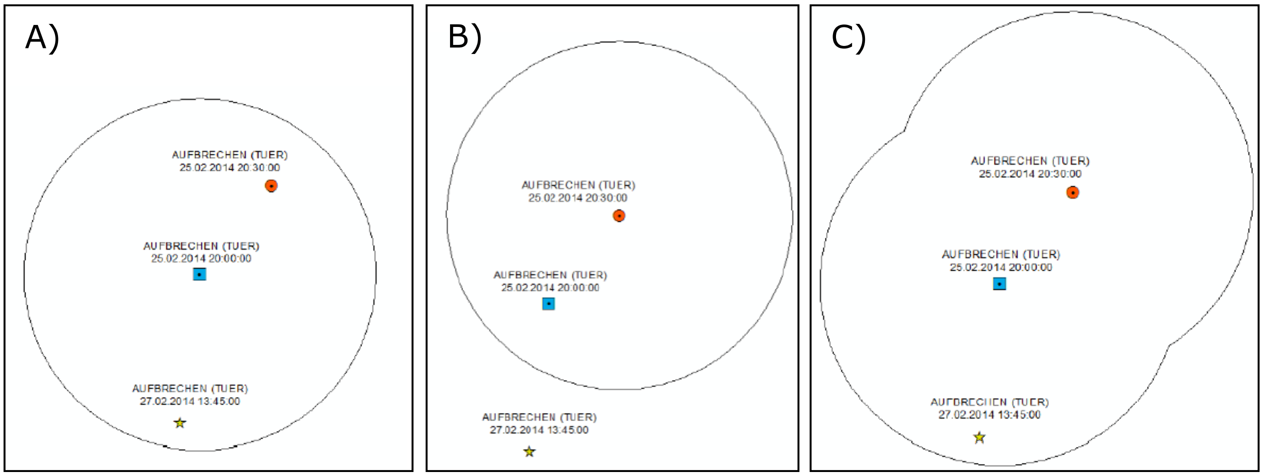

Figure 3: Different Radii Types for the Prediction Area

The next parameter setting is called offence duration. In general, this setting is predefined by 72 hours. This 72-hour time frame excludes all criminal events that took longer than 72 hours. Such event data were excluded, because the maximum time frame for the observation period is three full days or 72 hours. Therefore, it cannot be said, whether events with a longer start and end difference than 72 hours hit the observation period or not, because the start time (or end time) is outside of the time period. According to that, the criminal offence could have happened before the observation period even when the end time is in the observation period. The offence duration parameter is always set to 72 hours in this study. The last parameter allows the user to define the date frame of the whole analysis. This date frame can be particular days or years.

After some test trails with different parameter settings it can be said that the more parameters are selected, for example three different sizes of radii, the more time it takes to run the analysis. The most efficient parameter settings for the analysis are reduced to one specific forecast radius (e.g., 400 meters), one observation period (e.g., 3 days), one forecast period (5 days), and two different districts. With this parameter selection, the analysis can run for all seven years (or 2,556 days).

Moreover, all five "types of entry" should be selected. In general, this scenario takes around 8 hours to investigate around 50,000 points over seven years and only for one specific crime type. The program runs very reliable and the output is stored in a csv format file (Table 6). Each value is separated with a space. First, the investigated date is entered together with the end time of the daily investigation. Then, the size of the forecasting radius is provided, followed by the observation and prediction period. The next columns show the number of predicted Near Repeats and real Near Repeats. Based on this output, it is hard to say how precise the forecast analysis was.

19.12.2015	23:59:59	400	5	3	8	4	0	0	0	0	8	4	0
20.12.2015	23:59:59	400	5	3	4	7	0	0	0	0	4	6	0
21.12.2015	23:59:59	400	5	3	4	3	0	0	0	0	6	2	0
22.12.2015	23:59:59	400	5	3	4	0	0	0	0	0	5	1	0
23.12.2015	23:59:59	400	5	3	4	1	0	0	0	0	4	1	0
24.12.2015	23:59:59	400	5	3	5	0	1	0	0	0	5	0	1
25.12.2015	23:59:59	400	5	3	3	4	0	0	0	0	3	4	0
26.12.2015	23:59:59	400	5	3	2	0	0	0	0	0	2	0	0
27.12.2015	23:59:59	400	5	3	1	2	0	0	0	0	1	2	0
28.12.2015	23:59:59	400	5	3	4	1	0	0	0	0	4	1	0
29.12.2015	23:59:59	400	5	3	4	0	0	0	0	0	4	1	0
30.12.2015	23:59:59	400	5	3	3	0	0	0	1	0	3	0	0
31.12.2015	23:59:59	400	5	3	2	0	0	0	0	0	2	0	0

Table 6: CriPA Analysis stored in a CSV File

The next part in the CriPA Analysis is the post-processing work of the output tables. Fortunately, a csv file can be imported to MS Excel very easily. To improve the presentation of the output, a number of calculations and formatting has to be done. First of all, each column receives a precise name and every analysis of a district is stored in one document. An easy step is to calculate the total for all incorrectly predicted crimes and also the total for all correctly predicted crimes. This needs to be done for all districts. As a result of that many different choices of parameters, many tables, and totals need to be compared and stored separately. An example for a summary result table is provided in Table 7. It shows the necessary parameter settings: Year, space (radius lengths in meter), the observation time, and the timeframe of the prediction. The column "O_G_W" means that the radius was drawn around the first crime in the observation period and the analysis area is Vienna. The value in the first row represents the number of days in which at least one Near Repeat was predicted. The second row represents the total number of predicted Near Repeats. The column "O_ED_W" presents the value of Near Repeats that were found. The first row says that in 141 days (out of one year) at least one Near Repeat was found. The second column says that in total 251 Near Repeats were found in this specific analysis. After the post-processing and visualization of the analysis, the result and evaluation process can start.

year	Space	Time	ProgTime	O_G_W	O_ED_W
2015	500	5	3	302	141
			SUM	732	251

Table 7: The Result of the Post-Processing

3.5.2.2. Hot Spot Analysis

The Hot Spot Analysis starts with the Kernel Density Estimation (KDE). To calculate the Kernel Density Estimation CrimeStat IV is used. ArcMap is used for the result visualization. The first step of the KDE is to load the required shape file into CrimeStat and fill in the required fields. The required x and y coordinates have to be declared in CrimeStat. After the variables setting, the user has to define a regular grid area. In this study this grid area represents the city of Vienna. Then, a cell size needs to be defined. This is required because the resulting area of the KDE is divided into columns and rows. Therefore, the cell size is determined by a specific number of columns that need to be set. The number of columns depends on the project area. For an analysis the size of Vienna a column number of 100 seems to be appropriate. For more detailed analysis, such as particular districts, about 300 columns should be selected, because the previous defined grid area is set for the entire city of Vienna. In the next input window, the parameters for the KDE are defined. These parameters include the method of interpolation, the choice of bandwidth, a minimum sample size, and the area units. In Figure 4 the final parameter setting for a KDE is shown. The method of interpolation can be normal, uniform, quartic, triangular, or negative exponential. Based on previous test trails, a quartic interpolation method and an adaptive bandwidth delivered the most appropriate results. Therefore, this parameter setting is used for this Hot Spot analysis. Moreover, to interpret and compare results it is easier, if the analyses where done with the same parameter settings. The parameter minimum sample size defines the minimum number of crime events that fall underneath the selected kernel function for a Kernel Density Estimation. This number depends on the number of crime events in the dataset. In general, the minimum sample size is about 1 to 3 percent of the total number of crime events. In Figure 4, more than 51,000 crime events are investigated, therefore the minimum sample size for an analysis is set to 1,600.

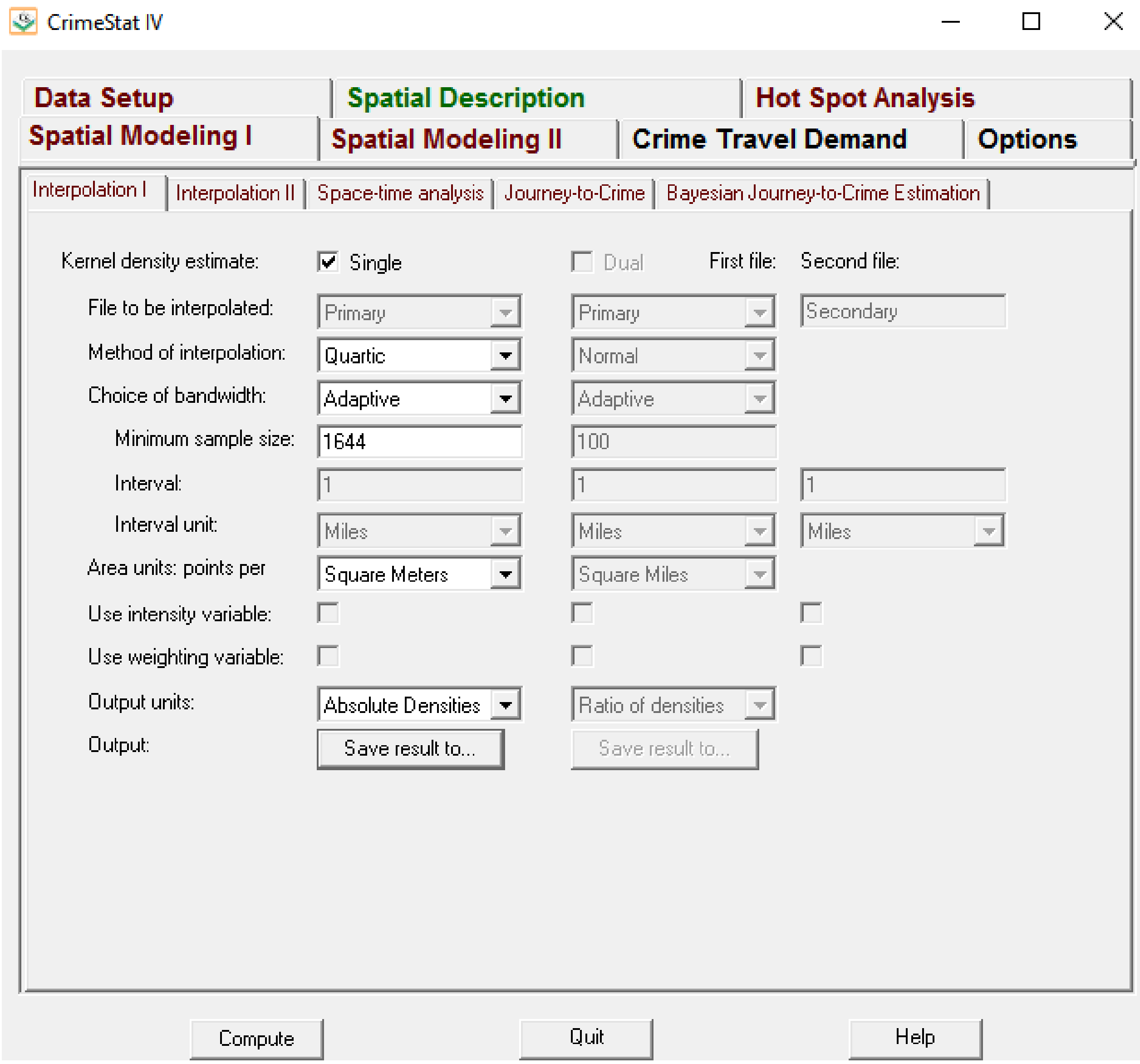

Figure 4: Parameter Settings for the Kernel Density Estimation

Another type of Hot Spot Analysis it the Nearest Neighbor Hierarchical Cluster Method (NHHC). This cluster analysis is included in CrimeStat IV. It is a risk-based technique but involves elements of clumping (Levine 2006). It identifies groups of incidents that are locally close. Then, these points are clustered together. This process is repeated until all points are grouped into a single cluster. The NNHC defines a threshold distance and compares them to all pairs of points. Only points that are closer should be selected for the clustering (Grubesic 2006).

For this analysis different parameters were set. First, the minimum number of points that form a cluster should be around 1.5 percent of the total number of points. Second, for the type of search radius default settings are used, by choosing a probability level of 0.05. In CrimeStat IV the fifth position from left of the scale bar is selected (see Figure 5), which defines this probability level. The results can be visualized as standard deviational ellipses or convex hulls. The advantage of convex hulls is that they have a high accuracy and that they have a higher density (Levine 2015). For this analysis both convex hulls and ellipses are used.

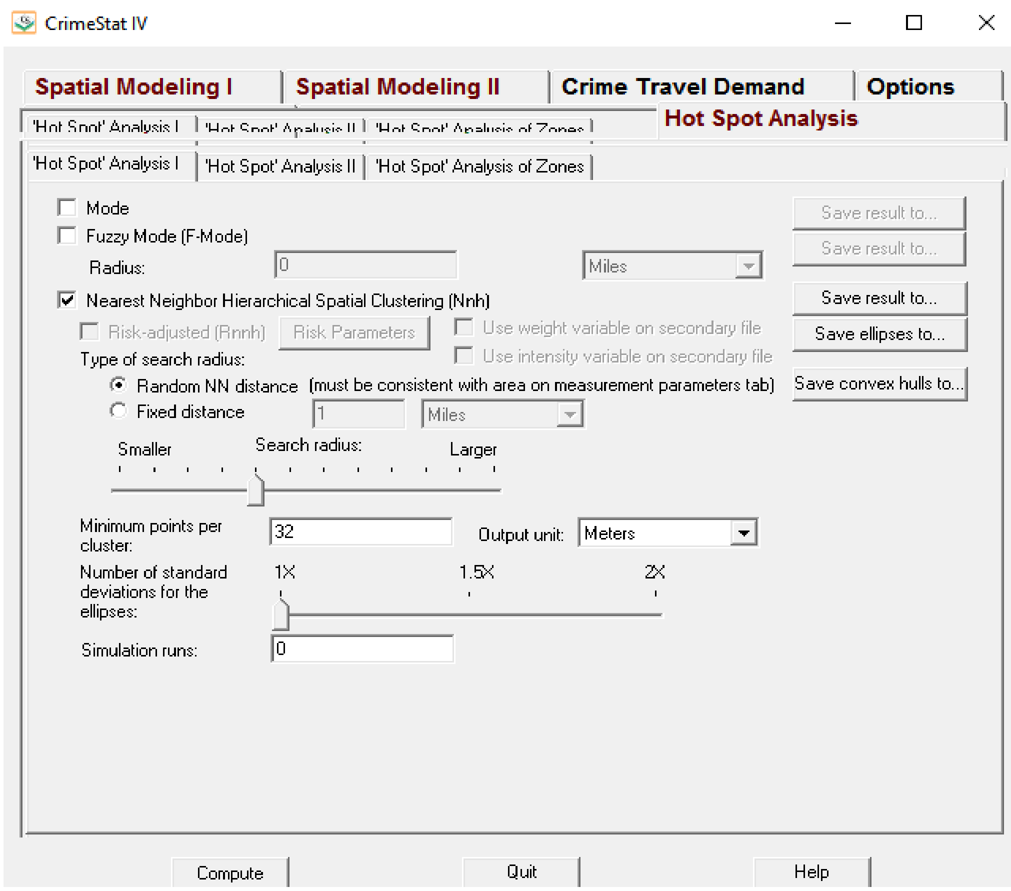

Figure 5: Parameter Settings for the NNHC Analysis

3.6. Summary

To sum up, Chapter 3 includes the description of the specific project area, the data preparation, and the implementation of the analyses. The first two subchapters give a better understanding of the research problem and the methods of solutions. Then, the project area and the crime data are described in detail. Chapter 3.5 shows how the different analysis methods are used and how they work. In the beginning of the implementation part, the used software and tools are named. This is followed by the analysis chapter and a step by step documentation for each analysis is provided. On the one hand the CriPA analysis is discussed and on the other hand the implementation of the Hot Spot analysis is shown. The analysis part includes the procedure of the applied analysis, the post-processing, the evaluation, and the visualization of the results.

4. Results and Interpretation

The fourth chapter presents the results and findings of the study. In the beginning the results of the CriPA analysis are discussed, followed by the results of the Hot Spot Analysis. Then, the evaluations of both results are presented.

4.1. Results of the CriPA Analysis

In the beginning all nine different crime types were analysed with the CriPA demonstrator. Preliminary results showed that only four crime types match the settings for the CriPA analysis. The reasons why the CriPA demonstrator cannot analyse all crime types is because four out of nine crime types do not have enough offences for an analysis. The four crime types with too little crimes in Vienna for the past seven years are bank robbery (266), company robbery (1,978), handbag theft (2,742), and phone theft (3,082). Result of the CriPA analysis for these four crime types are only statistically significant in very few cases, more specifically Near Repeats were found in only 0 – 10 cases. One more crime type (car theft) could not be analysed with the CriPA analysis because most of such crime types do not have a way of entry. Therefore, in order to do a Near Repeat analysis, the related code for this particular crime type would need to be. As a result, only car burglaries, house burglaries, apartment burglaries, and business burglaries were used for further analysis. All four crime types show significant results. Additionally, not all results of the CriPA analysis can be shown and discussed in this chapter. Therefore, only selected analysis for specific years and districts are presented. The selection of Cold and Hot Spot areas is based on the crime density in each district. In addition, a table with the crime density for each district was calculated. This table is shown in the Appendix A. Districts with a very large or small number of crimes per square kilometers were selected for the CriPA analysis and result interpretation.

Table 8 shows the overall results of the CriPA analysis for four different crime types. The four different crime types are car burglary, house burglary, apartment burglary, and business burglary. The analysis includes all crime events of these four crime types from 2009 to 2015 in Vienna. Therefore, the study area for this particular result is Vienna. The parameters radius type, radius size, Near Repeat period, and forecast period are appropriately selected based on prior test runs. The radius type is set as a merged buffer radius (ORNR) around two points in the observation period (see Sub Chapter 3.5.1.). The length of the radius is 400 meters, the Near Repeat or observation period is five days, and the forecast period is three days. These settings were identified as the optimal results during a previous evaluation process (see Sub Chapter 4.3.). As is shown in Table 8, the most number of predictions where achieved for apartment burglaries (2,090). In addition, apartment crimes also have the highest total number of hits (1,137). The Hit Rate, which can also be used for the evaluation process, has its highest value with 0.89 percent for car burglaries. It can be said that predictions for car burglaries are the most successful predictions among the four crime types analysed. Nearly 90% of the predicted car burglaries could predict an offence correctly with the CriPA demonstrator. It should be noted that this high Hit Rate represents the analysis of 68,223 car burglaries in Vienna from 2009 to 2015. The last index in Table 8 represents the Decline Rate. This is the number of correctly predicted crimes divided by the total number of crimes. This evaluation index shows that the prediction for future car burglaries could only be made for 0.35 percent of all car burglaries (68,223). In other words, 0.35 percent of all car burglaries could be predicted by the CriPA analysis.

Crime Type	Period	District	Radius Type	Radius	NR Period	Forecast Period	Predictions	Hits	Hit Rate	Offences	Decline Rate
car burglary	total	Vienna	ORNR	400	5	3	271	241	0,89	68223	0,35%
house	total	Vienna	ORNR	400	5	3	228	44	0,19	9585	0,46%
apartment	total	Vienna	ORNR	400	5	3	2090	1137	0,54	42679	2,66%
business	total	Vienna	ORNR	400	5	3	1448	933	0,64	36468	2,56%

Table 8: CriPA Results for Four Different Crime Types from 2009-2015

Based on the previous result, the following CriPA analyses were done for some selected districts. The selected districts were on the one hand two rather low crime districts (Döbling and Donaustadt) and on the other hand two rather high crime districts (Margareten and Josefstadt). These analyses were done to see where and why the CriPA software works best.

Crime Type	Period	District	Radius Type	Radius	NR Period	Forecast Period	Predictions	Hits	Hit Rate	Offences	Decline Rate
apartment	total	Döbling	ORNR	400	5	3	55	15	0,27	1990	0,75%
apartment	total	Margareten	ORNR	400	5	3	147	100	0,68	1894	5,28%
apartment	total	Donaustadt	ORNR	400	5	3	34	7	0,21	1850	0,38%
apartment	total	Josefstadt	ORNR	400	5	3	106	53	0,50	1010	5,25%

Table 9: Result of the CriPA Analysis for Apartment Burglaries in Four Different Districts

The following result table (Table 9) shows a CriPA analysis result in these four different districts. The districts "Döbling" (19th district) and "Donaustadt" (22nd district) represents two Cold Spot districts. The two other districts, "Margareten" and "Josefstadt", are districts with rather high concentrations of crime. This table represents a significant difference between the prediction accuracy for in Cold Spot districts and in Hot Spot areas using the CriPA demonstrator. Both evaluation indices, the Hit Rate and the Decline Rate, are much higher in the two Hot Spot districts than in the two Cold Spot districts. It therefore follows that for apartment burglaries the number of predictions and prediction hits is higher in Hot Spot areas than in Cold Spot areas.

Another interesting result shows the changes of the prediction accuracy over the seven years of the selected observation period. A selected result of this research analysis is presented in Table 10 for business burglaries in the 7th district (Neubau). Some interesting findings are shown in this table. First, it is shown that the number of business burglaries decreased from 320 in 2009 to 155 in 2015, which means a decline of 51.6 percent.

Crime Type	Period	District	Radius Type	Radius	NR Period	Forecast Period	Predictions	Hits	Hit Rate	Offences	Decline Rate
business	2009	Neubau	ORNR	400	5	3	3	1	0,33	320	0,31%
business	2010	Neubau	ORNR	400	5	3	0	0	-	226	0,00%
business	2011	Neubau	ORNR	400	5	3	1	1	1,00	164	0,61%
business	2012	Neubau	ORNR	400	5	3	7	2	0,29	244	0,82%
business	2013	Neubau	ORNR	400	5	3	3	0	0,00	254	0,00%
business	2014	Neubau	ORNR	400	5	3	45	23	0,51	174	13,22%
business	2015	Neubau	ORNR	400	5	3	42	29	0,69	155	18,71%

Table 10: Result of the CriPA Analysis for Business Burglaries in the 7th District of Vienna.

Second, the values for the Decline Rate increased significantly in 2014 and 2015. While the Decline Rate from 2009 to 2013 is between 0.0% and 0.82%, the Decline Rate in 2014 and 2015 is between 13.22% and 18.71%. Additionally, the number of hits decreased. The reason for this decrease is discussed in the following evaluation part (see Sub Chapter 4.3).

One last main finding of the CriPA analysis, which shows the prediction accuracy in high and low crime areas is mapped in Table 11. The given values (see Decline Rates) also supports the original assumption that forecasting with the CriPA demonstrator is more precise in high crime areas than in low crime areas. It also shows that the best forecasting results are made for apartment and business burglaries, based on the Decline Rate. But based on the Hit Rate (see Table 8), also car burglaries are well forecasted with the CriPA demonstrator.

Crime Type	Period	District	Radius Type	Radius	NR Period	Forecast Period	Predictions	Hits	Hit Rate	Offences	Decline Rate
apartment	2014	Döbling	ORNR	400	5	3	19	6	0,32	273	2,20%
apartment	2014	Donaustadt	ORNR	400	5	3	23	4	0,17	263	1,52%
apartment	2014	Josefstadt	ORNR	400	5	3	35	16	0,46	124	12,90%
apartment	2014	Margareten	ORNR	400	5	3	64	46	0,72	271	16,97%
business	2014	Döbling	ORNR	400	5	3	16	6	0,38	165	3,64%
business	2014	Hietzing	ORNR	400	5	3	16	4	0,25	86	4,65%
business	2014	Margareten	ORNR	400	5	3	47	16	0,34	127	12,60%
business	2014	Neubau	ORNR	400	5	3	45	23	0,51	174	13,22%
apartment	2015	Döbling	ORNR	400	5	3	25	6	0,24	176	3,41%
apartment	2015	Donaustadt	ORNR	400	5	3	11	3	0,27	179	1,68%
apartment	2015	Josefstadt	ORNR	400	5	3	34	15	0,44	119	12,61%
apartment	2015	Margareten	ORNR	400	5	3	41	13	0,32	193	6,74%
business	2015	Döbling	ORNR	400	5	3	15	10	0,67	152	6,58%
business	2015	Hietzing	ORNR	400	5	3	8	1	0,13	56	1,79%
business	2015	Margareten	ORNR	400	5	3	37	12	0,32	104	11,54%
business	2015	Neubau	ORNR	400	5	3	42	29	0,69	155	18,71%

Table 11: Result Table of the CriPA Analysis in 2014 and 2015 for Apartment and Business Burglaries

Complete results of the CriPA Analysis are listed in the Appendix B. The complete results include detailed results for each of the nine years (2007 - 2015) and for every crime type. Moreover, all results of several selected districts are presented. Furthermore, the results for the three different radii types of each analysis are also shown.

4.2. Results of the Hot Spot Analysis

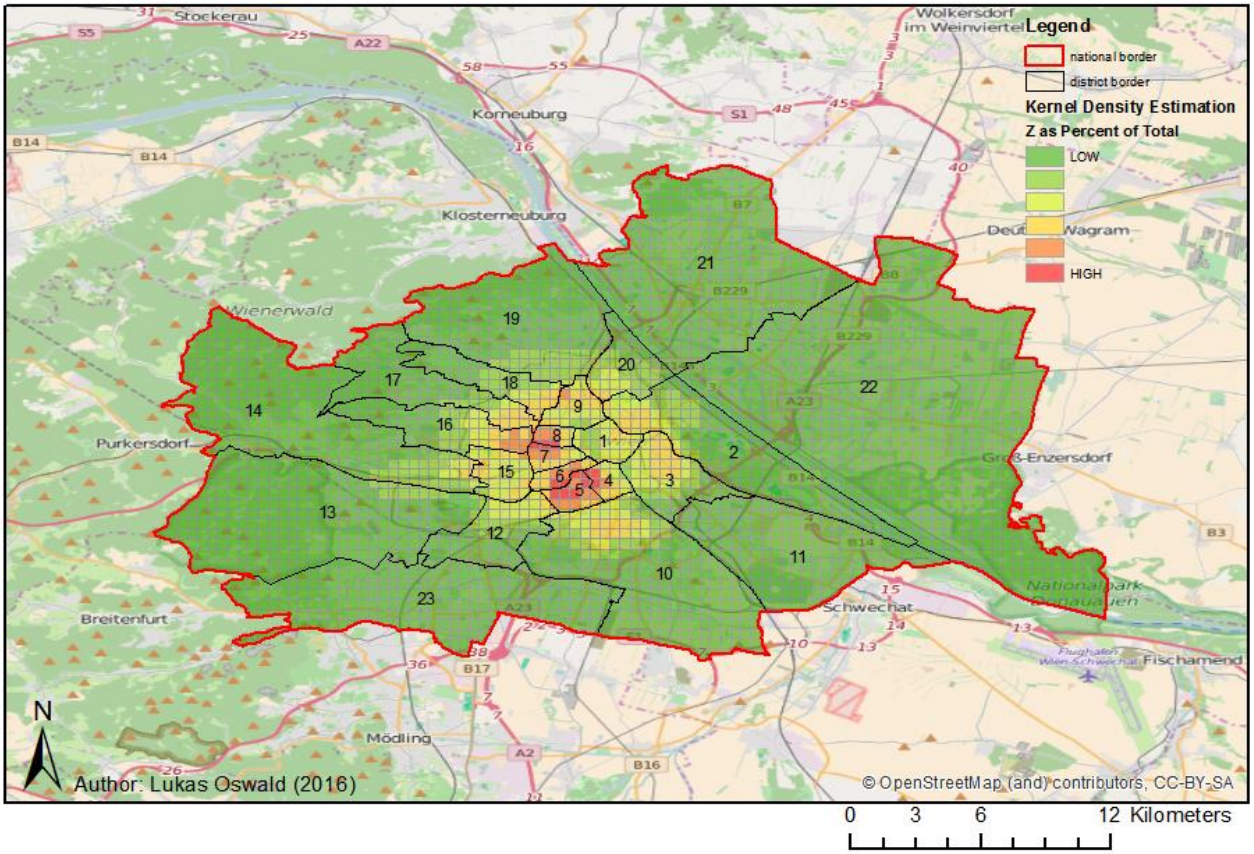

Figure 6: Kernel Density Estimation for Apartment Burglaries in Vienna (2009 - 2015)

The result of the Kernel Density Estimation for apartment burglaries is shown in Figure 6. This map shows the crime distribution for apartment burglaries over the last seven years. It can be said that the crime is concentrated in the inner city. In detail, crime Hot Spots are concentrated in the 4th, 5th, 6th, 7th, and 8th districts. The map also shows that the area with the highest crime events is located in the 5th district Margareten. The used parameter settings for this particular analysis are shown in Figure 4.

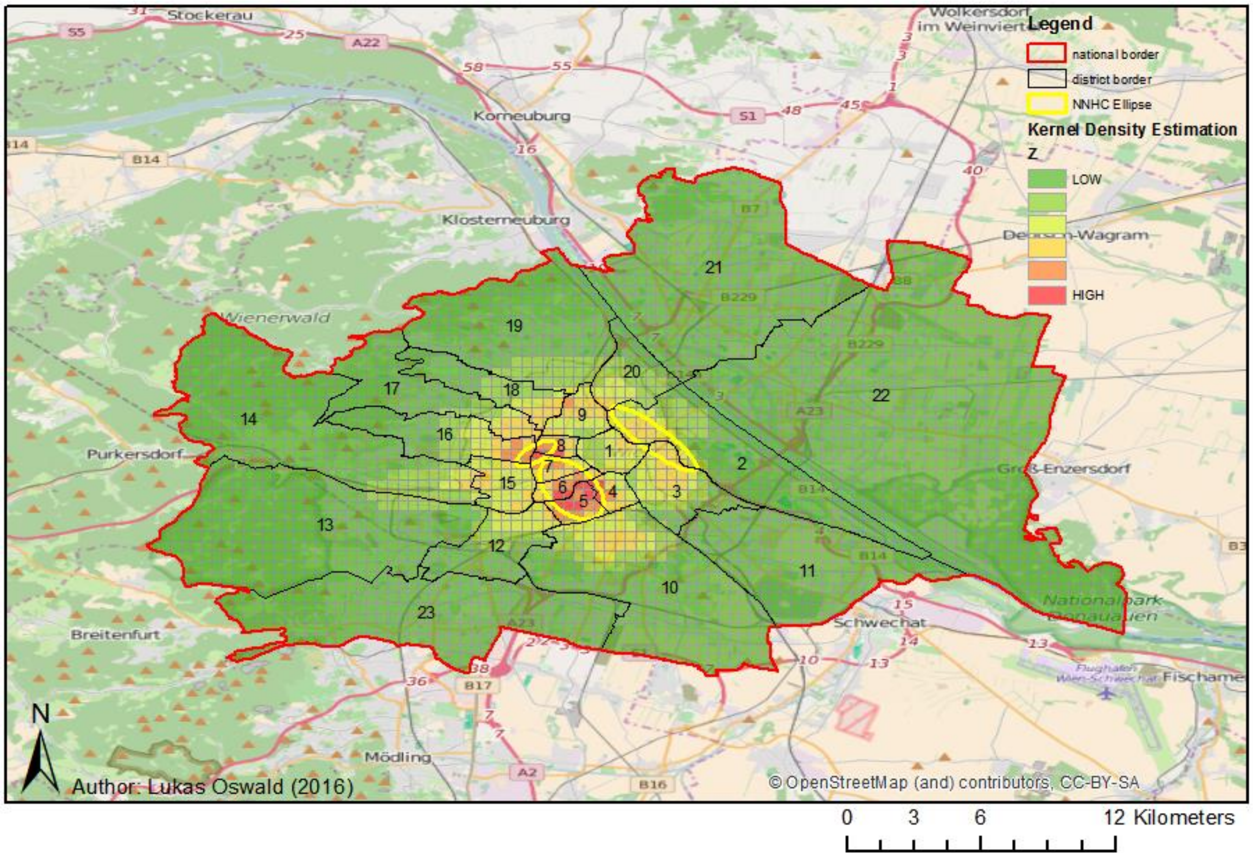

Figure 7: Nearest Neighbor Hierarchical Cluster Ellipses with the Kernel Density Estimation Map in the Background for Apartment Burglaries in Vienna (2009 – 2015)

In the next Figure (Figure 7) the results from the Nearest Neighbor Hierarchical Cluster analysis are included. There are three clusters or ellipses which are also located in the city center and very close to each other. The largest eclipse is located in districts 5, 6, and 7. This area is also the largest Hot Spot area of the KDE. A smaller Hot Spot is located in the 8th district immediately adjacent to the 7th district. In this area the second and smallest ellipse is found. The third eclipse is located in the second and third district, where the KDE shows a large area with medium to high density of crimes. This analysis was done with the parameter settings that are shown in Figure 5.

The next map (Figure 8) shows the result of the NNHC convex hulls for the same crime events and timeframe as in Figure 7. The convex hulls cover pretty much the same area as the ellipses and therefore only the inner city of Vienna is shown. The computed convex hulls are rather small because the crime is very concentrated in this area. Each hull includes at least 32 crime events.

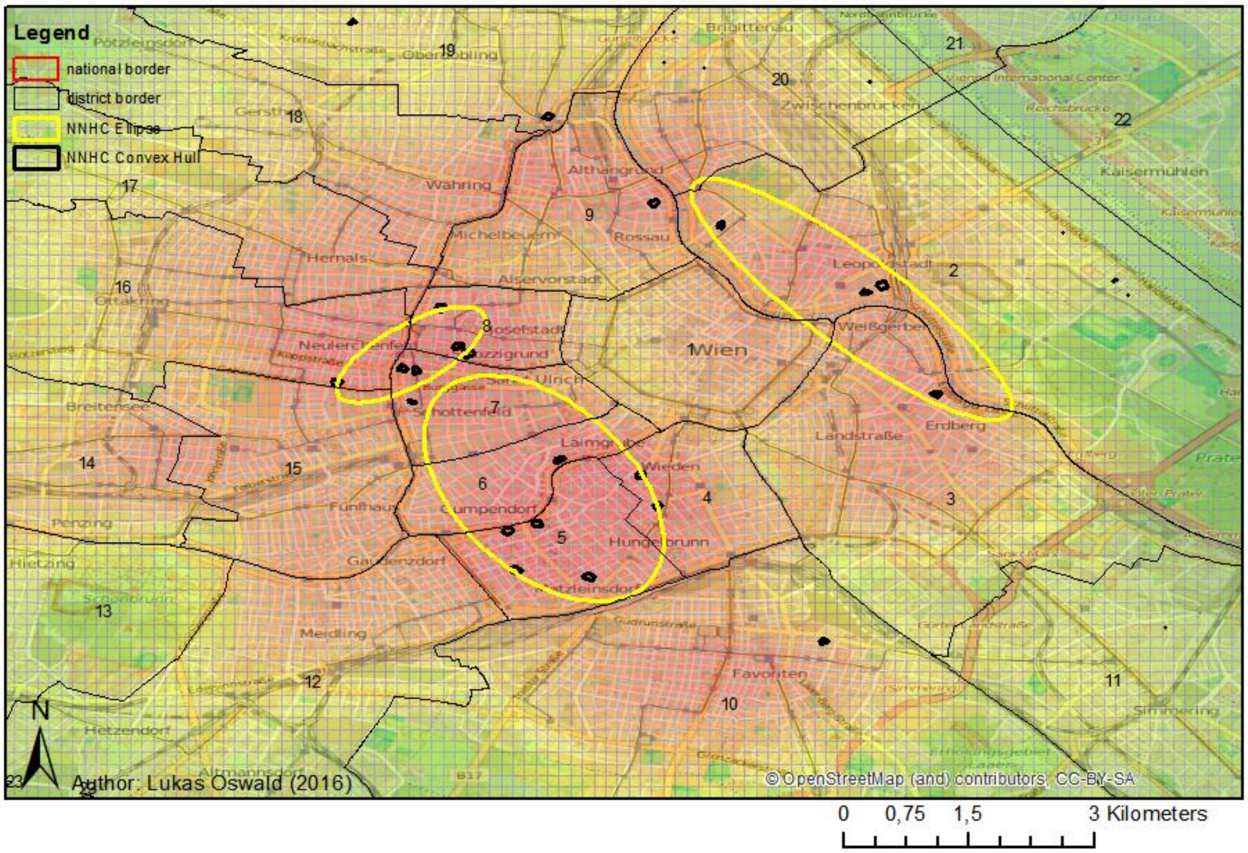

Figure 8: NNHC Convex Hulls for Apartment Burglaries between 2009 and 2015

Another Kernel Density Estimation and Nearest Neighbor Hierarchical Cluster Analysis was done similar to the CriPA result given in Table 8, where the Hit Rate for car burglaries in Vienna is nearly 90 percent. It would be interesting to know why the CriPA analysis was able to reach such a high value for car burglaries. Therefore, the Hot Spot analysis was done to show Hot Spots and crime concentrations. As shown in Figure 9, Hot Spots for car burglaries are also located in the inner city but Hot Spots are smaller compared to Hot Spots that where found for apartment burglaries. The “hottest” places are located around the 1st, 6th, and 7th districts. It can be interpreted that the high Hit Rate was reached because the crime is highly concentrated in smaller Hot Spots than in apartment burglaries Hot Spots. Maybe Hot Spots representing parking lots or a large area with free parking spaces.

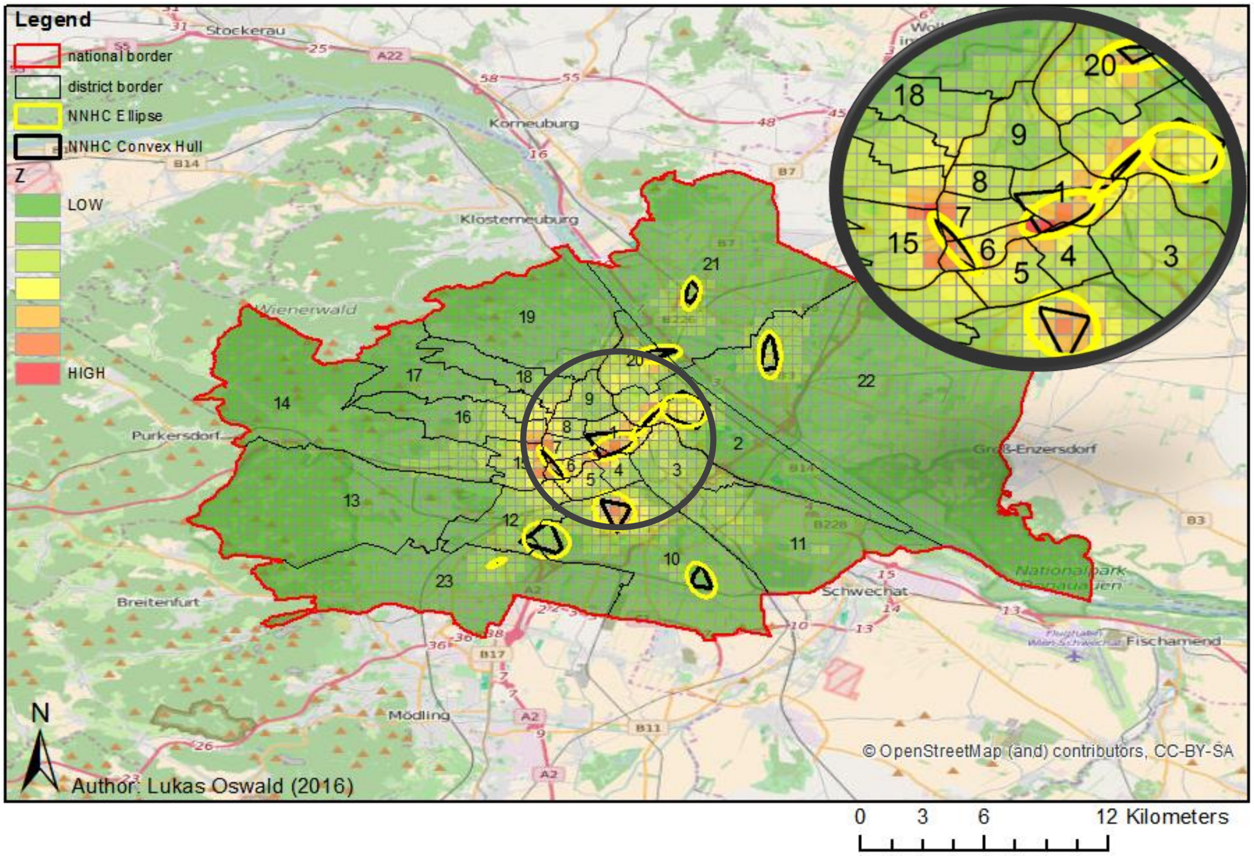

Figure 9: Nearest Neighbor Hierarchical Cluster Ellipses and Convex Hulls with the Kernel Density Estimation Map in the Background for Car Burglaries in Vienna (2009 – 2015)

4.3. Evaluation

On the one hand the evaluation of the Hot Spot and CriPA analyses was done by a visual interpretation and on the other hand different indices were applied and computed to validate the accuracy of the results. While the Hot Spot evaluation is done by a more visual evaluation approach, the emphasis of the CriPA software evaluation is on the computed indices.

As far as the CriPA result evaluation is concerned, it should be noted that there are two main easy but important indices. As shown in the previous result tables, the Hit Rate and the Decline percentage are common indices to evaluate the result.

The first main goal of this study was to find the right parameter settings to optimize the prediction process with the CriPA software. Therefore, an evaluation has to be done for each result that is based on different parameter settings. Table 12 represents the Hit Rate and Decline Rate values for three different lengths of the forecast radius. The two indices were calculated for four different districts. These four districts where on the one hand low crime areas ("Döbling" and "Donaustadt"), and on the other hand high crime areas ("Margareten" and "Josefstadt"). In areas all four districts, the Hit and Decline Rates increase with the length of the radius. The longer the radius, the better the results of the CriPA analysis. This conclusion can be made, because the Hit Rate, for example in Margareten, increased from 0.14 for a 200 meter' radius to 0.72 for a 400 meter' radius. And this trend is shown in all four districts and for both indices.

2014	Hit Rate			Decline Rate		
	200m	300m	400m	200m	300m	400m
Margareten	0,14	0,47	0,72	3,3%	11,1%	17,0%
Döbling	0,09	0,16	0,32	0,6%	1,1%	2,2%
Josefstadt	0,13	0,32	0,46	3,5%	9,1%	12,9%
Donaustadt	0,04	0,09	0,17	0,4%	0,8%	1,5%

Table 12: Evaluation for Three Different Radii Lengths Comparing the Hit Rate and the Decline Rate (Apartment Burglaries in 2014; Radius Type: ORNR)

The second investigated parameter setting deals with the radius type for the prediction area. As described in Sub Chapter 3.5.1. three different radius types exist, which can be selected in the CriPA software. These three types are shown with abbreviations "OR", "NR", and "ORNR" in the following Table 13. "OR" represents the radius around the first or original event in the observation period and "NR" is the abbreviation for the Near Repeat event of the original event in the observation period. "ORNR" is the merged area of the two previous mentioned radii. The radius size parameter in this analysis is set to 400 meters. The original assumption that the merged area will yield the most accurate result is true, because whenever a predicted crime is within the "OR" or "NR" computed circles, it also is within the merged area of both circles. Therefore, the number of hits in the "OR" circle cannot be higher than the number of hits in the "ORNR" area. But in contrast, the number of hits in the merged area can be higher than the number of hits in the circle area around the original event and also higher than the number of hits in the circle area around the Near Repeat event (see Table 13).

2014	Hit Rate			Decline Rate		
	OR	NR	ORNR	OR	NR	ORNR
Margareten	0,61	0,63	0,72	14,02%	14,02%	16,97%
Döbling	0,32	0,26	0,32	2,20%	1,83%	2,20%
Josefstadt	0,42	0,44	0,46	10,48%	11,29%	12,90%
Donaustadt	0,13	0,17	0,17	1,14%	1,50%	1,52%

Table 13: Evaluation Process for the Radius Type Comparing the Hit Rate and the Decline Rate (Apartment Burglaries in 2014; Radius Size 400 Meters)

Another important evaluation analysis concerns the increase of the Decline Rate in 2014 and 2015. This trend is presented in Table 10. A reason for that increase can be the increased precision collecting the "type of entry" description by the Federal Police. As already mentioned above the data to be analysed with CriPA are selected using five different ways of how the offender broke into the house. These five "brake-in" types have to be defined by the police. If this field is empty or the description is not precise enough, the crime will not be analysis or investigated by the CriPA software. Therefore, the police may have started to focus on a detailed description of this field in 2014 after an advice from the CriPA developer team. As shown in the left graphic in Figure 10, the number of cases categorized with a particular entry type rapidly increased between 2012 and 2014. The reason why this data category and the Decline Rate slightly decreased in 2015 can be because of the decrease in crime activities between 2014 and 2015. The diagram to the right in Figure 10 represents the CriPA results and the computed Decline Rate (also see Table 10).

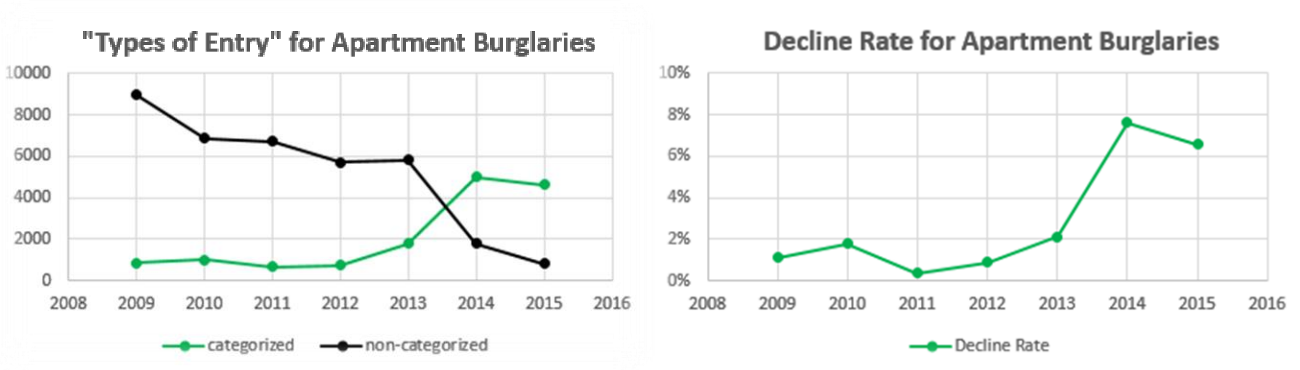

Figure 10: Comparison of the "Type of Entry" Category with the Decline Rate for Apartment Burglaries in Vienna from 2009-2015

It can be said that the police should focus on the detailed description and categorization of the "entry type" parameter. If all crimes are categorized with a more detailed code or description, it would result in better predictions using the CriPA demonstrator. In addition, the CriPA software should include a larger number of "type of entry" classes.

The evaluation for the Hot Spot analysis was done for both the KDE and the NNHC methods. To evaluate and compare their evaluation results with the CriPA results, the same indices were calculated for the same time frame and crime data. To evaluate the NNHC method and the KDE method, the Hit Rate and the PAI is calculated. After the Hot Spot evaluation, the Hit Rate is used to compare the results with the CriPA analysis results.

For the evaluation of the NNHC method, apartment burglaries for the first half of 2014 were selected. Then, the twelve first-order clusters are calculated for the selected crime locations, and later the cluster are visualized in ArcMap. After the visualization, the "Select by Location" tool is used to select and count all apartment burglaries in the second half of 2014 that fall into the Hot Spot areas (clusters) calculated with the apartment burglaries from the first half of 2014. The number of selected crimes is then used to calculate the HR and PAI indices.

Similar to the evaluation of the NNHC method, in the evaluation of the KDE also the number of apartment burglaries in 2014 is split up into two subsets. The first layer includes all apartment burglaries that happened in Vienna from January through June 2014 and the second layer includes all apartment burglaries that happened in Vienna from July through December 2014. Then, the Kernel Density Estimation Hot Spots are calculated with the January to June 2014 apartment burglaries. The quality of these Hot Spots to retrospectively forecast crime is evaluated with the July through December 2014 apartment burglaries. This method is also evaluated with the HR and the PAI. For the evaluation of the KDE Hot Spots (class with the highest density) is selected and saved as a new shape file to apply the "Select by Location" tool on the new layer. Finally, crimes can be counted and the HR and PAI is calculated.

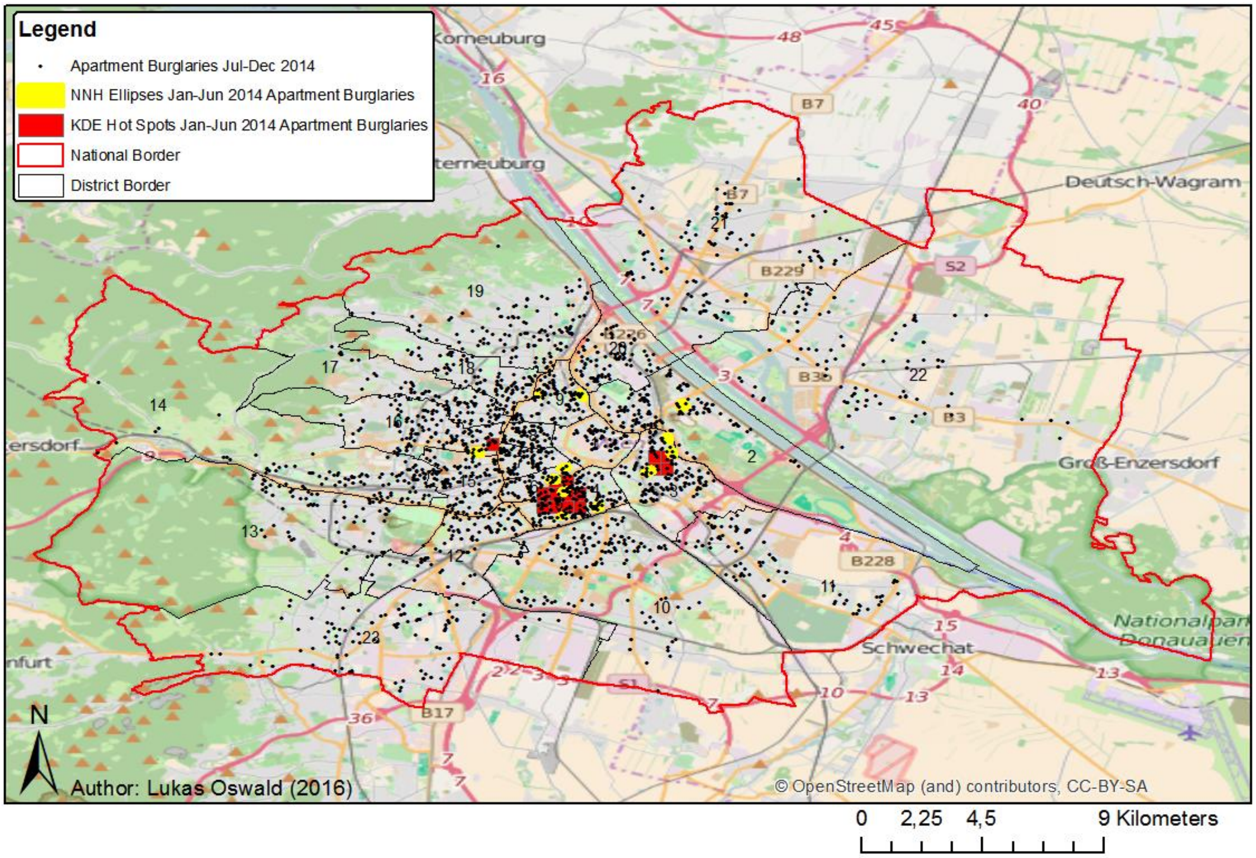

Figure 11: Hot Spots for the KDE -and NNHC Method

As is shown in Figure 11, to calculate the HR and PAI, the total size of the "hottest" KDE Hot Spots (red polygons) needs to be computed in ArcMap. Then, all future crimes (black points) can be selected that are within the Hot Spot layer.

Crime Type	Period	Year	Area	Forecast Method	Size of Hot Spot or Cluster [km²]	Crimes in predicted Area	Size of Study Area [km²]	Total Crimes	Hit Rate	PAI
apartment burglaries	July - December	2014	Vienna	KDE Hot Spots	2,1411	122	414,87	2509	4,86%	9,42
apartment burglaries	July - December	2014	Vienna	NNHC Ellipse	0,6403	61	414,87	2509	2,43%	15,75
				Merged	2,7815	183	414,87	2509	7,29%	10,88

Table 14: Hit Rate and PAI for the KDE and NNHC Methods for Apartment Burglaries from July to December 2014

The Hit Rate and PAI for the prediction quality of the Hot Spot analysis for apartment burglaries in 2014 are presented in Table 14. The result shows that the Hit Rate for the KDE is significant higher (4.86%) than the Hit Rate for the NNHC method (2,43%). If these two areas are merged and used for a prediction area, the Hit Rate would be 7.29%. Based on the PAI the NNHC Ellipse would be the best forecasting method for future crimes.

Finally, these results can be compared with the CriPA results. The CriPA results in Table 15 show that the Hit Rate for apartment burglaries in the second half of 2014 with the best parameter setting is 6.735%. The Hit Rate for the same time frame with the KDE method is 4.86% and for the NNHC method is 2.43%. Therefore, it can be said that the CriPA forecast method is somewhat better than both Hot Spot methods for apartment burglaries in 2014.

Crime Type	Period	Year	Area	Forecast Method	Radius Type	Radius [m]	NR Period [days]	Forecast Period [days]	Hits	Total Crimes	Hit Rate
apartment burglaries	July - December	2014	Vienna	CriPA	NR	400	5	3	130	2509	5,18%
apartment burglaries	July - December	2014	Vienna	CriPA	OR	400	5	3	141	2509	5,62%
apartment burglaries	July - December	2014	Vienna	CriPA	ORNR	400	5	3	169	2509	6,74%

Table 15: Hit Rate for the CriPA Analysis for Apartment Burglaries from July to December 2014

In Figure 12, the Hit Rate comparison for this evaluation is summarized. It can be said that the CriPA analysis has the highest Hit Rate for apartment burglaries in the second half of 2014. This evaluation can be applied to any other CriPA result. The findings may depend on the crime type and year. In this case, only one crime type and year was compared, but the evaluation result in this particular analysis is rather obvious.

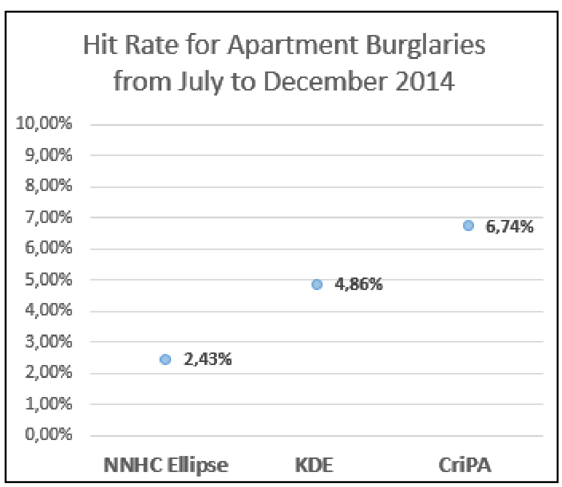

Figure 12: Hit Rate Comparison for Different Forecasting Methods for Apartment Burglaries from July to December 2014

5. Discussion

5.1. Critical Reflection

It can be said that the accuracy of the CriPA demonstrator forecasting depends on several factors. On the one hand the police can significantly influence the analysis results with their input into the Security Monitor. The quality of the data stored in the SIMO has a high level, but there are still data with rather low quality. The number of errors and empty fields needs to decrease in order for a more successful application of the CriPA software in real time. Also the description for stolen goods or the type of entry should be more precise to improve the forecasting. A further aspect which has to be considered is that the CriPA software is still in a prototype phase and parameter changes require a lot of time and work efforts. Moreover, the CriPA post-processing part takes a long time and is not easy to understand because the output is presented only in columns and rows. Maybe simple statistical values, like the number of overall predictions or hits should be directly included into the script.

5.2. Are the Applied Methods appropriate?

In general, the applied retrospective methods for crime analysis are applicable. The most difficult challenge was to work with the CriPA demonstrator. Compared to other software like CrimeStat IV or ArcGIS, the CriPA demonstrator specializes on one method, namely finding Near Repeats. It takes a lot of time to prepare crime data for the CriPA analysis and as already mentioned previously it takes a long time to interpret and present the results. Therefore, the greatest effort is spent from data preparation through the presentation of the results of the analysis when using the CriPA software. The least amount of effort has been the Hot Spot Analysis. Working with CrimeStat IV is very easy and quick to carry out. To sum up, both methods for crime analysis are applicable to the data used in this research.

5.3. Have the Expected Results and Goals of the Thesis been Reached?

Overall, the expected results and goals of this research thesis were reached. The CriPA software was tested and results were compared and evaluated. In detail, it can be said that the analysis process with the CriPA software took a long time but in the end a lot of results and tables could be presented. As a consequence, for the huge amount of effort to get these results, the evaluation and comparison is not as detailed as expected. Additionally, the Hot Spot Analysis could also show more detail. For example, a Risk Terrain Modelling (RTM) could have been done to compare its forecast results with that of the CriPA demonstrator.

6. Conclusions and Future Work

6.1. Summary

To sum up, it can be said that the Crime Predictive Analytics Demonstrator is a reliable analyse tool or software module which finds Near Repeats events easily. The results show that the predictive ability in Hot Spot areas is comparatively higher than in Cold Spots areas. The Hit Rate in Hot Spots areas, in general, varies between 35 and 75 percent. Moreover, the Decline Rate can reach 17% in concentrated crime areas (e.g. Margareten in 2014). In Cold Spot areas the predictive ability of the CriPA software is comparatively low. The maximum Hit Rate percentage in Cold Spot districts is nearly 31%, while the maximum for Hot Spot districts is 75 %. For the police this tool can be very useful because the Near Repeat approach can tell them when and where a crime can happen again in the near future. The Hot Spot analysis on the other hand only shows the police, where it is most possible to have future events but not when.

6.2. Conclusions

It can be concluded that the CriPA demonstrator can be used for crime prediction and prevention. Even when parameter settings are not optimized, significant and relevant results could be made. To improve the data quality, it would be necessary to increase cooperation with the BK. It was important to show how the CriPA demonstrator works and how each parameter setting changes the resulting predictive ability. In addition, it should be noted said that the CriPA software needs to be further developed. For example, a user interface for an easier handling and understanding would be very useful.

6.3. Future Work

This thesis research provides suggestions for different kind of future projects. On the one hand the CriPA software could be extended with the previously mentioned suggestions and on the other hand the crime data quality could be discussed and improved in the future.

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Appendix A

The Appendix includes a table that shows the distribution of crime data in Vienna for the relevant crime types and a table with the complete result values of the CriPA analyses.

Table Appendix A: Distribution of Crimes in Vienna

Zip Code	District Name	km²	car burglaries	crimes/km²	business burglaries	crimes/km²	apartment burglaries	crimes/km²	house burglaries	crimes/km²
	Vienna	414,87	81525	196,51	39541	95,31	51380	123,85	11542	27,82
1010	1. Innere Stadt	2,87	3766	1312,76	2569	895,50	1339	466,75	4	1,39
1020	2. Leopoldstadt	19,24	6292	326,99	2225	115,63	3114	161,83	165	8,57
1030	3. Landstraße	7,40	595	80,43	2308	311,99	3293	445,14	24	3,24
1040	4. Wieden	1,78	1982	1116,49	1304	734,56	1698	956,51	3	1,69
1050	5. Margareten	2,01	2252	1119,49	1538	764,55	2330	1158,26	2	0,99
1060	6. Mariahilf	1,46	2374	1631,52	1315	903,73	1449	995,82	3	2,06
1070	7. Neubau	1,61	1942	1207,53	1664	1034,67	1477	918,39	5	3,11
1080	8. Josefstadt	1,09	1422	1304,65	891	817,47	1174	1077,12	4	3,67
1090	9. Alsergrund	2,97	595	200,51	1374	463,03	1977	666,24	5	1,68
1100	10. Favoriten	31,83	9216	289,55	3588	112,73	4711	148,01	885	27,81
1110	11. Simmering	23,26	5232	224,97	1846	79,38	1770	76,11	441	18,96
1120	12. Meidling	8,10	3981	491,30	1724	212,76	2536	312,97	398	49,12
1130	13. Hietzing	37,71	1570	41,63	595	15,78	1641	43,51	850	22,54
1140	14. Penzing	33,76	3093	91,61	1522	45,08	2566	76,00	989	29,29
1150	15. Rudolfsheim	3,92	3807	971,56	2223	567,32	2402	613,00	60	15,31
1160	16. Ottakring	8,67	3492	402,64	2154	248,36	2928	337,61	386	44,51
1170	17. Hernals	11,39	2419	212,36	1065	93,49	1739	152,66	431	37,84
1180	18. Währing	6,35	2126	334,95	820	129,19	2070	326,13	237	37,34
1190	19. Döbling	24,94	2987	119,75	1009	40,45	2364	94,77	816	32,71
1200	20. Brigittenau	5,71	4252	744,60	1498	262,32	2147	375,98	66	11,56
1210	21. Floridsdorf	44,44	6013	135,30	2221	49,97	2560	57,60	1579	35,53
1220	22. Donaustadt	102,30	7538	73,69	2075	20,28	2209	21,59	2799	27,36
1230	23. Liesing	32,06	4579	142,82	2013	62,79	1886	58,82	1390	43,35

Appendix B

Table Appendix B: The Complete Result Table of the CriPA Analysis (Results for Different Districts, Radii Types, and Years)

Crime Type	Period	District	Radius Type	Radius	NR Period	Forecast Period	Predictions	Hits	Hit Rate	Offences	Decline Rate
apartment	2009	Döbling	OR	400	5	3	1	0	0,00	372	0,00%
apartment	2009	Döbling	ORNR	400	5	3	1	0	0,00	372	0,00%
apartment	2009	Döbling	NR	400	5	3	0	0	-	372	0,00%
apartment	2010	Döbling	NR	400	5	3	3	0	0,00	325	0,00%
apartment	2010	Döbling	OR	400	5	3	3	0	0,00	325	0,00%
apartment	2010	Döbling	ORNR	400	5	3	4	0	0,00	325	0,00%
apartment	2011	Döbling	NR	400	5	3	0	0	-	277	0,00%
apartment	2011	Döbling	OR	400	5	3	0	0	-	277	0,00%
apartment	2011	Döbling	ORNR	400	5	3	0	0	-	277	0,00%
apartment	2012	Döbling	NR	400	5	3	0	0	-	262	0,00%
apartment	2012	Döbling	OR	400	5	3	0	0	-	262	0,00%
apartment	2012	Döbling	ORNR	400	5	3	0	0	-	262	0,00%
apartment	2013	Döbling	NR	400	5	3	6	3	0,50	305	0,98%
apartment	2013	Döbling	OR	400	5	3	6	3	0,50	305	0,98%
apartment	2013	Döbling	ORNR	400	5	3	6	3	0,50	305	0,98%
apartment	2014	Döbling	NR	400	5	3	19	5	0,26	273	1,83%
apartment	2014	Döbling	ORNR	400	5	3	19	6	0,32	273	2,20%
apartment	2014	Döbling	OR	400	5	3	18	6	0,33	273	2,20%
apartment	2015	Döbling	OR	400	5	3	24	2	0,08	176	1,14%
apartment	2015	Döbling	NR	400	5	3	25	4	0,16	176	2,27%
apartment	2015	Döbling	ORNR	400	5	3	25	6	0,24	176	3,41%
apartment	total	Döbling	OR	400	5	3	52	11	0,21	1990	0,55%

Crime Type	Period	District	Radius Type	Radius	NR Period	Forecast Period	Predictions	Hits	Hit Rate	Offences	Decline Rate
apartment	2010	Donaustadt	ORNR	400	5	3	0	0	-	247	0,00%
apartment	2011	Donaustadt	NR	400	5	3	0	0	-	257	0,00%
apartment	2011	Donaustadt	OR	400	5	3	0	0	-	257	0,00%
apartment	2011	Donaustadt	ORNR	400	5	3	0	0	-	257	0,00%
apartment	2012	Donaustadt	NR	400	5	3	0	0	-	252	0,00%
apartment	2012	Donaustadt	OR	400	5	3	0	0	-	252	0,00%
apartment	2012	Donaustadt	ORNR	400	5	3	0	0	-	252	0,00%
apartment	2013	Donaustadt	NR	400	5	3	0	0	-	229	0,00%
apartment	2013	Donaustadt	OR	400	5	3	0	0	-	229	0,00%
apartment	2013	Donaustadt	ORNR	400	5	3	0	0	-	229	0,00%
apartment	2014	Donaustadt	NR	400	5	3	23	4	0,17	263	1,52%
apartment	2014	Donaustadt	OR	400	5	3	23	3	0,13	263	1,14%
apartment	2014	Donaustadt	ORNR	400	5	3	23	4	0,17	263	1,52%
apartment	2015	Donaustadt	NR	400	5	3	11	3	0,27	179	1,68%
apartment	2015	Donaustadt	OR	400	5	3	11	3	0,27	179	1,68%
apartment	2015	Donaustadt	ORNR	400	5	3	11	3	0,27	179	1,68%
apartment	total	Donaustadt	NR	400	5	3	34	7	0,21	1850	0,38%
apartment	total	Donaustadt	OR	400	5	3	34	6	0,18	1850	0,32%
apartment	total	Donaustadt	ORNR	400	5	3	34	7	0,21	1850	0,38%
apartment	2009	Josefstadt	NR	400	5	3	4	0	0,00	187	0,00%
apartment	2009	Josefstadt	OR	400	5	3	3	0	0,00	187	0,00%
apartment	2009	Josefstadt	ORNR	400	5	3	5	0	0,00	187	0,00%
apartment	2010	Josefstadt	NR	400	5	3	14	11	0,79	169	6,51%
apartment	2010	Josefstadt	OR	400	5	3	14	10	0,71	169	5,92%
apartment	2010	Josefstadt	ORNR	400	5	3	15	11	0,73	169	6,51%
apartment	2011	Josefstadt	NR	400	5	3	3	1	0,33	147	0,68%
apartment	2011	Josefstadt	OR	400	5	3	3	1	0,33	147	0,68%
apartment	2011	Josefstadt	ORNR	400	5	3	3	1	0,33	147	0,68%
apartment	2012	Josefstadt	NR	400	5	3	6	4	0,67	120	3,33%
apartment	2012	Josefstadt	OR	400	5	3	6	6	1,00	120	5,00%
apartment	2012	Josefstadt	ORNR	400	5	3	7	7	1,00	120	5,83%
apartment	2013	Josefstadt	NR	400	5	3	7	3	0,43	144	2,08%
apartment	2013	Josefstadt	OR	400	5	3	5	1	0,20	144	0,69%
apartment	2013	Josefstadt	ORNR	400	5	3	7	3	0,43	144	2,08%
apartment	2014	Josefstadt	NR	400	5	3	32	14	0,44	124	11,29%
apartment	2014	Josefstadt	OR	400	5	3	31	13	0,42	124	10,48%
apartment	2014	Josefstadt	ORNR	400	5	3	35	16	0,46	124	12,90%
apartment	2015	Josefstadt	NR	400	5	3	28	9	0,32	119	7,56%
apartment	2015	Josefstadt	OR	400	5	3	32	11	0,34	119	9,24%
apartment	2015	Josefstadt	ORNR	400	5	3	34	15	0,44	119	12,61%
apartment	total	Josefstadt	NR	400	5	3	94	42	0,45	1010	4,16%
apartment	total	Josefstadt	OR	400	5	3	94	42	0,45	1010	4,16%
apartment	total	Josefstadt	ORNR	400	5	3	106	53	0,50	1010	5,25%
apartment	2009	Margareten	OR	400	5	3	7	6	0,86	357	1,68%
apartment	2009	Margareten	NR	400	5	3	6	11	1,83	357	3,08%
apartment	2009	Margareten	ORNR	400	5	3	7	13	1,86	357	3,64%
apartment	2010	Margareten	NR	400	5	3	9	3	0,33	316	0,95%
apartment	2010	Margareten	ORNR	400	5	3	12	7	0,58	316	2,22%
apartment	2010	Margareten	OR	400	5	3	13	16	1,23	316	5,06%
apartment	2011	Margareten	NR	400	5	3	3	0	0,00	278	0,00%
apartment	2011	Margareten	OR	400	5	3	4	0	0,00	278	0,00%
apartment	2011	Margareten	ORNR	400	5	3	4	0	0,00	278	0,00%
apartment	2012	Margareten	NR	400	5	3	5	4	0,80	183	2,19%
apartment	2012	Margareten	OR	400	5	3	6	5	0,83	183	2,73%
apartment	2012	Margareten	ORNR	400	5	3	6	5	0,83	183	2,73%
apartment	2013	Margareten	OR	400	5	3	12	3	0,25	296	1,01%
apartment	2013	Margareten	ORNR	400	5	3	13	6	0,46	296	2,03%
apartment	2013	Margareten	NR	400	5	3	10	5	0,50	296	1,69%
apartment	2014	Margareten	OR	400	5	3	62	38	0,61	271	14,02%
apartment	2014	Margareten	NR	400	5	3	60	38	0,63	271	14,02%
apartment	2014	Margareten	ORNR	400	5	3	64	46	0,72	271	16,97%
apartment	2015	Margareten	OR	400	5	3	39	9	0,23	193	4,66%
apartment	2015	Margareten	NR	400	5	3	33	10	0,30	193	5,18%
apartment	2015	Margareten	ORNR	400	5	3	41	13	0,32	193	6,74%
apartment	total	Margareten	OR	400	5	3	143	77	0,54	1894	4,07%
apartment	total	Margareten	NR	400	5	3	126	71	0,56	1894	3,75%
apartment	total	Margareten	ORNR	400	5	3	147	100	0,68	1894	5,28%
apartment	2009	Vienna	OR	400	5	3	88	78	0,89	8337	0,94%
apartment	2009	Vienna	NR	400	5	3	88	82	0,93	8337	0,98%
apartment	2009	Vienna	ORNR	400	5	3	88	91	1,03	8337	1,09%
apartment	2010	Vienna	NR	400	5	3	141	101	0,72	6619	1,53%
apartment	2010	Vienna	OR	400	5	3	141	106	0,75	6619	1,60%

Crime Type	Period	District	Radius Type	Radius	NR Period	Forecast Period	Predictions	Hits	Hit Rate	Offences	Decline Rate
apartment	2010	Vienna	ORNR	400	5	3	148	119	0,80	6619	1,80%
apartment	2011	Vienna	OR	400	5	3	41	16	0,39	5997	0,27%
apartment	2011	Vienna	NR	400	5	3	41	20	0,49	5997	0,33%
apartment	2011	Vienna	ORNR	400	5	3	41	22	0,54	5997	0,37%
apartment	2012	Vienna	NR	400	5	3	72	38	0,53	5214	0,73%
apartment	2012	Vienna	OR	400	5	3	72	40	0,56	5214	0,77%
apartment	2012	Vienna	ORNR	400	5	3	72	47	0,65	5214	0,90%
apartment	2013	Vienna	OR	400	5	3	195	107	0,55	6449	1,66%
apartment	2013	Vienna	NR	400	5	3	195	115	0,59	6449	1,78%
apartment	2013	Vienna	ORNR	400	5	3	194	137	0,71	6449	2,12%
apartment	2014	Vienna	NR	400	5	3	840	342	0,41	5583	6,13%
apartment	2014	Vienna	OR	400	5	3	830	366	0,44	5583	6,56%
apartment	2014	Vienna	ORNR	400	5	3	823	426	0,52	5583	7,63%
apartment	2015	Vienna	NR	400	5	3	731	241	0,33	4480	5,38%
apartment	2015	Vienna	OR	400	5	3	730	251	0,34	4480	5,60%
apartment	2015	Vienna	ORNR	400	5	3	724	295	0,41	4480	6,58%
apartment	total	Vienna	NR	400	5	3	2108	939	0,45	42679	2,20%
apartment	total	Vienna	OR	400	5	3	2097	964	0,46	42679	2,26%
apartment	total	Vienna	ORNR	400	5	3	2090	1137	0,54	42679	2,66%
business	2009	Döbling	NR	400	5	3	0	0	-	182	0,00%
business	2009	Döbling	OR	400	5	3	0	0	-	182	0,00%
business	2009	Döbling	ORNR	400	5	3	0	0	-	182	0,00%
business	2010	Döbling	NR	400	5	3	0	0	-	212	0,00%
business	2010	Döbling	OR	400	5	3	0	0	-	212	0,00%
business	2010	Döbling	ORNR	400	5	3	0	0	-	212	0,00%
business	2011	Döbling	NR	400	5	3	0	0	-	232	0,00%
business	2011	Döbling	OR	400	5	3	0	0	-	232	0,00%
business	2011	Döbling	ORNR	400	5	3	0	0	-	232	0,00%
business	2012	Döbling	NR	400	5	3	0	0	-	237	0,00%
business	2012	Döbling	OR	400	5	3	0	0	-	237	0,00%
business	2012	Döbling	ORNR	400	5	3	0	0	-	237	0,00%
business	2013	Döbling	NR	400	5	3	1	0	0,00	260	0,00%
business	2013	Döbling	OR	400	5	3	1	0	0,00	260	0,00%
business	2013	Döbling	ORNR	400	5	3	1	0	0,00	260	0,00%
business	2014	Döbling	NR	400	5	3	15	4	0,27	165	2,42%
business	2014	Döbling	OR	400	5	3	14	5	0,36	165	3,03%
business	2014	Döbling	ORNR	400	5	3	16	6	0,38	165	3,64%
business	2015	Döbling	NR	400	5	3	14	10	0,71	152	6,58%
business	2015	Döbling	OR	400	5	3	15	9	0,60	152	5,92%
business	2015	Döbling	ORNR	400	5	3	15	10	0,67	152	6,58%
business	total	Döbling	NR	400	5	3	30	14	0,47	1440	0,97%
business	total	Döbling	OR	400	5	3	30	14	0,47	1440	0,97%
business	total	Döbling	ORNR	400	5	3	32	16	0,50	1440	1,11%
business	2009	Hietzing	NR	400	5	3	0	0	-	99	0,00%
business	2009	Hietzing	OR	400	5	3	0	0	-	99	0,00%
business	2009	Hietzing	ORNR	400	5	3	0	0	-	99	0,00%
business	2010	Hietzing	NR	400	5	3	0	0	-	107	0,00%
business	2010	Hietzing	OR	400	5	3	0	0	-	107	0,00%
business	2010	Hietzing	ORNR	400	5	3	0	0	-	107	0,00%
business	2011	Hietzing	NR	400	5	3	0	0	-	82	0,00%
business	2011	Hietzing	OR	400	5	3	0	0	-	82	0,00%
business	2011	Hietzing	ORNR	400	5	3	0	0	-	82	0,00%
business	2012	Hietzing	NR	400	5	3	0	0	-	63	0,00%
business	2012	Hietzing	OR	400	5	3	0	0	-	63	0,00%
business	2012	Hietzing	ORNR	400	5	3	0	0	-	63	0,00%
business	2013	Hietzing	NR	400	5	3	1	0	0,00	53	0,00%
business	2013	Hietzing	OR	400	5	3	1	0	0,00	53	0,00%
business	2013	Hietzing	ORNR	400	5	3	1	0	0,00	53	0,00%
business	2014	Hietzing	NR	400	5	3	16	4	0,25	86	4,65%
business	2014	Hietzing	OR	400	5	3	16	4	0,25	86	4,65%
business	2014	Hietzing	ORNR	400	5	3	16	4	0,25	86	4,65%
business	2015	Hietzing	NR	400	5	3	7	1	0,14	56	1,79%
business	2015	Hietzing	OR	400	5	3	8	1	0,13	56	1,79%
business	2015	Hietzing	ORNR	400	5	3	8	1	0,13	56	1,79%
business	total	Hietzing	NR	400	5	3	24	5	0,21	546	0,92%
business	total	Hietzing	OR	400	5	3	25	5	0,20	546	0,92%
business	total	Hietzing	ORNR	400	5	3	25	5	0,20	546	0,92%
business	2009	Margareten	NR	400	5	3	0	0	-	181	0,00%
business	2009	Margareten	OR	400	5	3	0	0	-	181	0,00%
business	2009	Margareten	ORNR	400	5	3	0	0	-	181	0,00%
business	2010	Margareten	NR	400	5	3	3	2	0,67	178	1,12%
business	2010	Margareten	OR	400	5	3	3	2	0,67	178	1,12%

Crime Type	Period	District	Radius Type	Radius	NR Period	Forecast Period	Predictions	Hits	Hit Rate	Offences	Decline Rate
business	2010	Margareten	ORNR	400	5	3	3	2	0,67	178	1,12%
business	2011	Margareten	NR	400	5	3	6	1	0,17	104	0,96%
business	2011	Margareten	OR	400	5	3	6	1	0,17	104	0,96%
business	2011	Margareten	ORNR	400	5	3	6	1	0,17	104	0,96%
business	2012	Margareten	NR	400	5	3	10	8	0,80	106	7,55%
business	2012	Margareten	OR	400	5	3	10	8	0,80	106	7,55%
business	2012	Margareten	ORNR	400	5	3	10	8	0,80	106	7,55%
business	2013	Margareten	NR	400	5	3	1	2	2,00	114	1,75%
business	2013	Margareten	OR	400	5	3	1	2	2,00	114	1,75%
business	2013	Margareten	ORNR	400	5	3	1	2	2,00	114	1,75%
business	2014	Margareten	NR	400	5	3	40	13	0,33	127	10,24%
business	2014	Margareten	OR	400	5	3	39	15	0,38	127	11,81%
business	2014	Margareten	ORNR	400	5	3	47	16	0,34	127	12,60%
business	2015	Margareten	NR	400	5	3	29	8	0,28	104	7,69%
business	2015	Margareten	OR	400	5	3	34	12	0,35	104	11,54%
business	2015	Margareten	ORNR	400	5	3	37	12	0,32	104	11,54%
business	total	Margareten	NR	400	5	3	89	34	0,38	914	3,72%
business	total	Margareten	OR	400	5	3	93	40	0,43	914	4,38%
business	total	Margareten	ORNR	400	5	3	104	41	0,39	914	4,49%
business	2009	Neubau	NR	400	5	3	3	1	0,33	320	0,31%
business	2009	Neubau	OR	400	5	3	2	0	0,00	320	0,00%
business	2009	Neubau	ORNR	400	5	3	3	1	0,33	320	0,31%
business	2010	Neubau	NR	400	5	3	0	0	-	226	0,00%
business	2010	Neubau	OR	400	5	3	0	0	-	226	0,00%
business	2010	Neubau	ORNR	400	5	3	0	0	-	226	0,00%
business	2011	Neubau	NR	400	5	3	1	0	0,00	164	0,00%
business	2011	Neubau	OR	400	5	3	1	1	1,00	164	0,61%
business	2011	Neubau	ORNR	400	5	3	1	1	1,00	164	0,61%
business	2012	Neubau	NR	400	5	3	7	2	0,29	244	0,82%
business	2012	Neubau	OR	400	5	3	7	1	0,14	244	0,41%
business	2012	Neubau	ORNR	400	5	3	7	2	0,29	244	0,82%
business	2013	Neubau	NR	400	5	3	2	0	0,00	254	0,00%
business	2013	Neubau	OR	400	5	3	3	0	0,00	254	0,00%
business	2013	Neubau	ORNR	400	5	3	3	0	0,00	254	0,00%
business	2014	Neubau	NR	400	5	3	36	15	0,42	174	8,62%
business	2014	Neubau	OR	400	5	3	38	17	0,45	174	9,77%
business	2014	Neubau	ORNR	400	5	3	45	23	0,51	174	13,22%
business	2015	Neubau	NR	400	5	3	36	20	0,56	155	12,90%
business	2015	Neubau	OR	400	5	3	38	21	0,55	155	13,55%
business	2015	Neubau	ORNR	400	5	3	42	29	0,69	155	18,71%
business	total	Neubau	NR	400	5	3	85	38	0,45	1537	2,47%
business	total	Neubau	OR	400	5	3	89	40	0,45	1537	2,60%
business	total	Neubau	ORNR	400	5	3	101	56	0,55	1537	3,64%
business	2009	Vienna	NR	400	5	3	20	15	0,75	6522	0,23%
business	2009	Vienna	OR	400	5	3	20	16	0,80	6522	0,25%
business	2009	Vienna	ORNR	400	5	3	20	16	0,80	6522	0,25%
business	2010	Vienna	NR	400	5	3	33	23	0,70	6057	0,38%
business	2010	Vienna	OR	400	5	3	33	18	0,55	6057	0,30%
business	2010	Vienna	ORNR	400	5	3	33	26	0,79	6057	0,43%
business	2011	Vienna	NR	400	5	3	16	1	0,06	4860	0,02%
business	2011	Vienna	OR	400	5	3	16	2	0,13	4860	0,04%
business	2011	Vienna	ORNR	400	5	3	16	2	0,13	4860	0,04%
business	2012	Vienna	NR	400	5	3	40	31	0,78	5136	0,60%
business	2012	Vienna	OR	400	5	3	40	34	0,85	5136	0,66%
business	2012	Vienna	ORNR	400	5	3	40	36	0,90	5136	0,70%
business	2013	Vienna	NR	400	5	3	44	18	0,41	5296	0,34%
business	2013	Vienna	OR	400	5	3	44	18	0,41	5296	0,34%
business	2013	Vienna	ORNR	400	5	3	44	20	0,45	5296	0,38%
business	2014	Vienna	NR	400	5	3	686	396	0,58	4586	8,63%
business	2014	Vienna	OR	400	5	3	683	420	0,61	4586	9,16%
business	2014	Vienna	ORNR	400	5	3	665	498	0,75	4586	10,86%
business	2015	Vienna	NR	400	5	3	639	260	0,41	4011	6,48%
business	2015	Vienna	OR	400	5	3	638	284	0,45	4011	7,08%
business	2015	Vienna	ORNR	400	5	3	630	335	0,53	4011	8,35%
business	total	Vienna	NR	400	5	3	1478	744	0,50	36468	2,04%
business	total	Vienna	OR	400	5	3	1474	792	0,54	36468	2,17%
business	total	Vienna	ORNR	400	5	3	1448	933	0,64	36468	2,56%
car burglary	2009	Döbling	NR	400	5	3	0	0	-	828	0,00%
car burglary	2009	Döbling	OR	400	5	3	0	0	-	828	0,00%
car burglary	2009	Döbling	ORNR	400	5	3	0	0	-	828	0,00%
car burglary	2010	Döbling	OR	400	5	3	8	3	0,38	628	0,48%
car burglary	2010	Döbling	NR	400	5	3	10	6	0,60	628	0,96%

Crime Type	Period	District	Radius Type	Radius	NR Period	Forecast Period	Predictions	Hits	Hit Rate	Offences	Decline Rate
car burglary	2010	Döbling	ORNR	400	5	3	10	6	0,60	628	0,96%
car burglary	2011	Döbling	NR	400	5	3	1	0	0,00	606	0,00%
car burglary	2011	Döbling	OR	400	5	3	1	0	0,00	606	0,00%
car burglary	2011	Döbling	ORNR	400	5	3	1	0	0,00	606	0,00%
car burglary	2012	Döbling	NR	400	5	3	0	0	-	601	0,00%
car burglary	2012	Döbling	OR	400	5	3	0	0	-	601	0,00%
car burglary	2012	Döbling	ORNR	400	5	3	0	0	-	601	0,00%
car burglary	2013	Döbling	NR	400	5	3	0	0	-	674	0,00%
car burglary	2013	Döbling	OR	400	5	3	0	0	-	674	0,00%
car burglary	2013	Döbling	ORNR	400	5	3	0	0	-	674	0,00%
car burglary	2014	Döbling	NR	400	5	3	1	0	0,00	637	0,00%
car burglary	2014	Döbling	OR	400	5	3	1	0	0,00	637	0,00%
car burglary	2014	Döbling	ORNR	400	5	3	1	0	0,00	637	0,00%
car burglary	2015	Döbling	NR	400	5	3	0	0	-	631	0,00%
car burglary	2015	Döbling	OR	400	5	3	0	0	-	631	0,00%
car burglary	2015	Döbling	ORNR	400	5	3	0	0	-	631	0,00%
car burglary	total	Döbling	OR	400	5	3	10	3	0,30	1995	0,15%
car burglary	total	Döbling	NR	400	5	3	12	6	0,50	1995	0,30%
car burglary	total	Döbling	ORNR	400	5	3	12	6	0,50	1995	0,30%
car burglary	2009	Hietzing	NR	400	5	3	0	0	-	207	0,00%
car burglary	2009	Hietzing	OR	400	5	3	0	0	-	207	0,00%
car burglary	2009	Hietzing	ORNR	400	5	3	0	0	-	207	0,00%
car burglary	2010	Hietzing	NR	400	5	3	1	0	0,00	208	0,00%
car burglary	2010	Hietzing	OR	400	5	3	1	0	0,00	208	0,00%
car burglary	2010	Hietzing	ORNR	400	5	3	1	0	0,00	208	0,00%
car burglary	2011	Hietzing	NR	400	5	3	2	0	0,00	143	0,00%
car burglary	2011	Hietzing	OR	400	5	3	3	0	0,00	143	0,00%
car burglary	2011	Hietzing	ORNR	400	5	3	3	0	0,00	143	0,00%
car burglary	2012	Hietzing	NR	400	5	3	0	0	-	115	0,00%
car burglary	2012	Hietzing	OR	400	5	3	0	0	-	115	0,00%
car burglary	2012	Hietzing	ORNR	400	5	3	0	0	-	115	0,00%
car burglary	2013	Hietzing	NR	400	5	3	0	0	-	88	0,00%
car burglary	2013	Hietzing	OR	400	5	3	0	0	-	88	0,00%
car burglary	2013	Hietzing	ORNR	400	5	3	0	0	-	88	0,00%
car burglary	2014	Hietzing	NR	400	5	3	0	0	-	66	0,00%
car burglary	2014	Hietzing	OR	400	5	3	0	0	-	66	0,00%
car burglary	2014	Hietzing	ORNR	400	5	3	0	0	-	66	0,00%
car burglary	2015	Hietzing	NR	400	5	3	0	0	-	61	0,00%
car burglary	2015	Hietzing	OR	400	5	3	0	0	-	61	0,00%
car burglary	2015	Hietzing	ORNR	400	5	3	0	0	-	61	0,00%
car burglary	total	Hietzing	NR	400	5	3	3	0	0,00	888	0,00%
car burglary	total	Hietzing	OR	400	5	3	4	0	0,00	888	0,00%
car burglary	total	Hietzing	ORNR	400	5	3	4	0	0,00	888	0,00%
car burglary	2009	Margareten	OR	400	5	3	6	1	0,17	936	0,11%
car burglary	2009	Margareten	ORNR	400	5	3	6	1	0,17	936	0,11%
car burglary	2009	Margareten	NR	400	5	3	3	1	0,33	936	0,11%
car burglary	2010	Margareten	OR	400	5	3	2	0	0,00	866	0,00%
car burglary	2010	Margareten	NR	400	5	3	4	1	0,25	866	0,12%
car burglary	2010	Margareten	ORNR	400	5	3	4	1	0,25	866	0,12%
car burglary	2011	Margareten	NR	400	5	3	5	2	0,40	729	0,27%
car burglary	2011	Margareten	OR	400	5	3	6	3	0,50	729	0,41%
car burglary	2011	Margareten	ORNR	400	5	3	6	3	0,50	729	0,41%
car burglary	2012	Margareten	NR	400	5	3	1	0	0,00	598	0,00%
car burglary	2012	Margareten	OR	400	5	3	1	0	0,00	598	0,00%
car burglary	2012	Margareten	ORNR	400	5	3	1	0	0,00	598	0,00%
car burglary	2013	Margareten	OR	400	5	3	1	0	0,00	673	0,00%
car burglary	2013	Margareten	NR	400	5	3	2	1	0,50	673	0,15%
car burglary	2013	Margareten	ORNR	400	5	3	2	1	0,50	673	0,15%
car burglary	2014	Margareten	NR	400	5	3	0	0	-	713	0,00%
car burglary	2014	Margareten	OR	400	5	3	0	0	-	713	0,00%
car burglary	2014	Margareten	ORNR	400	5	3	0	0	-	713	0,00%
car burglary	2015	Margareten	OR	400	5	3	2	0	0,00	669	0,00%
car burglary	2015	Margareten	NR	400	5	3	2	1	0,50	669	0,15%
car burglary	2015	Margareten	ORNR	400	5	3	2	1	0,50	669	0,15%
car burglary	total	Margareten	OR	400	5	3	18	4	0,22	2574	0,16%
car burglary	total	Margareten	ORNR	400	5	3	21	7	0,33	2574	0,27%
car burglary	total	Margareten	NR	400	5	3	17	6	0,35	2574	0,23%
car burglary	2009	Mariahilf	NR	400	5	3	7	4	0,57	401	1,00%
car burglary	2009	Mariahilf	OR	400	5	3	6	2	0,33	401	0,50%
car burglary	2009	Mariahilf	ORNR	400	5	3	9	4	0,44	401	1,00%
car burglary	2010	Mariahilf	NR	400	5	3	4	2	0,50	246	0,81%
car burglary	2010	Mariahilf	OR	400	5	3	8	4	0,50	246	1,63%

Crime Type	Period	District	Radius Type	Radius	NR Period	Forecast Period	Predictions	Hits	Hit Rate	Offences	Decline Rate
car burglary	2010	Mariahilf	ORNR	400	5	3	8	4	0,50	246	1,63%
car burglary	2011	Mariahilf	NR	400	5	3	2	1	0,50	167	0,60%
car burglary	2011	Mariahilf	OR	400	5	3	1	0	0,00	167	0,00%
car burglary	2011	Mariahilf	ORNR	400	5	3	2	1	0,50	167	0,60%
car burglary	2012	Mariahilf	NR	400	5	3	3	2	0,67	176	1,14%
car burglary	2012	Mariahilf	OR	400	5	3	4	3	0,75	176	1,70%
car burglary	2012	Mariahilf	ORNR	400	5	3	4	3	0,75	176	1,70%
car burglary	2013	Mariahilf	NR	400	5	3	4	2	0,50	220	0,91%
car burglary	2013	Mariahilf	OR	400	5	3	4	1	0,25	220	0,45%
car burglary	2013	Mariahilf	ORNR	400	5	3	5	2	0,40	220	0,91%
car burglary	2014	Mariahilf	NR	400	5	3	1	0	0,00	194	0,00%
car burglary	2014	Mariahilf	OR	400	5	3	1	0	0,00	194	0,00%
car burglary	2014	Mariahilf	ORNR	400	5	3	1	0	0,00	194	0,00%
car burglary	2015	Mariahilf	NR	400	5	3	1	3	3,00	260	1,15%
car burglary	2015	Mariahilf	OR	400	5	3	1	3	3,00	260	1,15%
car burglary	2015	Mariahilf	ORNR	400	5	3	1	3	3,00	260	1,15%
car burglary	total	Mariahilf	NR	400	5	3	22	14	0,64	1664	0,84%
car burglary	total	Mariahilf	OR	400	5	3	25	13	0,52	1664	0,78%
car burglary	total	Mariahilf	ORNR	400	5	3	30	17	0,57	1664	1,02%
car burglary	2009	Vienna	ORNR	400	5	3	73	95	1,30	15549	0,61%
car burglary	2009	Vienna	NR	400	5	3	73	80	1,10	15549	0,51%
car burglary	2009	Vienna	OR	400	5	3	73	86	1,18	15549	0,55%
car burglary	2010	Vienna	ORNR	400	5	3	95	70	0,74	12145	0,58%
car burglary	2010	Vienna	OR	400	5	3	96	53	0,55	12145	0,44%
car burglary	2010	Vienna	NR	400	5	3	96	66	0,69	12145	0,54%
car burglary	2011	Vienna	ORNR	400	5	3	58	36	0,62	9537	0,38%
car burglary	2011	Vienna	NR	400	5	3	58	30	0,52	9537	0,31%
car burglary	2011	Vienna	OR	400	5	3	58	33	0,57	9537	0,35%
car burglary	2012	Vienna	ORNR	400	5	3	27	29	1,07	7937	0,37%
car burglary	2012	Vienna	NR	400	5	3	27	23	0,85	7937	0,29%
car burglary	2012	Vienna	OR	400	5	3	27	25	0,93	7937	0,31%
car burglary	2013	Vienna	ORNR	400	5	3	9	7	0,78	8787	0,08%
car burglary	2013	Vienna	NR	400	5	3	9	5	0,56	8787	0,06%
car burglary	2013	Vienna	OR	400	5	3	9	7	0,78	8787	0,08%
car burglary	2014	Vienna	NR	400	5	3	3	0	0,00	8737	0,00%
car burglary	2014	Vienna	OR	400	5	3	3	0	0,00	8737	0,00%
car burglary	2014	Vienna	ORNR	400	5	3	3	0	0,00	8737	0,00%
car burglary	2015	Vienna	ORNR	400	5	3	6	4	0,67	8141	0,05%
car burglary	2015	Vienna	OR	400	5	3	6	3	0,50	8141	0,04%
car burglary	2015	Vienna	NR	400	5	3	6	4	0,67	8141	0,05%
car burglary	total	Vienna	ORNR	400	5	3	271	241	0,89	68223	0,35%
car burglary	total	Vienna	OR	400	5	3	272	207	0,76	68223	0,30%
car burglary	total	Vienna	NR	400	5	3	272	208	0,76	68223	0,30%
house	2009	Döbling	NR	400	5	3	0	0	-	0	-
house	2009	Döbling	OR	400	5	3	0	0	-	0	-
house	2009	Döbling	ORNR	400	5	3	0	0	-	0	-
house	2010	Döbling	NR	400	5	3	0	0	-	0	-
house	2010	Döbling	OR	400	5	3	0	0	-	0	-
house	2010	Döbling	ORNR	400	5	3	0	0	-	0	-
house	2011	Döbling	NR	400	5	3	0	0	-	1	0,00%
house	2011	Döbling	OR	400	5	3	0	0	-	1	0,00%
house	2011	Döbling	ORNR	400	5	3	0	0	-	1	0,00%
house	2012	Döbling	NR	400	5	3	0	0	-	0	-
house	2012	Döbling	OR	400	5	3	0	0	-	0	-
house	2012	Döbling	ORNR	400	5	3	0	0	-	0	-
house	2013	Döbling	NR	400	5	3	0	0	-	0	-
house	2013	Döbling	OR	400	5	3	0	0	-	0	-
house	2013	Döbling	ORNR	400	5	3	0	0	-	0	-
house	2014	Döbling	NR	400	5	3	0	0	-	0	-
house	2014	Döbling	OR	400	5	3	0	0	-	0	-
house	2014	Döbling	ORNR	400	5	3	0	0	-	0	-
house	2015	Döbling	NR	400	5	3	3	0	0,00	0	-
house	2015	Döbling	OR	400	5	3	3	0	0,00	0	-
house	2015	Döbling	ORNR	400	5	3	3	0	0,00	0	-
house	total	Döbling	NR	400	5	3	3	0	0,00	1	0,00%
house	total	Döbling	OR	400	5	3	3	0	0,00	1	0,00%
house	total	Döbling	ORNR	400	5	3	3	0	0,00	1	0,00%
house	2009	Margareten	NR	400	5	3	0	0	-	114	0,00%
house	2009	Margareten	OR	400	5	3	0	0	-	114	0,00%
house	2009	Margareten	ORNR	400	5	3	0	0	-	114	0,00%
house	2010	Margareten	NR	400	5	3	0	0	-	110	0,00%
house	2010	Margareten	OR	400	5	3	0	0	-	110	0,00%

Crime Type	Period	District	Radius Type	Radius	NR Period	Forecast Period	Predictions	Hits	Hit Rate	Offences	Decline Rate
house	2010	Margareten	ORNR	400	5	3	0	0	-	110	0,00%
house	2011	Margareten	NR	400	5	3	0	0	-	120	0,00%
house	2011	Margareten	OR	400	5	3	0	0	-	120	0,00%
house	2011	Margareten	ORNR	400	5	3	0	0	-	120	0,00%
house	2012	Margareten	NR	400	5	3	0	0	-	67	0,00%
house	2012	Margareten	OR	400	5	3	0	0	-	67	0,00%
house	2012	Margareten	ORNR	400	5	3	0	0	-	67	0,00%
house	2013	Margareten	NR	400	5	3	0	0	-	86	0,00%
house	2013	Margareten	OR	400	5	3	0	0	-	86	0,00%
house	2013	Margareten	ORNR	400	5	3	0	0	-	86	0,00%
house	2014	Margareten	NR	400	5	3	0	0	-	53	0,00%
house	2014	Margareten	OR	400	5	3	0	0	-	53	0,00%
house	2014	Margareten	ORNR	400	5	3	0	0	-	53	0,00%
house	2015	Margareten	NR	400	5	3	0	0	-	82	0,00%
house	2015	Margareten	OR	400	5	3	0	0	-	82	0,00%
house	2015	Margareten	ORNR	400	5	3	0	0	-	82	0,00%
house	total	Margareten	NR	400	5	3	0	0	-	632	0,00%
house	total	Margareten	OR	400	5	3	0	0	-	632	0,00%
house	total	Margareten	ORNR	400	5	3	0	0	-	632	0,00%
house	2009	Vienna	NR	400	5	3	17	2	0,12	1722	0,12%
house	2009	Vienna	OR	400	5	3	17	2	0,12	1722	0,12%
house	2009	Vienna	ORNR	400	5	3	17	3	0,18	1722	0,17%
house	2010	Vienna	NR	400	5	3	1	0	0,00	1394	0,00%
house	2010	Vienna	OR	400	5	3	1	0	0,00	1394	0,00%
house	2010	Vienna	ORNR	400	5	3	1	0	0,00	1394	0,00%
house	2011	Vienna	NR	400	5	3	1	0	0,00	1334	0,00%
house	2011	Vienna	OR	400	5	3	1	0	0,00	1334	0,00%
house	2011	Vienna	ORNR	400	5	3	1	0	0,00	1334	0,00%
house	2012	Vienna	ORNR	400	5	3	1	1	1,00	1360	0,07%
house	2012	Vienna	NR	400	5	3	1	1	1,00	1360	0,07%
house	2012	Vienna	OR	400	5	3	1	1	1,00	1360	0,07%
house	2013	Vienna	ORNR	400	5	3	4	4	1,00	1102	0,36%
house	2013	Vienna	NR	400	5	3	4	4	1,00	1102	0,36%
house	2013	Vienna	OR	400	5	3	4	4	1,00	1102	0,36%
house	2014	Vienna	OR	400	5	3	85	9	0,11	1347	0,67%
house	2014	Vienna	NR	400	5	3	85	11	0,13	1347	0,82%
house	2014	Vienna	ORNR	400	5	3	85	11	0,13	1347	0,82%
house	2015	Vienna	NR	400	5	3	120	22	0,18	1326	1,66%
house	2015	Vienna	OR	400	5	3	119	22	0,18	1326	1,66%
house	2015	Vienna	ORNR	400	5	3	119	25	0,21	1326	1,89%
house	total	Vienna	OR	400	5	3	228	38	0,17	9585	0,40%
house	total	Vienna	NR	400	5	3	229	40	0,17	9585	0,42%
house	total	Vienna	ORNR	400	5	3	228	44	0,19	9585	0,46%