The modifiable areal unit problem (MAUP) in the spatial analysis of crime and socio-economic indicators

The Marshall Plan Scholarship Paper

by

Cehong Luo

Supervisors

Host University
Prof. Dr. **Gernot Paulus**
School of Spatial Information Management, Carinthia University of Applied Sciences

Home University
Prof. Dr. **Michael Leitner**
Department of Geography and Anthropology Louisiana State University, Baton Rouge, USA

October 2023

Acknowledgments

I would like to express my heartfelt gratitude to all those whose contributions made this research possible, and my time in Villach, Austria truly enjoyable.

Foremost, I extend my deep appreciation to my two esteemed advisors, Dr. Gernot Paulus of the Spatial Information Management program at Carinthia University of Applied Sciences (CUAS) in Villach, Austria, and Dr. Michael Leitner of the Department of Geography and Anthropology at Louisiana State University (LSU) in Baton Rouge, USA. Their unwavering guidance, invaluable expertise, and insightful feedback greatly enriched the quality of this study.

I am profoundly thankful to the Austrian Marshall Plan Foundation, which provided me with this extraordinary opportunity and offered vital financial support for my research and stay in Austria. Their support was instrumental in making this journey possible.

I must also extend my gratitude to Ms. Alexandra Maurer from the CUAS International Office. Her remarkable patience in handling paperwork, addressing my inquiries, and organizing social events was invaluable. I also treasure the wonderful moments shared with fellow scholars, staff, and students, including my student buddy, Julian Bosch, at CUAS. Your warm hospitality and assistance in helping me acclimate to life in Villach made my journey productive and joyful.

Lastly, I want to express my heartfelt thanks to my family and friends for their unwavering support, infinite patience, and unwavering understanding throughout this journey.

This work stands as a testament to the collective effort and support of all those mentioned above.

Thank you all!

Table of Contents

List of Tables

List of Figures

Abstract

The primary objective of this study is to delve into the intricate interplay between the modifiable areal unit problem (MAUP) and the identification of crime hot spots in Vienna, Austria. MAUP is an encompassing concept involving two crucial dimensions: zonation, which pertains to how geographical boundaries are delineated, and scale, which is contingent on the size of these geographical units. To scrutinize this, it harnessed crime point data spanning the period from 2014 to 2019 in Vienna. The analytical approach entailed both an evaluation of crime hot spots and the aggregation of data using various administrative geographical units. Notably, it also introduced three types of uniformly designed units—hexagons, triangles, and squares—at four distinct sizes, namely 0.01, 0.0625, 0.25, and 1 square kilometer, to ascertain the impact of scale in the context of MAUP. To comprehensively assess the spatial autocorrelation in crime distribution, four distinct methodologies were applied: the global Moran's I, Geary's C, Local Moran's I, and Getis-Ord Gi*. The outcomes unveiled the intricate effects of the MAUP, both in terms of zonation and scale. This elucidated the inherent challenges related to the delineation of geographical boundaries and the potential bias introduced by the size and shape of the geographical units. Expanding the scope of investigation, this study also delves into the complexities introduced by the Modifiable Temporal Unit Problem (MTUP). Here, it explored spatiotemporal hot spot analysis, encompassing various temporal levels, including seasonally, monthly, weekly, and daily intervals. The exploration of MTUP brought to light the multifaceted nature of temporal considerations in crime analysis, underscoring the need for a nuanced understanding of time-based modifiability in conjunction with spatial factors. In conclusion, this study provides a multifaceted examination of the modifiable areal unit problem in the context of crime hot spot analysis. By considering both spatial and temporal dimensions, the findings shed light on the intricate interplay of factors influencing the detection of crime hot spots, contributing to a more holistic understanding of this critical area of research.

Chapter 1. Introduction

A substantial lineage of research has been devoted to the examination of criminal phenomena within geographic entities. Among these entities, neighborhoods and micro-places have surfaced as the predominant units of spatial analysis employed to comprehend variations in criminal patterns within urban settings (Schnell et al., 2022). Nevertheless, studies grounded in geographical delineations encounter a significant analytical issue known as the modifiable areal unit problem (MAUP), positing that the constitution of spatial units can wield substantial influence upon research outcomes (Gerell, 2016). The MAUP, a term chiefly recognized in geographical and statistical scholarship, pertains to the susceptibility and inconsistency of analysis findings when disparate areal units are employed for the reporting and quantification of data (Zhang & Kukadia, 2005). Coined in its definitive form by Openshaw and Taylor (1979), this problem encompasses two closely interrelated quandaries, namely the scaling problem and the zoning problem (Zhou et al., 2022). The scaling problem materializes when alterations in data's spatial resolution occur, achieved through the subdivision into smaller units or aggregation into larger ones, while the zoning problem emerges when novel demarcations are imposed upon a given region, thereby yielding a fresh zoning configuration (Wong, 2004). The integrity of inferences drawn from analyses of aggregated spatial data becomes tenuous due to the MAUP, as outcomes tend to fluctuate in response to the degree of aggregation and the arrangement of the zoning framework (Jelinski & Wu, 1996). The issue of scale has gained pronounced prominence within the realm of geographical criminology, driven by escalating interest in minute-scale geographic units of investigation, particularly in the context of hotspot analyses pertaining to crime at micro-places. It has been posited that smaller units possess advantages, given their direct perceptibility to individuals and heightened homogeneity relative to larger units (Gerell, 2016).

Deckard and Schnell (2022) have conducted extensive research concerning the distribution of crime within micro-geographic areas, yielding two foundational insights pertaining to the interplay of crime and location: firstly, the discernible concentration of criminal activity within a limited number of locales; and secondly, the sustained endurance of these concentrations across temporal dimensions. A substantial body of scholarly inquiry has arisen, emphasizing the persistence of crime distributions over time. Contemporary scholarship scrutinizing the temporal dynamics of crime hotspots has noted that urban environments harbor a select number of "chronic crime hotspots," wherein elevated crime levels endure across extended timeframes. Within the realm of longitudinal investigations into crime concentration, the prevailing temporal unit of analysis has overwhelmingly been the year. The deployment of annual data facilitates the exploration of protracted temporal spans, thereby enabling the comprehensive evaluation of overarching trends in crime dispersions within micro-geographic contexts. Nevertheless, a cautionary stance is warranted when gauging the steadiness of crime hotspots based solely on annual crime data, as the existence of seasonal fluctuations in crime incidence has been well-established for decades. However, the intricacies of the temporal distribution of crime, as well as developmental patterns within individual years, remain relatively uncharted, particularly at the granular monthly level.

This study embarks on an investigation into the spatial configurations characterizing crime hotspots, simultaneously shedding light on how the manipulation of geographic units engenders fresh dimensions in comprehending the MAUP vis-à-vis the spatial manifestation of crime hotspots. The analysis of crime hotspots holds paramount importance, predominantly serving as a strategic tool for law enforcement agencies and governmental entities striving to identify regions beset by elevated crime rates. This, in turn, facilitates the targeted allocation of interventions and resources to these specific areas. Given the tangible influence exerted by the MAUP on the identification of crime hotspots—defined as clusters marked by heightened criminal activity—its ramifications warrant dedicated exploration within this study. Multiple spatial units are employed herein: census blocks, census block size-equivalent uniform units (namely hexagons, squares, and triangles), and uniformly designed units of varying dimensions (ranging from 0.01 to 1 square kilometer). It's imperative to acknowledge that the identification of hotspots is further conditioned by the choice of clustering methodologies. Consequently, three distinct clustering techniques are harnessed in this inquiry: Global Moran’s I, Local Moran's I, Geary's C, and Getis Ord Gi*. The purview of this study encompasses an examination of crime hotspots through diverse clustering methods, employing varied areal units, within the geographic confines of Vienna, Austria, thereby accentuating the ramifications of the MAUP. Moreover, recognizing a noted dearth in the exploration of monthly fluctuations in crime concentration—specifically in the realm of the stability of crime hotspots in longitudinal studies (Deckard & Schnell, 2022)—this investigation extends its purview to scrutinize crime hotspot patterns across yearly, monthly, and weekly intervals, thereby underscoring the Modifiable Temporal Unit Problem (MTUP). Both realms of analysis are integral for a holistic understanding of the spatial distribution of crime within urban landscapes. In conclusion, this study culminates in the application of a spatiotemporal approach, thereby illustrating crime hotspot patterns from a chronological perspective.

Chapter 2. Literature Review

2.1. Crime Hotspots

The concentration of crime within specific locations, known as crime hotspots, has been widely acknowledged in the literature (Sherman et al., 1989; Malleson & Andresen, 2016). Law enforcement agencies and governmental bodies have increasingly employed hotspots as focal points for targeted interventions and resource allocation to combat high crime rates (McKay, 2018). In the past three decades, scholars and practitioners in the field of crime prevention have underscored the potential advantages of concentrating efforts on crime-prone areas (Braga et al., 2019a). Two key theoretical mechanisms underpin the effectiveness of hotspots policing: deterrence and the reduction of crime opportunities (Braga et al., 2019b). Hot spots policing, also referred to as place-based policing, encompasses various police strategies, all characterized by the common emphasis on directing resources to locations with high crime concentrations, with interventions tailored to the specific needs of each area (Weisburd & Telep, 2014).

Historical studies in crime hotspot analysis have consistently supported the premise that focusing police efforts on high-activity crime locations can yield positive outcomes in crime prevention (Braga, 2001). An early exemplar of this approach was the Hot Spots Patrol Experiment in Minneapolis, as explored by Sherman and Weisburd (1995). Braga's review (2001) covered various studies, seven out of nine of which reported significant reductions in both crime and disorder. It's worth noting that multiple studies contributed to this body of knowledge.

Furthermore, the significance of hotspots policing and the attention to small geographic units in identifying crime hotspots have been elucidated in several articles (Weisburd & Telep, 2014). The objective is to scrutinize small geographic areas, identifying those with heightened crime rates and subsequently targeting police interventions in these locales. The smaller the geographic unit, the more effective the analysis—a precaution against the Modifiable Areal Unit Problem (MAUP). If units are too large, hidden crime hotspots within these areas may remain unnoticed. Nevertheless, it's essential to recognize that some level of aggregation is inevitable unless each individual crime location is analyzed, introducing concerns related to the MAUP (McKay, 2018). This underscores the importance of choosing the appropriate geographic unit for analysis to maximize police effectiveness.

Concerns regarding crime displacement and diffusion effects are salient in hotspots policing strategies. Targeting interventions in one area could potentially lead to crime relocating to nearby regions (McKay, 2018). Conversely, there is the possibility of a positive spillover effect, where crime reduction in the targeted area influences the broader environment in which these strategies are implemented (Vandeviver & Bernasco, 2017). However, assessing such effects remains challenging, and studies offer mixed evidence (Weisburd & Telep, 2014; Braga, 2001). In fact, a recent comprehensive review (Braga et al., 2019a) found that hot spots policing has been notably effective in crime prevention. The review identified 78 tests across 65 studies, with 62 of them reporting significant crime reductions in areas employing this strategy. Importantly, the review indicated that any crime displacement resulting from hot spots policing was limited, often accompanied by unintended crime prevention benefits. Furthermore, problem-oriented policing, with its focus on addressing specific recurring issues in crime hotspots, appeared to yield more substantial overall crime reduction effects compared to traditional policing methods. Despite challenges in implementing the ideal version of problem-oriented policing, even a less comprehensive approach showed promise in directing police crime prevention efforts effectively.

2.2. The MAUP

The MAUP has been a subject of contemplation and scrutiny since Openshaw's pioneering work in 1984. It kindles a theoretical debate concerning the accuracy of geographical units in representing reality versus serving as mere surrogates for specific locations. This prompts us to question the extent to which these units genuinely encapsulate the characteristics and dynamics of the areas they represent in research (Gerell, 2016). The MAUP instills a veil of uncertainty over the credibility of conclusions drawn from analyses of aggregated spatial data. This uncertainty arises from the likelihood that outcomes may oscillate with variations in aggregation levels and the configuration of zoning systems (Jelinski & Wu, 1996). It is a pervasive concern that resonates in a plethora of geographical inquiries, spanning diverse domains, including the spatial distribution of crime.

The essence of the MAUP revolves around the fundamental realization that there exists a multitude of ways to delineate spatial boundaries and partition space into discrete units, thereby generating diverse spatial partitioning systems (Wong, 2008). These systems operate along two principal dimensions: the spatial dimension, where distinct configurations are employed to partition space while keeping the number of areal units constant within the study region, and the scalar dimension, which involves partitioning the study region into varying levels of granularity. This variability in detail can yield disparate outcomes. For instance, in some studies, geographical units like neighborhoods may inadequately capture the social boundaries or phenomena under investigation, inadvertently violating the research objective, which strives to minimize within-unit variation and maximize between-unit variation (Gerell, 2016). Notably, it has been observed that with larger units of analysis, correlation coefficients tend to exhibit magnified values (Openshaw, 1984). The aggregation of data into larger analytical units can result in reduced variance, while the zonation problem can exert an impact on both variance and mean outcomes (Tita and Radil, 2010). Hence, it becomes imperative to meticulously consider the appropriateness of chosen geographical units to engender meaningful and valid results.

The MAUP extends its far-reaching influence into the realms of statistical and spatial analysis, primarily through scale and zone effects. The nature of scale or zone has been identified as a potent driver of alterations in analytical results and derived patterns (Openshaw, 1977). Statistical analysis outcomes prove to be highly sensitive to the aerial unit in which data is collected. Cluster analysis, another statistical technique, has lately garnered attention due to its vulnerability to the MAUP (Zahrani, 2020). Clusters, signifying groups of phenomena or data points with greater similarity relative to other event groups within an area, are instrumental in understanding localized patterns, including crime hotspots (McKay, 2018). Performing cluster analysis across multiple scales aids in unraveling the MAUP's impact on this methodology. McKay (2018) employed four distinct clustering methods to identify crime hotspots at two scales—data zone level and output area level—yielding divergent outcomes. Within each technique, results exhibited variability contingent upon the chosen scale. Fotheringham and Wong (1991) pioneered efforts to document the scale and zone effect of the MAUP on multivariate regression analysis. Their investigation unveiled that the relationship between variables in their model underwent transformations predicated on the aggregation scale and zone adopted. While some research endeavors suggest that the MAUP's impact may have been overstated, as findings comparing different geographical units tend to yield similar results (Gerell, 2016), nuanced variations in homogeneity and spatial heterogeneity persist. The selection of a spatial unit remains pivotal in shaping the contours of the analysis.

2.3. The MTUP

The examination of the temporal stability of high-crime locations represents a relatively recent venture within criminology (Deckard & Schnell, 2022). While existing research, as well as the MAUP, has primarily concentrated on determining the appropriate geographic unit for analysis, the temporal unit has received comparatively less attention. Consequently, a substantial body of literature has emerged positing the existence of enduring crime hotspots that persist for extended periods, sometimes spanning years or even decades. These conclusions are often rooted in crime data characterized by limited variations in both spatial and temporal dimensions. To address these issues, Cöltekin et al. (2011) introduced the concept of the Modifiable Temporal Unit Problem (MTUP), drawing an analogy to the MAUP. The MTUP underscores how concerns related to temporal granularity can introduce bias and influence the interpretation of statistical hypotheses within spatiotemporal analysis. The aggregation of data into larger temporal units, such as years, may obscure nuanced variations in crime concentration observable at smaller time intervals, such as months. In the context of temporal analysis, years represent some of the largest units available for studying micro-spatial crime patterns, albeit susceptible to the averaging effects inherent to their scope (Deckard & Schnell, 2022).

Cöltekin et al. (2011) classified the MAUP into three dimensions: duration (reflecting the time span), temporal resolution (indicating the frequency of data collection), and the point in time (signifying the timing of observations). Expanding upon this framework, Cheng and Adepeju (2014) delved into not only temporal aggregation but also temporal segmentation and boundaries, collectively constituting the MTUP. Temporal aggregation encompasses the conversion of fine time interval observations into coarser ones. Temporal segmentation, akin to the zoning effect observed in the MAUP, involves dividing the continuous time frame into segments of varying time intervals, such as days, weeks, months, or years. The boundary effect as the third aspect pertains to the influence of how temporal boundaries are defined on the identification of spatial distribution and the estimation of statistical parameters in the underlying temporal process. Cheng and Adepeju (2014) extend this concept to the temporal dimension by identifying the start and end points of a time series as its temporal extent or boundary. Manipulating the temporal length of a space-time process can result in changes to sample counts and alterations in mean and variance estimates.

Chapter 3. Study Area and Data

3.1. Study Area

The study area of this research is Vienna, Austria, a city of significant importance and rich diversity. Vienna, situated in the northeastern part of Austria along the banks of the Danube River, serves as both the largest city and the capital of the country. Functioning as one of the nine provinces of Austria, Vienna boasts a multifaceted character that makes it a compelling subject for this study. As of January 2023, Vienna is home to a thriving population of 1,982,097 residents, reflecting its status as the most populous city in Austria. The city's demographic landscape is exceptionally diverse, with individuals hailing from an impressive array of 180 different nationalities. This cultural tapestry adds depth to Vienna's identity, with over one third of its residents being foreign nationals. Notably, the top five nationalities represented among these foreign residents are Serbia, Germany, Turkey, Poland, and Romania, further contributing to Vienna's cosmopolitan atmosphere (Vienna in Figures - Urban Area, Population, Education, Economy, Transport, Public Administration, n.d.). Vienna's outstanding quality of life has earned it international acclaim. According to the Municipal Department 23 - Economic Affairs, Labour and Statistics, as of 1 January 2023, Vienna continues to stand as a beacon of liveability. In fact, it was ranked first in the 2023 Global Liveability Index by The Economist Intelligence Unit (The Global Liveability Index 2023, n.d.). This achievement is not an isolated one, as Vienna has consistently claimed the top spot in the 2022, 2019, and 2018 reports as well. This global recognition is a testament to the city's commitment to fostering an environment where residents and visitors alike can thrive.

Vienna's appeal is further underscored by its robust net migration figures. In 2022 alone, the city recorded a net migration of 49,647 individuals, a statistic that underscores its allure as a destination for people from across the world. Over the past decade, Vienna has exhibited a population growth rate that outpaces many other major European cities, including Rome, Paris, Berlin, and Madrid. This trend speaks to Vienna's enduring appeal and its ability to provide opportunities and a high quality of life for those who call it home. In 2022, Vienna recorded over 13.2 million overnight stays by tourists, underscoring its popularity as a global tourist hub. This influx of visitors adds another layer of dynamism to Vienna's cultural fabric, as it continues to be a place where people from diverse backgrounds converge. Geographically, Vienna encompasses an area of 414.9 square kilometers, divided into 23 distinctive districts. Each district contributes its own unique character to the city's mosaic, creating a dynamic urban landscape that invites exploration and study. Vienna's geographical diversity, combined with its demographic complexity and high liveability, makes it an ideal subject for the research undertaken in this study.

3.2. Data Sources

The crime data utilized in this study has been graciously provided by the Police Department of Vienna, Austria. This extensive dataset encompasses a total of 623,950 recorded crime incidents, spanning from January 1st, 2014, to December 31st, 2019. While this dataset is substantial, it's important to note that a portion of these incidents occurred outside the immediate boundaries of the city of Vienna. To be precise, 623,878 of these crime incidents transpired within the administrative confines of Vienna, as visually represented in Figure 1.

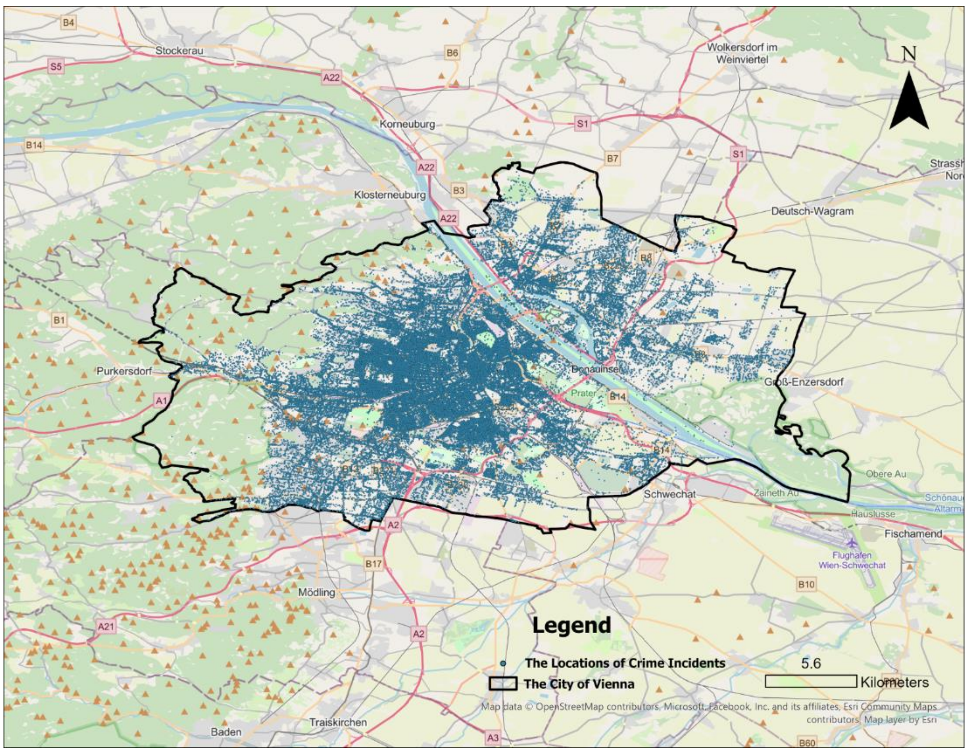

Figure 1. The location of crime incidents

This fine-grained data has been meticulously documented and organized within a comprehensive Excel file, comprising an array of 26 columns featuring intricate details and descriptions. These include unique identifiers (IDs), district information (Bezirk), street names (Strasse), geographical coordinates (latitude and longitude - Lat, Lon), the timeframe of each incident from commencement to conclusion (Tatzeit_von and Tatzeit_bis), the respective month (Monat), weekday (Wochentag), year (Jahr), and the nature of the offense (Delikt), among others.

In the context of this research, it specifically employs the geographical coordinates (latitude and longitude) to precisely geolocate each crime incident, facilitating precise spatial analysis. Additionally, this study relies on the 'Tatzeit_bis' column, indicating the time of conclusion for each criminal event, to enable comprehensive spatiotemporal analysis. It's worth noting that the 'Delikt' column, categorizing offenses into 11 distinct types, plays a pivotal role in this research. These crime categories encompass a broad spectrum of criminal activities, including Murder (Mord), Manslaughter (Totschlag), Bodily Injury (Koerperverletzung), Severe Bodily Injury (Schwere Koerperverletzung), Theft (Diebstahl), Severe Theft (Schwere Diebstahl), Theft with Weapons or by Burglary (Diebstahl Durch Einbruch OD. M. Waffen), Robbery (Raub), Severe Robbery (Schwere Raub), Rape (Vergewaltigung), and Arson (Brandstiftung).

To provide a comprehensive perspective, this study delves into analyses across different dimensions of crime data. While the total count of crimes is a crucial factor, it also recognize the importance of exploring patterns based on specific crime types. Thus, it has chosen to concentrate our analysis on three significant crime categories: Theft (comprising Diebstahl, Schwere Diebstahl, and Diebstahl Durch Einbruch OD. M. Waffen), Bodily Injury (encompassing Koerperverletzung and Schwere Koerperverletzung), and Robbery (encompassing Raub and Schwere Raub). These three categories have been identified as the most prevalent types of criminal activity within Vienna during the studied period, from 2014 to 2019. Notably, theft incidents emerged as the most widespread, constituting over 80% of the total recorded crimes, as illustrated in Figure 2. Out of 623,878 crime records in Vienna from 2014 to 2019, 523,355 wee thefts, 88,455 were body injury, and 9,327 were robbery.

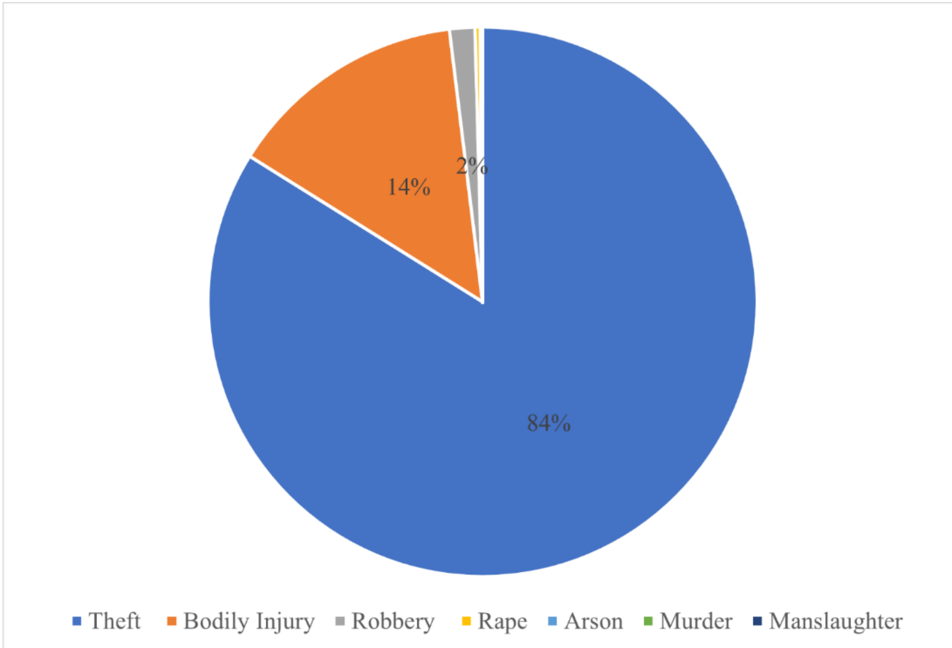

Figure 2. The distribution of crimes by crime types

This study boasts a robust and comprehensive dataset, meticulously collated from the Police Department of Vienna. With a focus on both the total volume of crimes and specific crime types, it endeavors to provide valuable insights into the dynamics of urban crime within Vienna's city limits. This analysis aims to shed light on not only the overall crime trends but also the nuanced variations within distinct crime categories. In addition, this study introduces specific areal units for the purpose of conducting spatial analysis. Initially, the analysis adopts census blocks as the primary areal units within Vienna. The city comprises a total of 1,364 census blocks, each characterized by its unique features. These census blocks exhibit a significant variation in size, with a mean area of 0.3 square kilometers and a median area of 0.08 square kilometers. As depicted in Figure 3, which illustrates the size distribution of census blocks, it's evident that the majority of these blocks are smaller than 0.4 square kilometers. Given the skewed nature of this distribution, utilizing the median size is more appropriate than the mean size for this analysis. To explore the potential zonal effects arising from the MAUP, uniform areal units have been carefully devised. These units, configured as Hexagons, Squares, and Triangles, have been meticulously sized to match the median area of census blocks, thus ensuring a standardized basis for comparison. Figure 4 provides an exemplary comparison between the utilization of census blocks and hexagons, both of which are equivalent in size to the median census block.

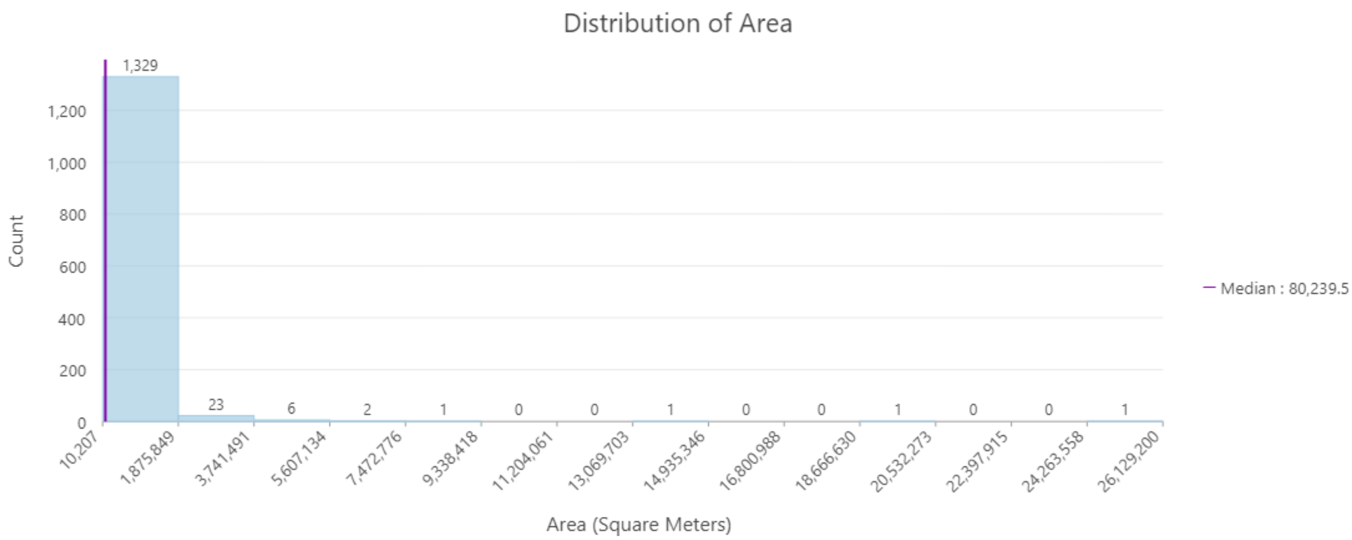

Figure 3. The distribution of the size of census block

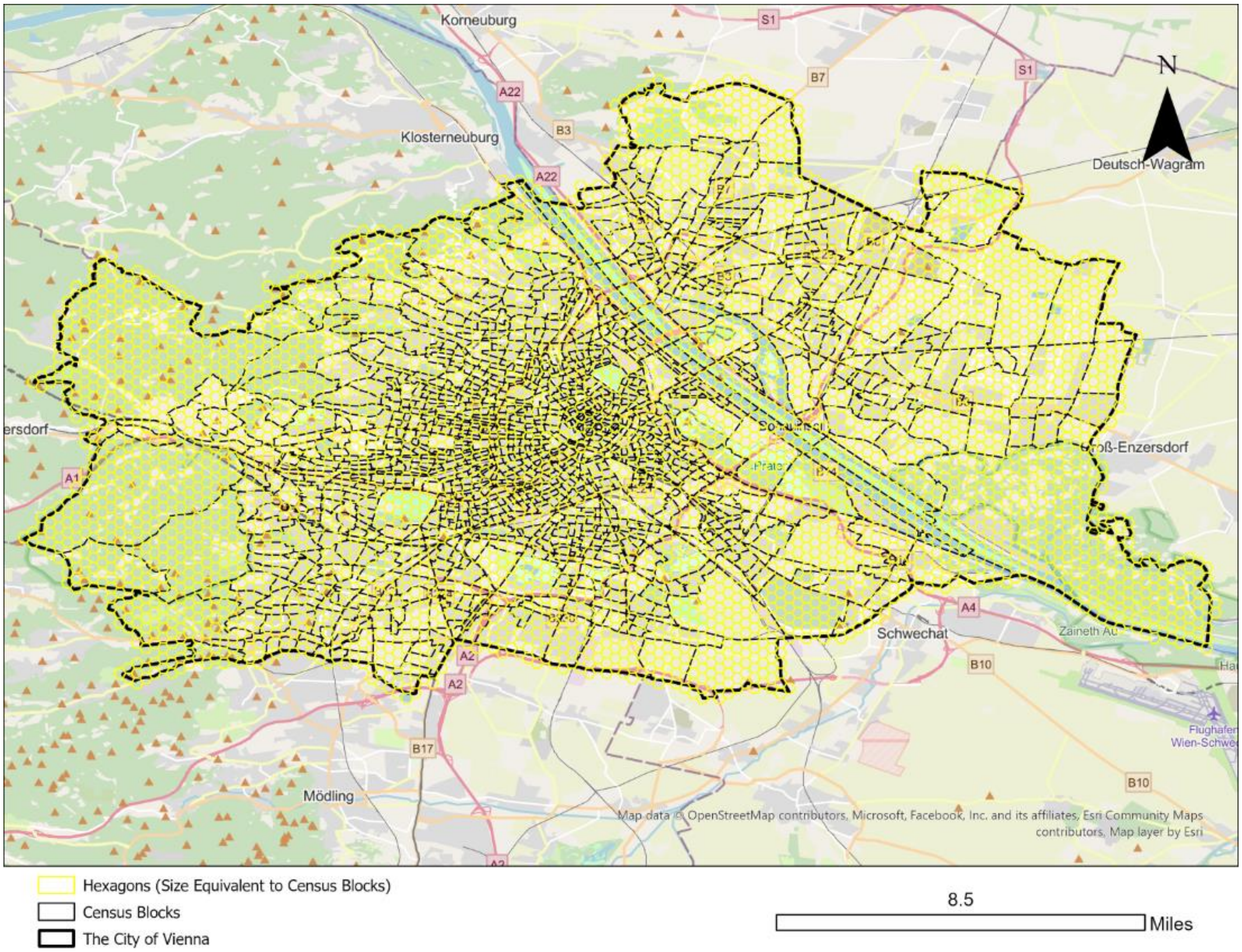

Figure 4. The census blocks and their size equivalent hexagons of Vienna

To further explore the scale effects stemming from the MAUP, an array of uniform units has been meticulously crafted, each varying in size. The progression begins with squares, characterized by sides measuring 100 meters, 250 meters, 500 meters, and 1,000 meters, which equate to areas of 0.01, 0.0625, 0.25, and 1 square kilometer, respectively. These squares serve as the foundational reference points for generating corresponding Triangles and Hexagons through the proficient employment of the Generate Tessellation tool available in ArcGIS Pro. This enables us to explore the implications of varying areal unit sizes on the spatial analysis, facilitating a comprehensive assessment of the MAUP across different scales.

By employing this multifaceted approach to defining areal units, this study ensures a examination of the MAUP's potential effects on spatial analysis outcomes, both at the zonal and scale levels. The comprehensive range of areal units considered, each meticulously tailored to specific criteria, equips us with a versatile toolkit for in-depth analysis and a nuanced understanding of spatial patterns within Vienna.

Chapter 4. Method

4.1. Identifying Crime Hotspots

To identify crime hotspots, this analysis employs four clustering methods. The initial two methods include Global Moran's I and Geary's C. Both Global Moran's I and Geary's C are employed to assess spatial autocorrelation within the dataset, aiming to reveal patterns of similarity or dissimilarity among data values at various locations. These statistics generate values that are subsequently compared to predefined thresholds or critical values, enabling a determination of statistical significance regarding the presence of spatial autocorrelation. The other two methods utilized are the Local Indicators of Spatial Association (LISA) techniques, namely, Local Moran's I and Getis-Ord Gi*. These techniques focus on identifying local spatial patterns, homing in on specific geographic areas or zones within the broader study area. Their primary objective is to pinpoint locations where data values exhibit noteworthy spatial clustering, whether it takes the form of high-high (HH) or low-low (LL) clustering. Both of these statistics produce localized values for each location within the study area, indicating whether a particular spot is part of a significant local cluster (e.g., a high-value cluster surrounded by high values) or not. To compute these methods, three geoprocessing tools are adopted: Global Moran's I, Local Moran's I, and Getis-Ord Gi*. The spatial autocorrelation tool within ArcGIS Pro software is employed for calculating Global Moran's I, while the cluster and outlier analysis function is applied to Anselin Local Moran's I. Finally, the hot spot analysis tool is utilized to compute Getis-Ord Gi*. For the implementation of LISA methods, the data is integrated into shapefiles representing Vienna at both the output area and data zone levels. To calculate Geary's C, this study relies on CrimeStat software.

Global Moran’s I

Spatial autocorrelation is a fundamental concept in spatial analysis, serving as a key indicator for the presence of spatial patterns in data. To assess spatial autocorrelation, Global Moran's I statistic is employed in this study. This statistic is widely used to determine whether there is spatial clustering (positive autocorrelation) or dispersion (negative autocorrelation) of data values across a geographic area.

Global Moran's I is calculated using the following equation:

$$I = \frac{N}{W} \frac{\Sigma_{i=1}^{N} \Sigma_{j=1}^{N} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\Sigma_{i=1}^{N} (x_i - \bar{x})^2} \quad (1)$$

Where:

N represents the total number of spatial units (in this case, geographical areas).

x_i and x_j are the values of the variable being analyzed in spatial units i and j, respectively.

$\bar{x}$ denotes the mean of all x_i values.

w_{ij} represents the spatial weight between spatial units i and j.

W is the sum of all spatial weights.

The numerator of equation (1) computes the sum of products of differences between each data value x_i and the mean value $\bar{x}$ across all spatial units, weighted by the spatial weights w_{ij}.This component assesses how each data value relates to its neighboring values. The denominator calculates the sum of squared differences of data values from the mean, providing a measure of data variance. Global Moran's I, named after Patrick Alfred Pierce Moran (1950), is a powerful tool in spatial analysis, enabling the quantification and assessment of spatial autocorrelation patterns within geographic data. Its application in this study serves as a foundational step in understanding the spatial distribution of crime incidents in Vienna and provides valuable insights for subsequent analyses.

Geary’s C

Geary's C is another widely used statistic for assessing spatial autocorrelation in geographical data. This statistic, like Moran's I, helps identify whether data values at different locations exhibit similarity (positive autocorrelation) or dissimilarity (negative autocorrelation) patterns across a geographic area.

Geary's C is calculated using the following equation:

$$C = \frac{(N-1)\Sigma_{i=1}^{N}\Sigma_{j=1}^{N}\omega_{ij}\left(x_i - x_j\right)^2}{2w\Sigma_{i=1}^{N}\Sigma_{j=1}^{N}\omega_{ij}\left(x_i - x_j\right)^2} \quad (2)$$

Where:

N represents the total number of spatial units (geographical areas).

x_i and x_j are the values of the variable being analyzed in spatial units i and j, respectively.

ω_{ij} denotes the spatial weight between spatial units i and j.

w is the sum of all spatial weights.

The numerator of equation (2) calculates the sum of squared differences between each data value x_i and the data value in its neighboring spatial unit x_j, weighted by the spatial weights ω_{ij}. This component measures how data values differ from their neighbors. The denominator computes a similar sum but also incorporates the sum of squared differences in data values across all spatial units. This component normalizes the statistic.

Geary's C, named after its developer R. C. Geary (1954), is a statistic with a rich history in spatial analysis. Geary introduced this statistic in the mid-1950s to assess spatial patterns in economic and geographical datasets. Since its inception, Geary's C has found applications in various fields, including urban planning, ecology, and criminology. One of the distinguishing features of Geary's C is its sensitivity to both positive and negative spatial autocorrelation, making it a versatile tool for understanding spatial relationships. Historically, it has been used to examine regional disparities, identify clustering of similar phenomena, and assess the spatial distribution of socioeconomic variables. Its application in this study serves as a complementary approach to Moran's I, contributing to a comprehensive understanding of spatial autocorrelation patterns in the context of crime incidents in Vienna.

Anselin Local Moran’s I

Anselin Local Moran's I (1995) is a spatial autocorrelation statistic used to reveal local patterns of spatial association within a geographical dataset. Unlike Global Moran's I, which provides a single value for the entire study area, Local Moran's I allows for the identification of spatial clusters at the local level, pinpointing areas with significant high-high or low-low spatial autocorrelation. It is particularly useful in detecting spatially clustered phenomena and exploring where specific high or low values are concentrated within a study region.

Anselin Local Moran's I is calculated for each spatial unit i in a dataset using the following equation:

$$I_i = \frac{(\chi_i - \bar{x})\left(\Sigma_{j=1}^{N} \omega_{ij}(x_j - \bar{x})\right)}{S_0^2} \quad (3)$$

Where:

I_i represents the local Moran's I value for spatial unit i.

χ_i is the value of the variable being analyzed in spatial unit i.

$\bar{x}$ denotes the mean value of the variable across all spatial units.

ω_{ij} is the spatial weight between spatial units i and j.

S_0^2 is a measure of the global variance of the variable.

The equation (3) calculates a local Moran's I value for each spatial unit, measuring the product of the deviation of a unit's value from the mean value $(\chi_i - \bar{x})$ and the sum of similar deviations for neighboring units, all weighted by the spatial weights ω_{ij}. This computation identifies whether a particular unit is part of a significant local cluster of similar values or not.

Anselin Local Moran's I is named after its developer, Luc Anselin, who introduced this statistic in the 1990s. It has since become a fundamental tool in spatial statistics and spatial analysis, widely used in fields such as geography, urban planning, epidemiology, and criminology. While both Global Moran's I and Anselin Local Moran's I assess spatial autocorrelation, their key difference lies in the scope of analysis. Global Moran's I provides a single value characterizing spatial autocorrelation for the entire dataset, while Local Moran's I produces a series of values, each corresponding to a specific spatial unit. Global Moran's I informs whether spatial autocorrelation exists in the dataset as a whole, while Local Moran's I identifies where within the study area this autocorrelation is concentrated. This distinction allows for a more nuanced understanding of spatial patterns at the local level, making Local Moran's I a valuable tool for exploring spatial heterogeneity.

Getis-Ord Gi*

Getis-Ord Gi* is a spatial statistic used for the identification of local spatial clusters and outliers within a geographical dataset. Developed by Arthur Getis and J. Keith Ord (1992), this statistic is instrumental in uncovering the spatial distribution of high or low values, making it a valuable tool in spatial analysis. In the context of studying crime spatial patterns in Vienna, Getis-Ord Gi* pinpoint areas with significantly high or low concentrations of crime incidents, enabling a deeper understanding of localized crime patterns.

Getis-Ord Gi* is calculated using the following equation:

$$G_i^* = \frac{\Sigma_{j=1}^{n} \omega_{ij} x_j^{-} - x \Sigma_{j=1}^{n} \omega_{ij}}{S\sqrt{\frac{n\Sigma_{j=1}^{n} \omega_{ij}^2 - \left(\Sigma_{j=1}^{n} \omega_{ij}\right)^2}{n-1}}} \quad (4)$$

Where:

G_i^* represents the Getis-Ord Gi* statistic for spatial unit i.

x_j is the value of the variable being analyzed in spatial unit j.

$\bar{x}$ denotes the mean value of the variable across all spatial units.

ω_{ij} is the spatial weight between spatial units i and j.

S represents the standard deviation of the variable.

n is the total number of spatial units.

The resulting statistic G_i^* signifies whether spatial clustering or spatial outliers exist for the variable at location i. Positive values indicate high values clustering, while negative values denote low values clustering.

4.2. Spatiotemporal Hotspots

To unveil spatial and temporal clusters, generate a space-time cube, and scrutinize emerging hotspots, this study employs a suite of specialized tools recommended by Wang and Liu (2023) within the ArcGIS Pro platform. These tools are instrumental in our pursuit of detecting spatiotemporal crime hotspots, providing a robust framework for our analysis. This approach unfolds in several key steps:

Visualizing Spatial-Temporal Trends: The initial step involves transforming raw crime data into a space-time cube representation. This cube is instrumental in capturing the simultaneous interplay of geographical and temporal dimensions. It visualizes these trends both in 2D and 3D formats, enabling a comprehensive understanding of how crime incidents are distributed across space and time.

Time Series Clustering: Next, it delves into time series clustering, a powerful technique for identifying temporal clusters. These clusters are elucidated based on their temporal proximity, allowing us to discern patterns of crime incidents over time. It complements spatial clustering by shedding light on how crimes evolve temporally.

Emerging Hot Spot Analysis: This tool identifies regions where crime incidents exhibit significant clustering both spatially and temporally. It discerns not only the presence of hotspots but also their temporal evolution. Upon the completion of emerging hotspot analysis, each bin within the space-time cube is equipped with essential statistical metrics, including z-scores, p-values, and hotspot classifications. We take a holistic view by evaluating the trends of hotspots and cold spots using the Mann–Kendall trend test (Purwanto et al., 2021). This multifaceted analysis yields a nuanced understanding of the spatiotemporal dynamics at play, resulting in the classification of each bin into one of 17 distinct categories. These categories encapsulate a spectrum of trends, such as the emergence of entirely new hotspots, the intensification or diminishment of existing ones, and the presence of sporadic hot and cold spots.

Chapter 5. Results

5.1. The Spatial Autocorrelation Pattern of Crime

The analysis undertaken in this study reveals a consistent pattern of spatial autocorrelation across a spectrum of spatial areal units. As depicted in Table 1, the global Moran's I values are 0.044, 0.482, 0.467, and 0.488 for the aggregation of all crime types within census blocks, squares that are equivalent in size to blocks, hexagons equivalent to blocks, and triangles equivalent to blocks, respectively. These values are accompanied by a notable level of statistical significance, reflected in the minuscule p-values of 0.0001 (which are well below the conventional significance threshold of 0.05). The undeniable statistical significance of these values indicates that the spatial distribution of crimes in Vienna is characterized by pronounced spatial clustering.

One particularly intriguing observation is the substantial difference between the global Moran's I value for crimes in census blocks and those in designed uniform spatial units. This distinction suggests a zonal effect of the MAUP. It is critical to recognize that these designed spatial units, including squares, hexagons, and triangles that are equivalent to blocks in size, do not fully encompass the geographical diversity seen in census blocks. The shape of census blocks varies significantly, leading to discrepancies in both size and spatial characteristics. By examining the results of spatial analysis, it becomes evident that altering the shape of spatial units exerts a tangible influence, thereby confirming the existence of the zonal effect of MAUP.

Furthermore, the scale effect of MAUP is prominently demonstrated by both the global Moran's I and Geary's C values. A noteworthy positive correlation is observed between the global Moran's I values and the size of designed spatial units (i.e., hexagons, squares, and triangles). In essence, as the spatial units increase in size, the global Moran's I value similarly exhibit an upward trend. The relationship between Geary's C and the scale of designed spatial units follows a discernable pattern, albeit with a negative orientation. Put simply, larger spatial units correspond to smaller Geary's C values. A deeper dive into Geary's C reveals a range spanning from 0 to a positive value. Specifically, a Geary's C value of 1 implies the absence of spatial autocorrelation. Values of C within the range of 0 to 1 suggest positive spatial autocorrelation, with values approaching zero as the level of autocorrelation intensifies. In contrast, C values exceeding 1 denote negative spatial autocorrelation, with higher C values indicating a more substantial degree of negative spatial autocorrelation. Notably, Geary's C is particularly sensitive to localized variations in neighboring areas as opposed to overarching global variations (Zhou & Liu, 2008).

It's worth mentioning that the p-values are not statistically significant for the largest designed spatial units in all three shapes (hexagons, triangles, and squares) as shown in Table 2-4. Consequently, both the scale effect and the zonal effect of MAUP are observed across the three major crime types: Theft, Bodily Injury, and Robbery. These crime categories exhibit similar spatial autocorrelation patterns as discussed previously. However, it's noteworthy that the Geary's C values are statistically significant when aggregating to the largest squares and triangles for bodily injury data, with values lower than 1, indicating a slight positive spatial autocorrelation, signifying that locations in close proximity exhibit similar values. This relationship, however, reverses when examining smaller spatial units, where Geary's C values exceed 1.

Table 1. The Moran's I and Geary's C values of aggregation of all crime types based on spatial units.

All Crime Types	*Global Moran's I*	*P-value*	*Geary's C*	*P-value*
Blocks	0.044	0.0001	1.058	0.0001
Squares equivalent to Blocks	0.482	0.0001	1.073	0.0001
Hexagons equivalent to Blocks	0.467	0.0001	1.070	0.0001
Triangles equivalent to Blocks	0.488	0.0001	1.073	0.0001
Squares equivalent to 0.01 Square Kilometer	0.256	0.0001	1.131	0.0001
Squares equivalent to 0.0625 Square Kilometer	0.458	0.0001	1.082	0.0001

Squares equivalent to 0.25 Square Kilometer	0.630	0.0001	1.034	0.0001
Squares equivalent to 1 Square Kilometer	0.732	0.0001	1.001	N.S.
Hexagons equivalent to 0.01 Square Kilometer	0.290	0.0001	1.130	0.0001
Hexagons equivalent to 0.0625 Square Kilometer	0.471	0.0001	1.076	0.0001
Hexagons equivalent to 0.25 Square Kilometer	0.622	0.0001	1.037	0.0001
Hexagons equivalent to 1 Square Kilometer	0.732	0.0001	1.001	N.S.
Triangles equivalent to 0.01 Square Kilometer	0.236	0.0001	1.131	0.0001
Triangles equivalent to 0.0625 Square Kilometer	0.491	0.0001	1.079	0.0001
Triangles equivalent to 0.25 Square Kilometer	0.596	0.0001	1.037	0.0001
Triangles equivalent to 1 Square Kilometer	0.742	0.0001	1.006	N.S.

Table 2. The Moran's I and Geary's C values of aggregation of theft based on spatial units.

Theft	*Moran's I*	*P-value*	*Geary's C*	*P-value*
Blocks	0.059489	0.0001	1.08323	0.0001
Squares equivalent to Blocks	0.465492	0.0001	1.07923	0.0001
Hexagons equivalent to Blocks	0.443215	0.0001	1.07756	0.0001
Triangles equivalent to Blocks	0.467462	0.0001	1.07921	0.0001
Squares equivalent to 0.01 Square Kilometer	0.243902	0.0001	1.13487	0.0001
Squares equivalent to 0.0625 Square Kilometer	0.435948	0.0001	1.08896	0.0001
Squares equivalent to 0.25 Square Kilometer	0.611522	0.0001	1.04098	0.0001
Squares equivalent to 1 Square Kilometer	0.72514	0.0001	1.01134	N.S.
Hexagons equivalent to 0.01 Square Kilometer	0.276736	0.0001	1.13151	0.0001
Hexagons equivalent to 0.0625 Square Kilometer	0.447909	0.0001	1.08199	0.0001
Hexagons equivalent to 0.25 Square Kilometer	0.607953	0.0001	1.04551	0.0001
Hexagons equivalent to 1 Square Kilometer	0.718574	0.0001	1.00574	N.S.
Triangles equivalent to 0.01 Square Kilometer	0.219647	0.0001	1.13466	0.0001
Triangles equivalent to 0.0625 Square Kilometer	0.47373	0.0001	1.08597	0.0001
Triangles equivalent to 0.25 Square Kilometer	0.563885	0.0001	1.04662	0.0001
Triangles equivalent to 1 Square Kilometer	0.732272	0.0001	1.01134	N.S.

Table 3. The Moran's I and Geary's C values of aggregation of body injury based on spatial units.

Body Injury	*Moran's I*	*P-value*	*Geary's C*	*P-value*
Blocks	0.037	0.0001	1.03825	0.01
Squares equivalent to Blocks	0.490255	0.0001	1.09958	0.0001
Hexagons equivalent to Blocks	0.479322	0.0001	1.09092	0.0001

Triangles equivalent to Blocks	0.492017	0.0001	1.09245	0.0001
Squares equivalent to 0.01 Square Kilometer	0.268385	0.0001	1.16225	0.0001
Squares equivalent to 0.0625 Square Kilometer	0.480908	0.0001	1.10166	0.0001
Squares equivalent to 0.25 Square Kilometer	0.616023	0.0001	1.02567	0.001
Squares equivalent to 1 Square Kilometer	0.713397	0.0001	**0.96582**	**0.05**
Hexagons equivalent to 0.01 Square Kilometer	0.26715	0.0001	1.15818	0.0001
Hexagons equivalent to 0.0625 Square Kilometer	0.455145	0.0001	1.11031	0.0001
Hexagons equivalent to 0.25 Square Kilometer	0.595158	0.0001	1.03358	0.0001
Hexagons equivalent to 1 Square Kilometer	0.640002	0.0001	0.98818	N.S.
Triangles equivalent to 0.01 Square Kilometer	0.302893	0.0001	1.16145	0.0001
Triangles equivalent to 0.0625 Square Kilometer	0.469124	0.0001	1.10637	0.0001
Triangles equivalent to 0.25 Square Kilometer	0.638573	0.0001	1.02267	0.01
Triangles equivalent to 1 Square Kilometer	0.716515	0.0001	**0.97363**	**0.05**

Table 4. The Moran's I and Geary's C values of aggregation of robbery based on spatial units.

Robbery	*Moran's I*	*P-value*	*Geary's C*	*P-value*
Blocks	0.073261	0.0001	1.02361	0.01
Squares equivalent to Blocks	0.555943	0.0001	1.10529	0.0001
Hexagons equivalent to Blocks	0.509993	0.0001	1.11389	0.0001
Triangles equivalent to Blocks	0.583746	0.0001	1.10297	0.0001
Squares equivalent to 0.01 Square Kilometer	0.310313	0.0001	1.09767	0.0001
Squares equivalent to 0.0625 Square Kilometer	0.552701	0.0001	1.10157	0.0001
Squares equivalent to 0.25 Square Kilometer	0.623639	0.0001	1.05011	0.0001
Squares equivalent to 1 Square Kilometer	0.68294	0.0001	0.99322	N.S.
Hexagons equivalent to 0.01 Square Kilometer	0.30906	0.0001	1.09438	0.0001
Hexagons equivalent to 0.0625 Square Kilometer	0.542846	0.0001	1.11172	0.0001
Hexagons equivalent to 0.25 Square Kilometer	0.614766	0.0001	1.0471	0.0001
Hexagons equivalent to 1 Square Kilometer	0.612302	0.0001	1.00345	N.S.
Triangles equivalent to 0.01 Square Kilometer	0.342594	0.0001	1.10326	0.0001
Triangles equivalent to 0.0625 Square Kilometer	0.525858	0.0001	1.12597	0.0001
Triangles equivalent to 0.25 Square Kilometer	0.67938	0.0001	1.04134	0.0001
Triangles equivalent to 1 Square Kilometer	0.701328	0.0001	0.99389	N.S.

In order to precisely delineate the spatial concentration of criminal incidents, an investigation into local autocorrelation was conducted. This analytical method serves to discriminate between outlying areas and cohesive clusters of neighboring units that collectively form more extensive spatial agglomerations (Mckay, 2018). As evident in the accompanying figures, the predominant portion of the study area falls within the not-significant category, indicative of areas demonstrating neither disproportionately high nor low crime counts concerning their immediate neighbors. Nonetheless, this study is particularly drawn to the clusters labeled as "high-high" and the groups identified as "high-low." These patterns bring to light the presence of crime hotspots.

As exemplified in Figure 5, a discernible concentration of criminal activities becomes apparent in the central and central-western sectors of Vienna, spanning from the 1st district (Innere Stadt) through the 9th district (Favoriten), 15th district (Rudolfsheim-Fünfhaus), the eastern part of the 16th district (Ottakring), 17th district (Hernals), to the 18th district (Währing). Numerous units within this geographical expanse exhibit high-high cluster patterns across various spatial units. However, the persistent influence of the MAUP is visibly manifested in Figure 5. Notably, the western part of Vienna predominantly assumes the low-low cluster classification, with several high-low outliers distributed throughout the region when data are aggregated at the block level. In stark contrast, within the realm of size-equivalent designed uniform units, only the westernmost suburb of Vienna aligns with the low-low cluster category, while the prevalence of high-low outliers in the western portion diminishes. Moreover, the high-high clusters adopt a more uniform distribution within central Vienna. Simultaneously, Figure 6, using results based on four scales of hexagons, underscores the discernible scale effect of the MAUP. As the spatial unit size increases, progressively finer details of the spatial crime pattern become obscured, resulting in the neglect, blurring, or masking of intricate spatial nuances. This phenomenon is corroborated by the observations presented in Table 5. It is important to note that these MAUP effects persist when focusing on specific types of crime, including theft, body injury, and robbery.

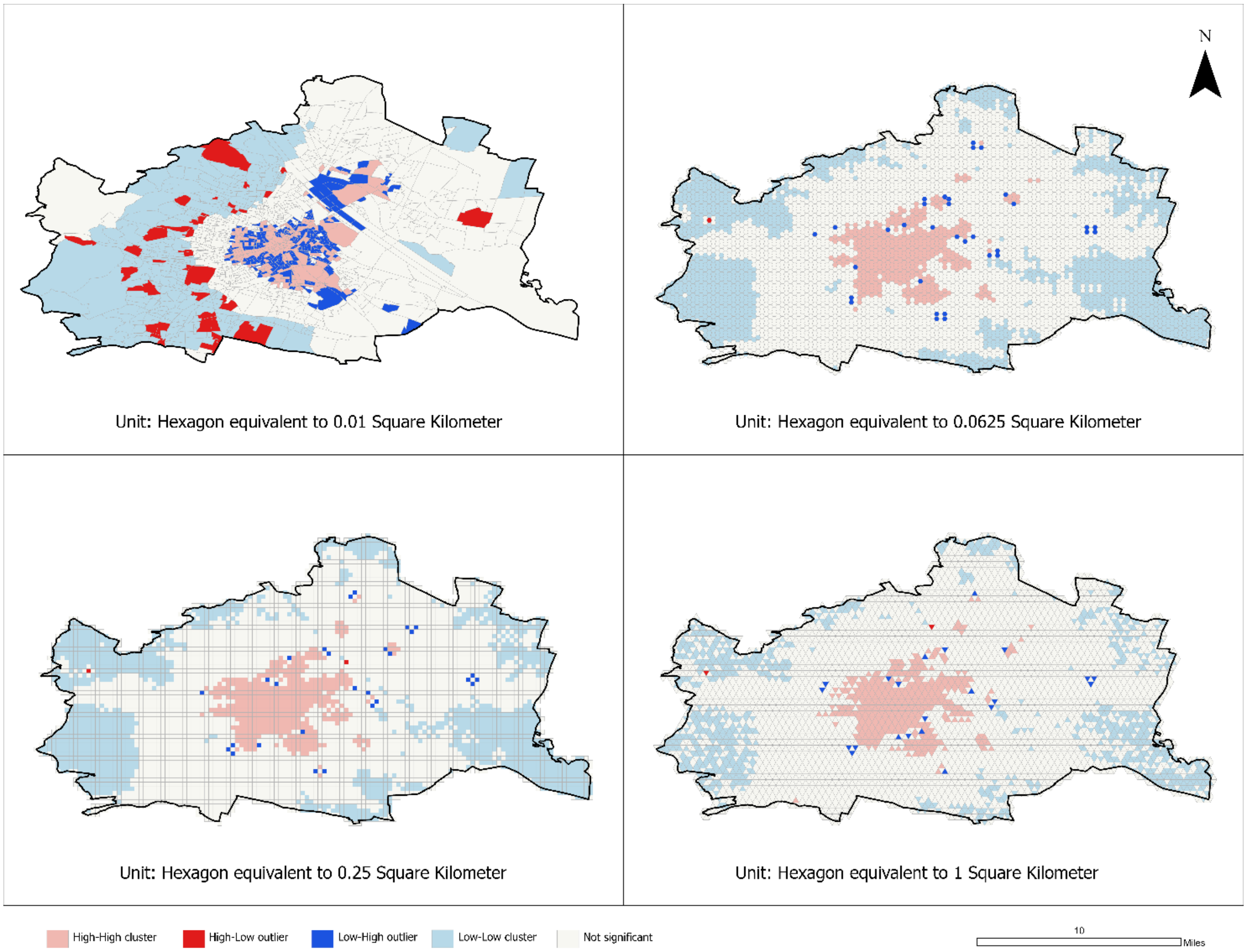

Figure 5. Local indicators of spatial association map of all crime types in Vienna at block level and its equivalent designed uniform units

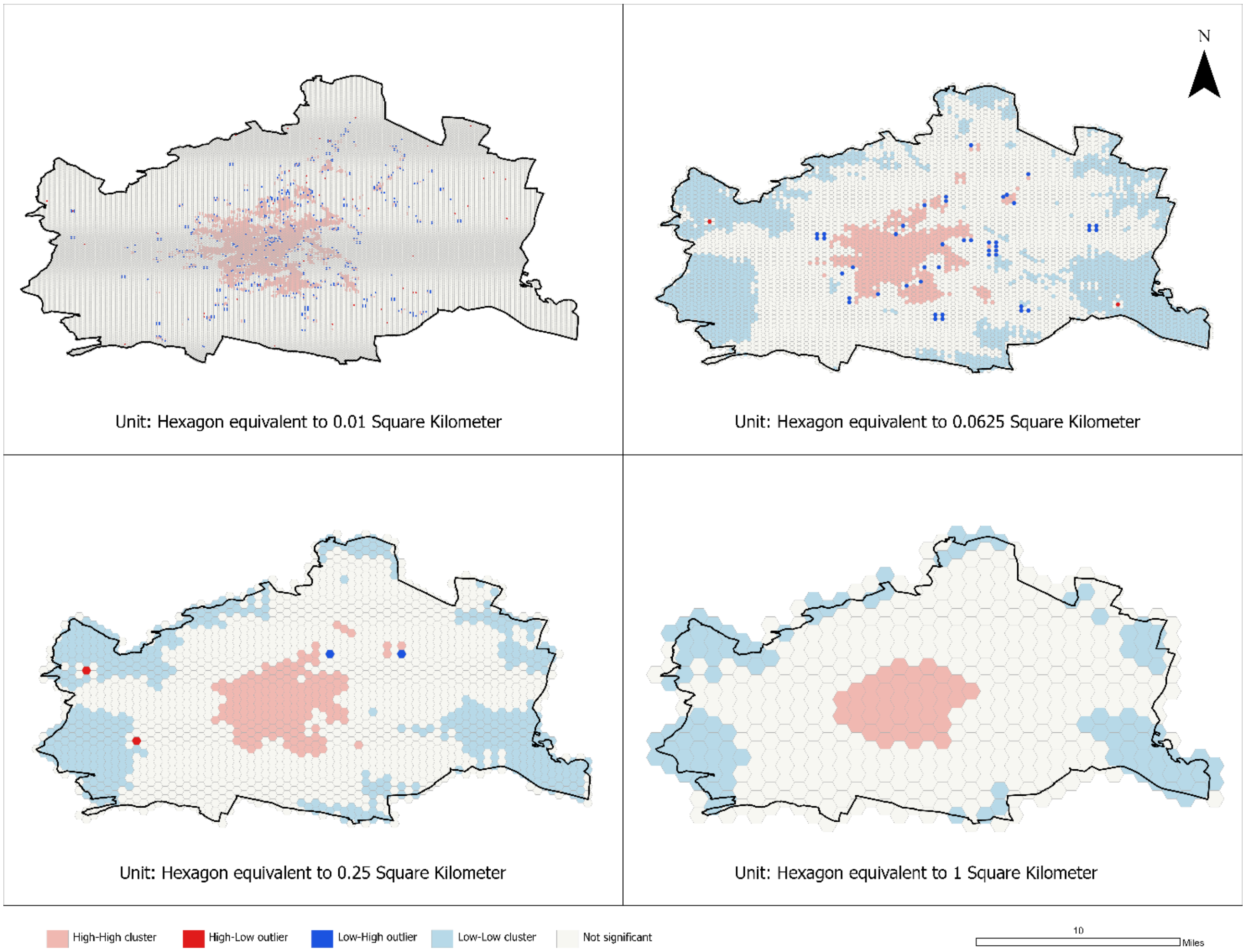

Figure 6. Local indicators of spatial association map of all crime types in Vienna at different scales of hexagons

Table 5. The percentage of each type of cluster analysis results of all crime types at each type of spatial unit.

Types of Spatial Unit	*Count of Unit*	*Percent of Low-Low Cluster*	*Percent of Low-High Outlier*	*Percent of Not Significant*	*Percent of High-Low Outlier*	*Percent of High-High Cluster*
Blocks	1364	20.89%	18.91%	44.35%	2.79%	13.05%
Squares equivalent to Blocks	5458	26.57%	0.51%	64.66%	0.04%	8.23%
Hexagons equivalent to Blocks	5447	26.66%	0.61%	64.92%	0.02%	7.80%
Triangles equivalent to Blocks	5501	15.43%	0.40%	76.40%	0.04%	7.73%
Squares equivalent to 0.01 Square Kilometer	42315	0.00%	1.15%	91.63%	0.12%	7.10%
Squares equivalent to 0.0625 Square Kilometer	6950	25.42%	0.60%	66.09%	0.09%	7.80%
Squares equivalent to 0.25 Square Kilometer	1814	24.97%	0.28%	65.88%	0.06%	8.82%
Squares equivalent to 1 Square Kilometer	490	23.06%	0.00%	68.78%	0.00%	8.16%
Hexagons equivalent to 0.01 Square Kilometer	42326	0.00%	1.17%	91.43%	0.10%	7.30%
Hexagons equivalent to 0.0625 Square Kilometer	6959	26.45%	0.63%	65.34%	0.03%	7.54%
Hexagons equivalent to 0.25 Square Kilometer	1809	25.76%	0.11%	65.34%	0.11%	8.68%
Hexagons equivalent to 1 Square Kilometer	492	21.14%	0.00%	71.34%	0.00%	7.52%
Triangles equivalent to 0.01 Square Kilometer	42477	0.00%	1.03%	92.09%	0.18%	6.70%
Triangles equivalent to 0.0625 Square Kilometer	7010	9.91%	0.49%	82.28%	0.01%	7.30%
Triangles equivalent to 0.25 Square Kilometer	1835	17.93%	0.22%	73.90%	0.11%	7.85%
Triangles equivalent to 1 Square Kilometer	508	9.06%	0.00%	84.25%	0.00%	6.69%

Similar to Local Moran's I, Getis Ord Gi* explores spatially contiguous clustering by examining neighboring areas to detect both high and low-value clusters (Mckay, 2018). The hotspots analysis conducted in ArcGIS Pro has generated the maps featured in Figure 7 and Figure 8.

In Figure 7, the manifestation of the zonal effect of the Modifiable Areal Unit Problem (MAUP) is apparent. Crime data aggregation at the block level reveals the presence of both hot and cold spots, whereas designed uniform units predominantly identify hot spots, designating the remaining units as "not significant." It is noteworthy that the variation in Getis Ord Gi* results among the three shapes of designed uniform units (Hexagons, Squares, and Triangles) is minimal, with all shapes primarily consisting of not significant areas and hotspots at 90%, 95%, and 99% significance levels. The spatial distribution of crime hotspots, as depicted in the maps, predominantly centers around the central and central-western regions of Vienna, consistent with the findings derived from Local Moran's I.

Simultaneously, Figure 8 offers insights into the conspicuous scale effect of the MAUP. As the spatial unit size expands, intricate details within the spatial crime pattern become increasingly obscured, leading to the neglect, blurring, or masking of subtle spatial intricacies. Larger spatial units, as the scale increases, identify expanded areas as hotspots. This phenomenon is further substantiated by the observations presented in Table 6, which illustrate a progressive increase in the percentage of hotspots with 99% confidence as the spatial unit size grows. This pattern is consistent across all three types of uniform units. Again, it is crucial to emphasize that the enduring influence of the MAUP persists even when focusing on specific crime categories, including theft, bodily harm, and robbery.

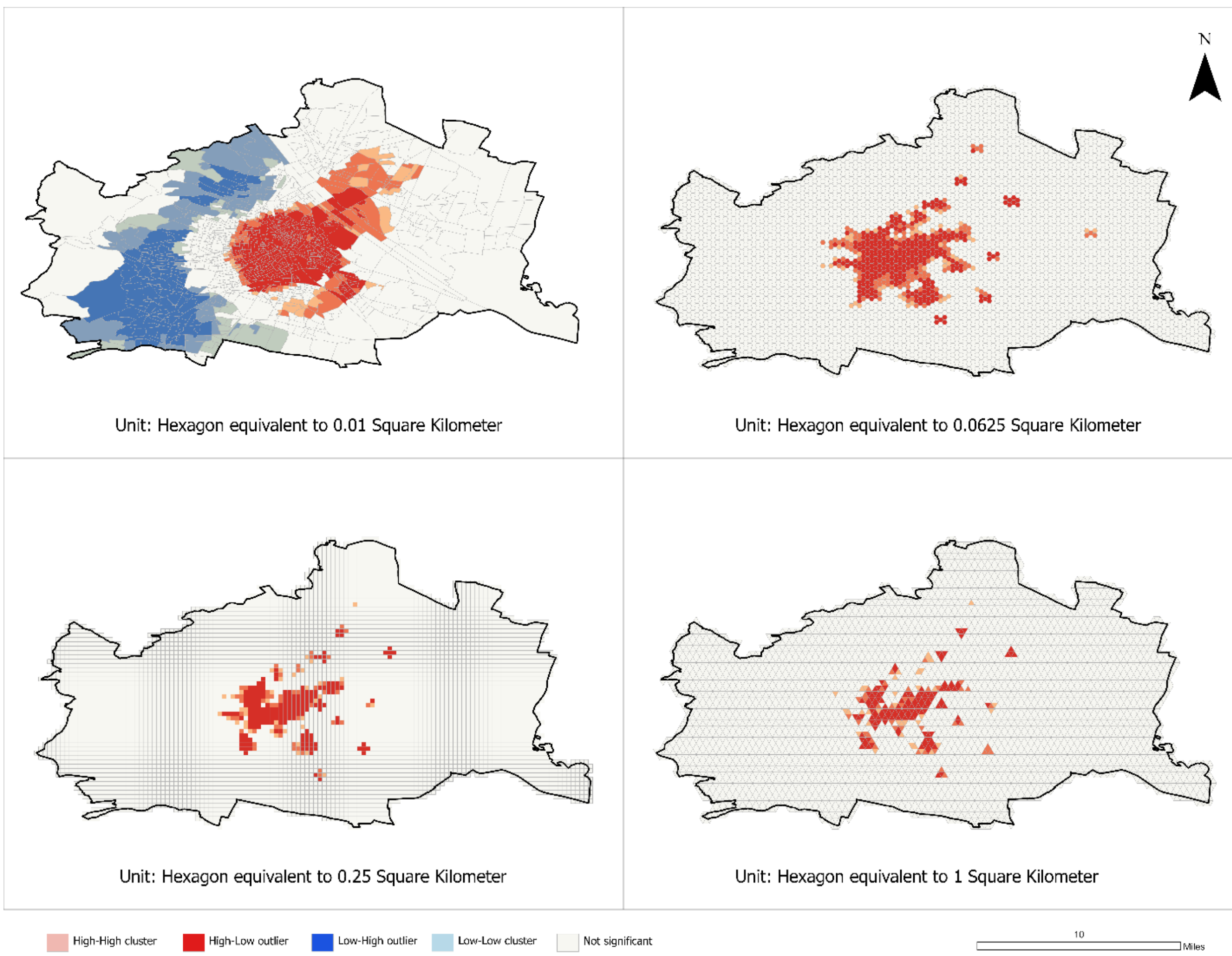

Figure 7. Map of the results of Getis Ord Gi* on all crime types in Vienna at block level and its equivalent designed uniform units

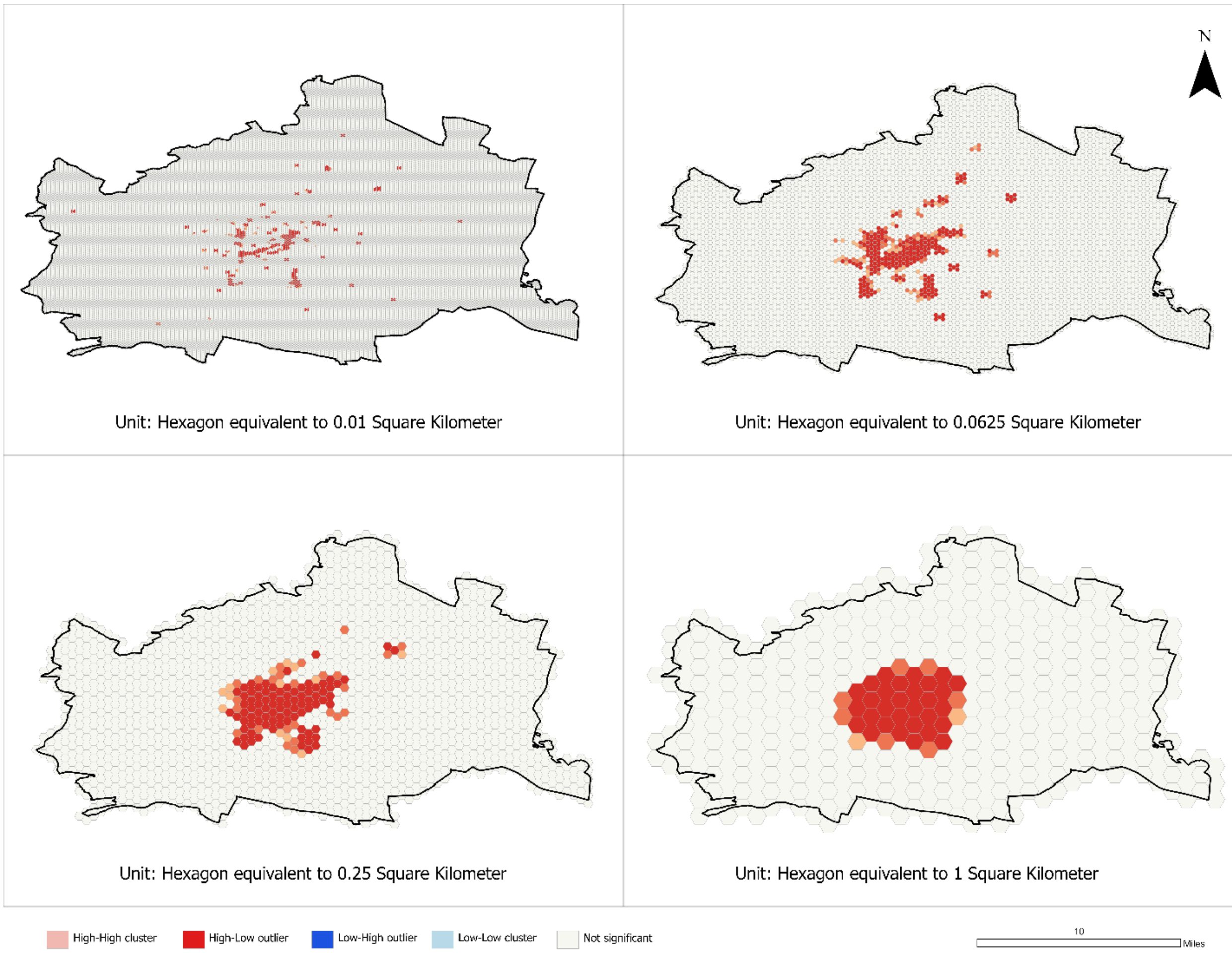

Figure 8. Map of the results of Getis Ord Gi* on all crime types in Vienna at different scales of hexagons

Table 6. The percentage of each type of Getis Ord Gi* results of all crime types at each type of spatial unit.

Types of Spatial Unit	*Count of Unit*	*Percent of Low Crime (Cold Spots or Not Significant)*	*Percent of Low-Medium Crime (Hot Spot 90% significance)*	*Percent of Medium Crime (Hot Spot 95% significance)*	*Percent of High Crime (Hot Spot 99% significance)*
Blocks	1364	56.74%	3.37%	7.70%	32.18%
Squares equivalent to Blocks	5458	95.05%	0.70%	0.92%	3.33%
Hexagons equivalent to Blocks	5447	91.44%	1.03%	1.96%	5.56%
Triangles equivalent to Blocks	5501	96.09%	0.65%	0.75%	2.51%
Squares equivalent to 0.01 Square Kilometer	42315	96.03%	0.94%	1.05%	1.99%
Squares equivalent to 0.0625 Square Kilometer	6950	91.93%	0.85%	2.00%	5.22%
Squares equivalent to 0.25 Square Kilometer	1814	89.47%	1.16%	1.82%	7.55%
Squares equivalent to 1 Square Kilometer	490	89.39%	0.61%	1.63%	8.37%
Hexagons equivalent to 0.01 Square Kilometer	42326	98.52%	0.14%	0.19%	1.15%
Hexagons equivalent to 0.0625 Square Kilometer	6959	95.36%	0.65%	0.82%	3.18%
Hexagons equivalent to 0.25 Square Kilometer	1809	93.20%	0.72%	1.38%	4.70%
Hexagons equivalent to 1 Square Kilometer	492	92.07%	0.41%	1.42%	6.10%
Triangles equivalent to 0.01 Square Kilometer	42477	98.79%	0.08%	0.13%	1.00%
Triangles equivalent to 0.0625 Square Kilometer	7010	96.60%	0.40%	0.54%	2.45%
Triangles equivalent to 0.25 Square Kilometer	1835	93.79%	0.98%	1.31%	3.92%
Triangles equivalent to 1 Square Kilometer	508	94.49%	0.59%	0.79%	4.13%

5.2. Spatiotemporal Hotspots

This section will describe the accessibility scores derived by the 2SFCA method at the grid level.

Figures 9 to 12 depict the spatiotemporal hotspots of total crime, theft, bodily injury, and robbery across four temporal scales (daily, weekly, monthly, and seasonally) and within two designed uniform shapes: squares and hexagons. The visual representations reveal a consistent trend wherein the majority of areas exhibit no discernible pattern, and cold spots are conspicuously absent. In alignment with the findings from Local Moran's I and Getis Ord Gi*, the spatiotemporal analysis identifies hotspots primarily in the central and central-western regions of Vienna. However, it is crucial to note that these hotspots exhibit distinct characteristics, as defined by ESRI:

1. New Hot Spot: These locations are statistically significant hot spots in the final time step and have not previously exhibited such significance.

2. Consecutive Hot Spot: This category encompasses locations with an uninterrupted run of at least two statistically significant hot spot bins in the final time-step intervals. The location has never been a statistically significant hot spot prior to this final run, and less than 90 percent of all bins are statistically significant hot spots.

3. Intensifying Hot Spot: Such locations have been statistically significant hot spots for 90 percent of the time-step intervals, including the final time step. Moreover, the intensity of clustering of high counts in each time step is increasing overall, and this increase is statistically significant.

4. Persistent Hot Spot: These locations have been statistically significant hot spots for 90 percent of the time-step intervals, with no discernible trend in the intensity of clustering over time.

5. Diminishing Hot Spot: Locations classified as diminishing hot spots have been statistically significant hot spots for 90 percent of the time-step intervals, including the final time step. In addition, the intensity of clustering in each time step is decreasing overall, and this decrease is statistically significant.

6. Sporadic Hot Spot: These locations are statistically significant hot spots only in the final time-step interval but have a history of intermittent hotspot identification. Less than 90 percent of the time-step intervals have been statistically significant hot spots, and none have been statistically significant cold spots.

Although the central and central-western regions of Vienna consistently harbor the majority of identified hotspots, the types of hotspots vary depending on temporal units and the shape of spatial units. This variation underscores the influence of the Modifiable Temporal Unit Problem (MTUP) and the zonal effect of the Modifiable Areal Unit Problem (MAUP). For instance, focusing on bodily injuries, we observe that while only a few sporadic hotspots are identified using a daily temporal unit, a significantly greater number of units are classified as persistent hotspots when the temporal unit changes to a seasonal scale. This pattern is consistent across all studied crime types, including total crime. Notably, larger temporal units tend to reveal more persistent hotspots, while smaller temporal units, such as daily intervals, yield fewer or even no persistent hotspots. Moreover, the zonal effect of the MAUP becomes apparent when analyzing the spatiotemporal results for robbery using a daily temporal unit; distinct patterns emerge when changing the spatial units.

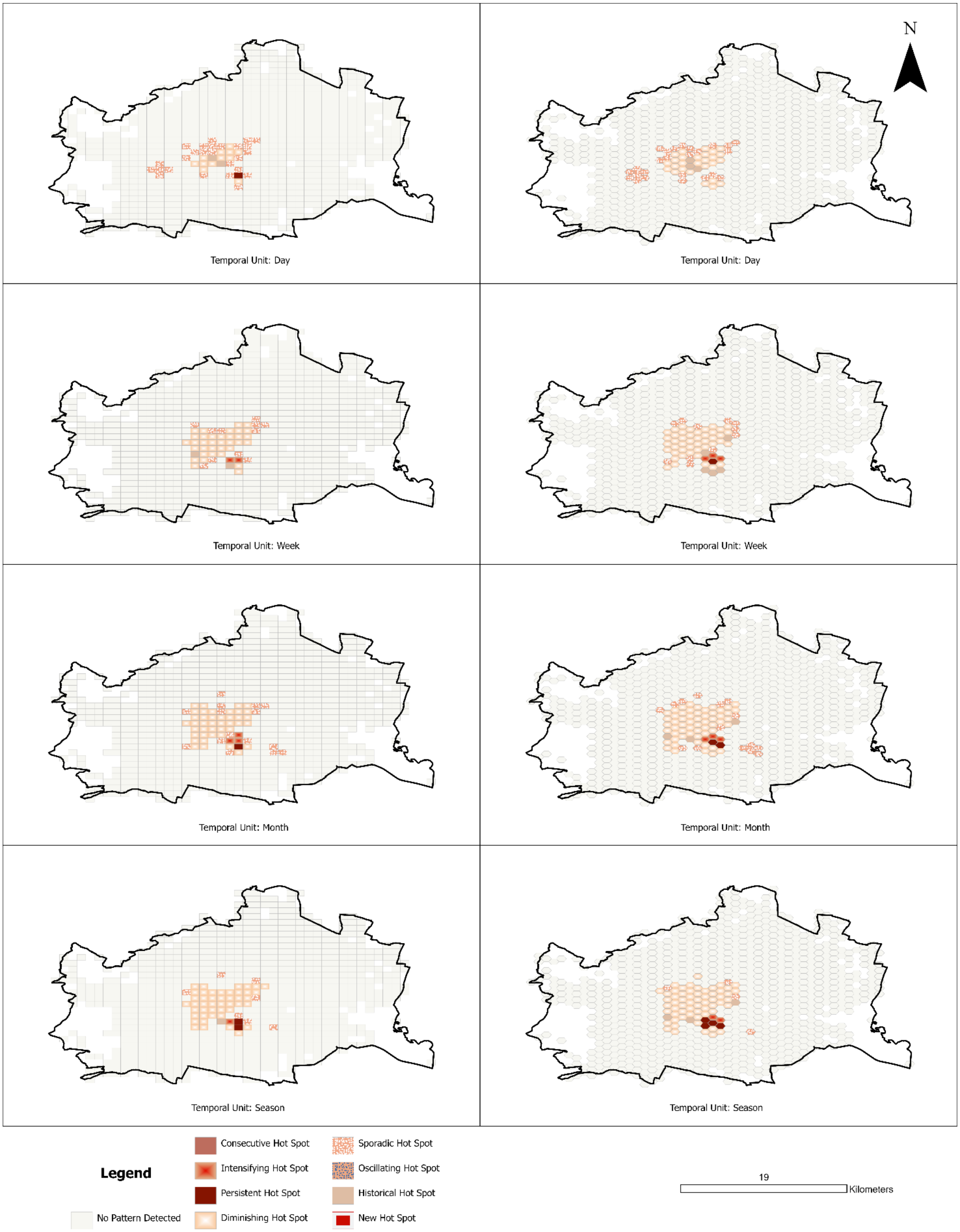

Figure 9. The maps of the results of emerging hotspots analysis of total crime

Figure 10. The maps of the results of emerging hotspots analysis of theft

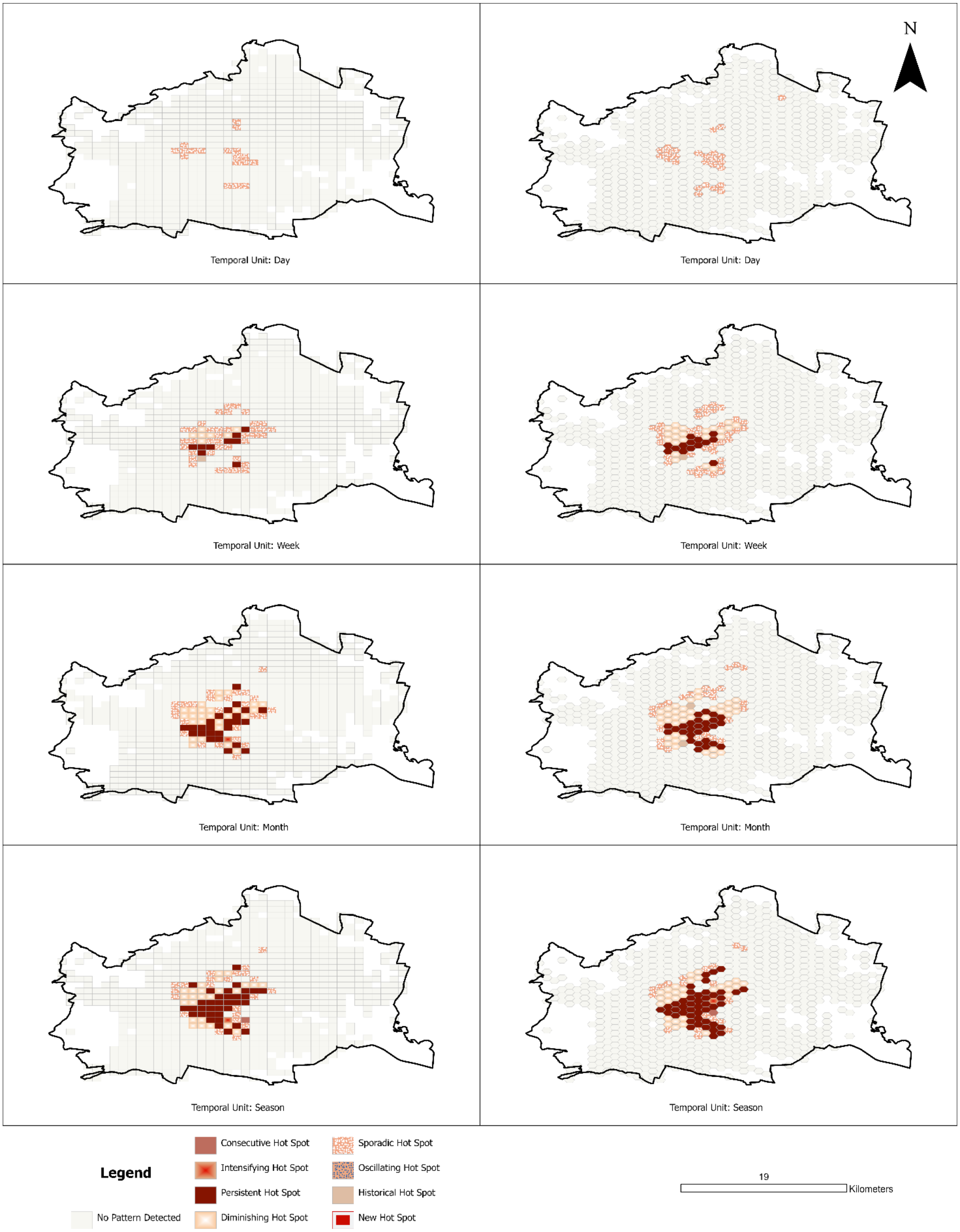

Figure 11. The maps of the results of emerging hotspots analysis of body injury

Figure 12. The maps of the results of emerging hotspots analysis of robbery

Chapter 6. Discussion

This study systematically explored the spatial patterns of crime in Vienna, Austria, employing four clustering methods: Global Moran’s I, Geary’s C, Local Moran's I, and Getis Ord Gi*. The investigation illuminated pivotal insights into the Modifiable Areal Unit Problem (MAUP), exposing the profound impact of spatial units and aggregation scales on crime analysis outcomes. The intricate interplay between spatial scales and crime patterns has been dissected, providing a nuanced understanding of how the choice of units significantly influences crime analysis results.

Local Moran's I, a cornerstone of our investigation, identified crime hotspots within the central and central-western regions of Vienna. The high-high cluster patterns from this analysis offer invaluable insights into the spatial distribution of criminal incidents. However, the MAUP's influence is evident, with different spatial units and aggregation scales leading to variations in hotspot detection. This underscores the importance of considering spatial scale in crime analysis. Reinforcing these findings, the application of Getis Ord Gi* affirms the existence of crime hotspots in the same central and central-western areas while highlighting the MAUP's influence, particularly concerning the aggregation scale. The discernible scale effect demonstrates how larger units obscure finer spatial nuances, emphasizing the need for nuanced spatial resolution in hotspot analysis.

The findings, consistently replicated across various types of crime, including theft, bodily injury, and robbery, underscore the persistent influence of the MAUP in the spatial analysis of crime. The zonal and scale effects that have surfaced throughout this study accentuate the complexity of spatial data analysis and underscore the necessity of accounting for these factors in research design.

Chapter 7. Future Work

Moreover, this study has delved into the temporal dynamics of crime in Vienna, Austria, shedding light on the Modifiable Temporal Unit Problem (MTUP). Scrutinizing temporal units and the shape of spatial units has brought to the fore the complexity of the interplay between the MAUP and the MTUP, emphasizing the need to consider both temporal and spatial scales when interpreting hotspot patterns. While the central and central-western regions of Vienna consistently hosted the majority of identified hotspots, our analysis exposed variations in hotspot types based on temporal units, reinforcing the interplay of the MAUP and the MTUP. Particularly noteworthy is the discovery that larger temporal units tend to reveal more persistent hotspots, while smaller units yield fewer or even no persistent hotspots.

One of the fundamental limitations inherent in any analysis of police crime data is the incidents that go unreported and, consequently, do not form part of recorded crime datasets. This enigmatic aspect of unreported crime can have a notable impact at smaller scales, potentially leading to misleading clustering results. Furthermore, this study focused on total crime rather than rates, and the challenge of finding attribute data to be linked with designed uniform units has been acknowledged. As a steppingstone for future research, a Monte Carlo simulation study could be pursued, allowing for the examination of the clustering performance within the context of the MAUP in situations where the true values are known. Additionally, exploring the impact of the MAUP and the MTUP on prospective crime hotspots—measured by indices such as hit rate, predictive accuracy index, and recapture rate index—could offer invaluable insights into the interplay between designed uniform units and prospective crime hotspots.

Chapter 8. Conclusion

In conclusion, this research underscores the importance of accounting for both temporal and spatial scales in spatiotemporal crime analysis. Policymakers and researchers alike must grasp the intricate interplay of MAUP and MTUP and its consequential impact on the identification and characterization of crime hotspots. These findings contribute to a more comprehensive understanding of the spatiotemporal dynamics of crime in Vienna, providing valuable insights for informed decision-making in crime prevention and resource allocation strategies. As cities grapple with the ongoing challenges of crime management, a nuanced understanding of the effects of temporal and spatial units is imperative for more effective and precise interventions. This research serves as a foundation for future exploration into the complexities of spatiotemporal crime analysis and offers a roadmap for addressing the interrelated challenges posed by the MAUP and the MTUP.

References

Anselin, L. (1995). Local Indicators of Spatial Association-LISA. *Geographical Analysis*, *27*(2), 93–115. https://doi.org/10.1111/j.1538-4632.1995.tb00338.x

Braga, A. A. (2001). The Effects of Hot Spots Policing on Crime. *The ANNALS of the American Academy of Political and Social Science*, *578*(1), 104–125. https://doi.org/10.1177/000271620157800107

Braga, A. A., Turchan, B. S., Papachristos, A. V., & Hureau, D. M. (2019a). Hot spots policing and crime reduction: an update of an ongoing systematic review and meta-analysis. *Journal of Experimental Criminology*, *15*(3), 289–311. https://doi.org/10.1007/s11292-019-09372-3

Braga, A. A., Turchan, B., Papachristos, A. V., & Hureau, D. M. (2019b). Hot spots policing of small geographic areas effects on crime. *Campbell Systematic Reviews*, *15*(3). https://doi.org/10.1002/cl2.1046

Cheng, T., & Adepeju, M. (2014). Modifiable Temporal Unit Problem (MTUP) and Its Effect on Space-Time Cluster Detection. *PLoS ONE*, *9*(6), e100465. https://doi.org/10.1371/journal.pone.0100465

Cöltekin, A., De Sabbata, S., Willi, C., Vontobel, I., Pfister, S., Kuhn, M., & Lacayo, M. (2011, July 2). *Modifiable temporal unit problem*. Www.zora.uzh.ch; University of Zurich. https://doi.org/10.5167/uzh-54263

Deckard, M., & Schnell, C. (2022). The Temporal (In)Stability of Violent Crime Hot Spots Between Months and The Modifiable Temporal Unit Problem. *Crime & Delinquency*, *69*(6-7), 001112872211284. https://doi.org/10.1177/00111287221128483

Fotheringham, A. S., & Wong, D. W. S. (1991). The Modifiable Areal Unit Problem in Multivariate Statistical Analysis. *Environment and Planning A: Economy and Space*, *23*(7), 1025–1044. https://doi.org/10.1068/a231025

Geary, R. C. (1954). The Contiguity Ratio and Statistical Mapping. *The Incorporated Statistician*, *5*(3), 115. https://doi.org/10.2307/2986645

Gerell, M. (2016). Smallest is Better? The Spatial Distribution of Arson and the Modifiable Areal Unit Problem. *Journal of Quantitative Criminology*, *33*(2), 293–318. https://doi.org/10.1007/s10940-016-9297-6

Getis, A., & Ord, J. K. (2010). The Analysis of Spatial Association by Use of Distance Statistics. *Geographical Analysis*, *24*(3), 189–206. https://doi.org/10.1111/j.1538-4632.1992.tb00261.x

Malleson, N., & Andresen, M. A. (2016). Exploring the impact of ambient population measures on London crime hotspots. *Journal of Criminal Justice*, *46*, 52–63. https://doi.org/10.1016/j.jcrimjus.2016.03.002

McKay, R. M. (2018). *Comparing Crime Hotspots at Different Areal Resolutions in Strathclyde* . https://theses.gla.ac.uk/41161/

Moran, P. A. P. (1950). Notes on Continuous Stochastic Phenomena. *Biometrika*, *37*(1/2), 17. https://doi.org/10.2307/2332142

Openshaw, S. (1977). A Geographical Solution to Scale and Aggregation Problems in Region-Building, Partitioning and Spatial Modelling. *Transactions of the Institute of British Geographers*, *2*(4), 459. https://doi.org/10.2307/622300

Openshaw, S. (1984) Concepts and techniques in modern geography number 38: the modifiable areal unit problem. Geo Books, Norwich

Purwanto, P., Utaya, S., Handoyo, B., Bachri, S., Astuti, I. S., Utomo, K. S. B., & Aldianto, Y. E. (2021). Spatiotemporal Analysis of COVID-19 Spread with Emerging Hotspot Analysis and Space–Time Cube Models in East Java, Indonesia. *ISPRS International Journal of Geo-Information*, *10*(3), 133. https://doi.org/10.3390/ijgi10030133

Schnell, C., DeWitt, S. E., & Spencer, M. D. (2022). The Role of Neighborhoods in the Age of

Crime Hot Spots: A Multi-Level Theory of the Spatial Distribution of Robbery in Chicago. *Crime & Delinquency*, *0*(0), 001112872211408. https://doi.org/10.1177/00111287221140836

Sherman, L. W., Gartin, P. R., & Buerger, M. E. (1989). Hot Spots Of Predatory Crime: Routine Activities And The Criminology Of Place. *Criminology*, *27*(1), 27–56. https://doi.org/10.1111/j.1745-9125.1989.tb00862.x

Sherman, L. W., & Weisburd, D. (1995). General deterrent effects of police patrol in crime "hot spots": A randomized, controlled trial. *Justice Quarterly*, *12*(4), 625–648. https://doi.org/10.1080/07418829500096221

The Global Liveability Index 2023. (n.d.). Economist Intelligence Unit. https://www.eiu.com/n/campaigns/global-liveability-index-2023/

Tita, G. E., & Radil, S. M. (2010). Making Space for Theory: The Challenges of Theorizing Space and Place for Spatial Analysis in Criminology. *Journal of Quantitative Criminology*, *26*(4), 467–479. https://doi.org/10.1007/s10940-010-9115-5

Vandeviver, C., & Bernasco, W. (2017). The geography of crime and crime control. *Applied Geography*, *86*, 220–225. https://doi.org/10.1016/j.apgeog.2017.08.012

Vienna in Figures - Urban Area, Population, Education, Economy, Transport, Public Administration. (n.d.). Www.wien.gv.at. https://www.wien.gv.at/english/administration/statistics/index.html#overview

Wang, F., & Liu, L. (2023). *Computational Methods and GIS Applications in Social Science*. CRC Press.

Weisburd, D., & Telep, C. W. (2014). Hot Spots Policing: What We Know and What We Need to Know. Journal of Contemporary Criminal Justice, 30(2), 200–220. https://doi.org/10.1177/1043986214525083

Wong, D. (2008). The Modifiable Areal Unite Problem (MAUP). In A. S. Fotheringham & P. A. Rogerson (Eds.), *The SAGE Handbook of Spatial Analysis*. SAGE.

Zahrani , B. (2020). *Evaluating The MAUP Scale Effects On Property Crime In San Francisco, California*.

Zhou, X., Lin, H. (2008). Geary's *C* . In: Shekhar, S., Xiong, H. (eds) Encyclopedia of GIS. Springer, Boston, MA. https://doi.org/10.1007/978-0-387-35