GEOGRAPHIC PROFILING – ENVIRONMENTAL AND OFFENDERS' BEHAVIOR PATTERNS OF ROBBERY CHARACTERISTICS

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INTRODUCTION

Understanding the geography of crime has become increasingly important in crime analysis. The connection between the characteristics of the criminal act, the characteristics of the place of a commission of criminal offence, as well as the perpetrator's performance methods in a geospatial environment indicate that the choice of intended target by the perpetrator is not random. Nevertheless, it is most often caused by some psychological and geospatial characteristics (Milojković & Petrović, 2019:10).

Spatial analysis of crime can play important role in the policing and the crime reduction process, it can be employed in both an exploratory and more confirmatory manner with the purpose of identifying how ecological factors influence the spatial pattern of crime. Crime mapping can help law enforcement and policy makers to explore crime patterns, offender mobility, and serial offences over space and time (Amoako, 2021; Butorac & Marinović, 2017). Ecological theories, such as routine activity theory and rational choice theory, suggest that crime occurs when motivated offenders and suitable targets converge in time and space (Anselin et al., 2000). Therefore, understanding the spatial and temporal components of crime patterns is crucial. In urban areas, crime is not random or homogeneous, so scientists aim to identify the environmental features of places that may contribute to crime (Di Bella et al., 2015). The movements of offenders and targets are influenced by their daily routines and the social and physical surroundings in which they interact (Kannan & Singh, 2021). For example, studies of the spatial patterns of robberies in urban environments have revealed that a small number of micro places generate a disproportionate number of robberies. Certain high-risk facilities, such as streets corners, bars, convenience stores, and banks, at places tend to experience a disproportionate amount of robbery (Braga, Hureau & Papa Christos, 2011). The length of the criminal path (journey to crime), or the distance between the offender's anchor point and the crime location, is an important spatial component (Andresen, Frank & Felson, 2014). The likelihood of committing a crime decreases as the distance from the anchor point increases, known as the distance decay effect. Factors such as local geography and decision-making processes influence the pattern of distance decay (O'Leary, 2011), which can be described using different decay functions (Hammond & Young, 2011). Numerous studies have demonstrated the distance decay effect in different types of crime and its relationship with various sociodemographic features (Hesseling, 1992; Koppen & Jansen 1998; Bernasco & Luyx, 2003; Bernasco & Nieuwbeerta, 2005; Bernasco, 2006). The spatial patterns of crime are not only influenced

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by the location, but also by the time of the crime. Understanding the temporal dimension of crime is crucial as it provides opportunities for crime based on spatial accessibility. Additionally, the social characteristics of offenders have been found to be significantly correlated with specific types of crime (Wang, Lee & Williams, 2019; Bernasco & Ruiter, 2018).

Crime patterns are analysed based on socio-demographic, temporal, and spatial attributes, and can be visualized by using graphs, tables, and maps (Wortley & Mazerolle, 2009; Milojković & Petrović, 2019). Geospatial data processing technology allows for a better understanding of crime patterns and the analysis of connections between socio-demographic, spatial, and temporal features. This information can be used for operational and strategic planning to enhance community security (Butorac, 2011). Though it is not the focus of this paper, it is certainly noteworthy to mention related studies on Kernel Density Mapping, hotspot identification, and predictive accuracy of crime maps. For example, the study by Milić, Popović, Mijalković, and Marinković (2019) specifically examines the effects of different classification methods on the accuracy of Kernel Density Estimation hotspot maps, recommending an incremental mean approach for optimal predictive results. Additionally, the study by Eman, Györkös, Lukman and Meško (2013) analyses property crime using GIS and identifies the *areas* having high *crime* intensity, i.e. the crime hotspots. The study by Milić (2013) highlights the benefits of combining computer automated geographic methods with field investigations for early crime detection and analysis of crime hot spots, emphasising the potential for improved policing and crime prevention through advanced analytical tools like GIS.

PURPOSE

Geographic profiling is a crime analysis technique that uses the locations of a connected series of crime sites to identify or to predict the offender patterns and to determine the most probable area of offender residence. This paper is a part of the research project *Geographic profiling of robberies in the area of the City of Zagreb*, which has been run since 2018. The project objectives are to investigate spatial patterns and related variables influencing the criminal path of robbers, as well as the temporal components of crime. The ultimate goal is to acquire new knowledge in perpetrators geo-profiling in order to make informed decisions based on the findings obtained. The use of geographical information systems (GIS) is necessary for crime analysts to explore data from various perspectives, such as date-based, spatial, and field attributes, to analyse crime data. GIS tools aid in investigating incident data and addressing specific problem subsets. Crime analysts contribute to the data-driven crime reduction efforts of law enforcement agencies by employing tactical and strategic analysis methods to identify short-term patterns and evaluate long-term crime issues and trends. Spatial analysis, in particular hotspot identification and criminal paths, are crucial in these methods. Crime analysts also assist investigations by analysing data to uncover criminal networks and comprehend suspect activity patterns.

DESIGN /METHOD/APPROACH

The research methodology involves collecting and processing police crime data on robbery crimes recorded and investigated in 2018 as well as publicly available geographical and census data to enhance the research findings. It utilises geospatial data processing technology to analyse crime patterns and connections between socio-demographic, spatial and temporal features of the criminal events. The study focuses on the use of GIS to analyse and visualise crime data. The analysis is only as good as the input data, and in this case, the data collected from the police administration had limitations in terms of spatial resolution due to the GDPR[2] protection of personal data of identifiable living individual. Respectively, personal data that has been de-identified, encrypted or pseudonymised, but can be used to re-identify a person, remains personal data and falls within the scope of the GDPR. Therefore, the spatial resolution of robbery locations and offender residency are determined at the neighbourhood level. In order to obtain more accurate criminal paths using street routing distances, additional sources were utilised to gather more detailed location data, whenever possible.

STUDY AREA

The study area includes the City of Zagreb and parts of the Zagreb County, specifically focusing on the robbery data in 2018 under the jurisdiction of the Police Directorate Zagreb (Figure 1). The City of Zagreb is divided into 17 administrative districts (Zagreb in Figures 2022), which are further classified into 11 neighbourhoods by police administration (Table 1). It covers an area of 641 km^2. Zagreb County consists of 9 towns and 25 municipalities, covering an area of 3 060 km^2. The study specifically includes the robbery data from 8 towns and 7 municipalities in Zagreb County, of total surface area of 1 903 km^2 (Table 1).

Zagreb is the capital and the largest city in Croatia, with a population of 767,131 citizens according to the 2021 census by Croatian Bureau of Statistics (Croatian Bureau of Statistics, 2022). It is also the only city in Croatia with a metropolitan area that exceeds one million people, including the towns from Zagreb County.

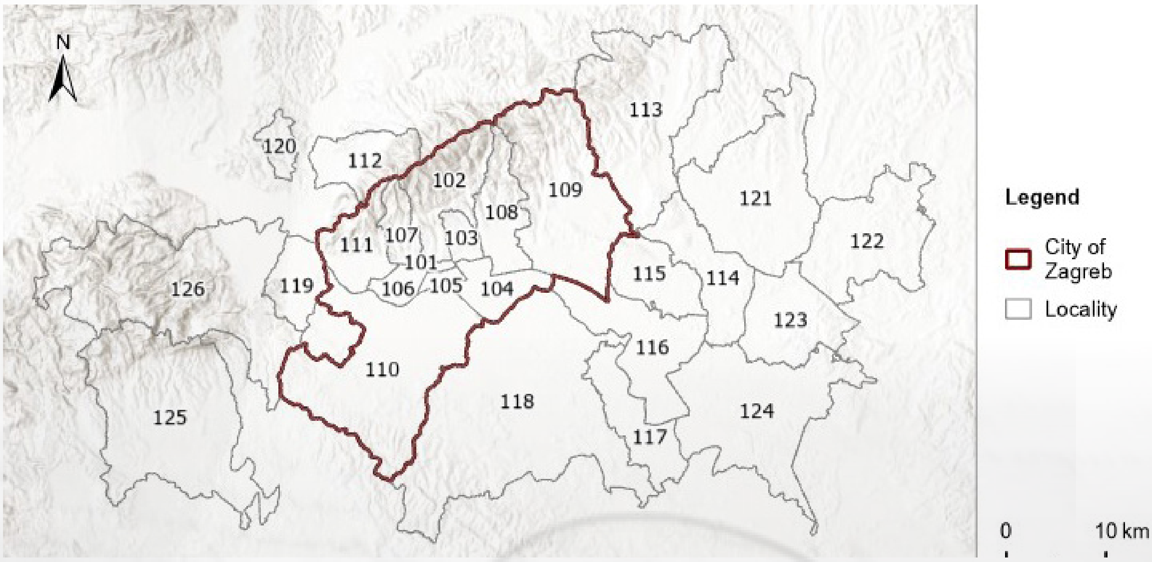

Figure 1. *The Study Area Encompasses the City of Zagreb and Parts of Zagreb County*

2 Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation). Accessed on May 20, 2024. https://eur-lex.europa.eu/eli/reg/2016/679/oj

Table 1. *Information Overview on Different Localities, Including Their Type, County, Number of Robberies, Population, Area in Square Kilometres, Ratio of Robberies per 1000 Inhabitants, and Ratio of Robberies per Square Kilometres*

County	Locality number	Locality	Locality type	Number of robberies	Population	Area [km²]	Robberies per 1000 inhabitants	Robberies per square km
City of Zagreb	101	Centar	Neighbourhood	18	34,268	3,02	0.525	5.968
	102	Medveščak	Neighbourhood	10	52,312	69,44	0.191	0.144
	103	Maksimir	Neighbourhood	27	51,626	14,97	0.523	1.804
	104	Peščenica	Neighbourhood	34	54,996	35,29	0.618	0.963
	105	Trnje	Neighbourhood	32	43,335	7,36	0.738	4.345
	106	Trešnjevka	Neighbourhood	75	124,390	15,64	0.603	4.794
	107	Črnomerec	Neighbourhood	8	39,858	24,18	0.201	0.331
	108	Dubrava	Neighbourhood	26	98,961	51,22	0.263	0.508
	109	Sesvete	Neighbourhood	13	70,868	165,22	0.183	0.079
	110	Novi Zagreb	Neighbourhood	76	131,542	206,50	0.578	0.368
	111	Susedgrad	Neighbourhood	14	97,831	48,40	0.143	0.289
Zagreb County	112	Bistra	Municipality	1	6,138	52,93	0.163	0.019
	113	Sveti Ivan Zelina	Town	1	13,729	185,94	0.073	0.005
	114	Brckovljani	Municipality	1	6,042	69,77	0.166	0.014
	115	Dugo Selo	Town	1	17,681	54,29	0.057	0.018
	116	Rugvica	Municipality	0	7,356	93,67	-	-
	117	Orle	Municipality	3	1,675	58,57	1.791	0.051
	118	Velika Gorica	Town	16	61,103	326,67	0.262	0.049
	119	Sveta Nedelja	Town	1	17,751	39,74	0.056	0.025
	120	Pušća	Municipality	0	2,445	17,03	-	-
	121	Vrbovec	Town	3	13,013	160,86	0.231	0.019
	122	Dubrava	Municipality	2	4,325	115,65	0.462	0.017
	123	Kloštar Ivanić	Municipality	0	5,485	77,45	-	-
	124	Ivanić-Grad	Town	2	12,369	173,52	0.162	0.012
	125	Jastrebarsko	Town	4	14,195	226,44	0.282	0.018
	126	Samobor	Town	1	36,181	251,46	0.028	0.004

DATA COLLECTION

This study is a part of the research project *Geographic profiling of robberies in the area of the City of Zagreb,* which has been carrying out since 2018, with the objective to investigate spatial patterns and related variables influencing the criminal path of robbers. The data on crime events and offenders were collected from the Criminal Intelligence Analysis Department of the MoI Criminal Police Directorate. In 2018, there were 369 reported cases of robberies, with 180 of them being solved. The data include information on crime variables such as date, time, target, location, and means of usage for all robberies, as well as offender variables such as age, sex, education level, employment, and residency for solved robberies. Due to the aforementioned General Data Protection Regulation (GDPR), location information is available at the neighbourhood level. To improve the accuracy of robbery target locations, media data from the Ministry of Interior's website were used to obtain more precise locations for 252 criminal events, including either street or exact location details. For the remaining data, the mean centroids of population for each neighbourhood (Figure 2) was used as the location of the robbery. The location of residency for offenders was also taken at the neighbourhood level, and the mean centroids of population for each neighbourhood was used as their location. Feature extraction is performed in three phases. The first phase involves conducting geocoding, where coordinates of the robberies are pinpointed using the projected Croatian coordinate reference system (HTRS96-TM). In the second phase, crimes are categorized on the basis of various variables such as the type of robbery, target, location, and means of usage. Lastly, additional information about the offender and the geographic and socio-demographic variables of the area are incorporated into the solved robbery cases, including an offender's age, sex, education level, employment, residency, and the different statuses of the 20 police stations of the Police Directorate Zagreb for the study area.

Geographic and census data were collected from open sources such as the Open Street Map (OSM) for street routing and the Urban Atlas from Copernicus Land Monitoring Service for the census data for 2018. The services of the Copernicus program are widely used in the analysis, planning, prediction, monitoring, data review, and data management of land, atmosphere, climate change, marine environment, security (border surveillance and maritime traffic), and crisis situations (Batina, 2020).

DATA ANALYSIS

In 2018, Zagreb experienced a total of 369 robbery incidents. A detailed analysis was conducted to determine the most common methods used to commit these robberies, the primary targets, socio-demographic influences, the criminal paths, and the locations where the robberies occurred.

The GIS methodology used in this study involved creating layers and themes to analyse the distribution of robberies in different localities. GIS is a useful tool for analysing crime data from various perspectives and can help identify patterns and trends. Spatial data in GIS can be visually represented by using different thematic maps, such as heat maps (Roland, Šiljeg & Batina, 2017). Since robbery data may not be evenly distributed by the locality due to differences in population density and locality area, the study used the ratios of robberies per population and robberies per the area. The population data used for these calculations were from the 2018 Census conducted by Urban Atlas.

The analysis was carried out on the solved robbery cases, considering information about the offender, as well as the geographic and socio-demographic determinants of the area. The aim was to identify the patterns in these cases. Additionally, the street routing was conducted to determine the most likely path taken by an offender from their home to a target location. The purpose of reconstructing the criminal paths is to analyse their spatial relationship with the offenders' crime locations and their socio-demographic data (age, sex, education level, type of robbery, etc.). To generate these paths, the shortest path algorithm is used.

Street routing is important for understanding the movement of offenders who commit robberies and for the analysing journey to crime. Distance decay functions are used to analyse the typical patterns of offenders' movement. By calibrating these functions and implementing other parameters described in this paper, a best fitted model can be created to predict offenders' residence more accurately (Butorac, Maurer & Gajski, 2021). However, the accuracy of the model can be reduced if the data used for spatial reconstruction are not properly calibrated, especially if there is a limited amount of input data (Gajski, Krtalić & Maurer, 2019). The results of this study are a starting point for further research of using distance decay modelling and calibration in this research project.

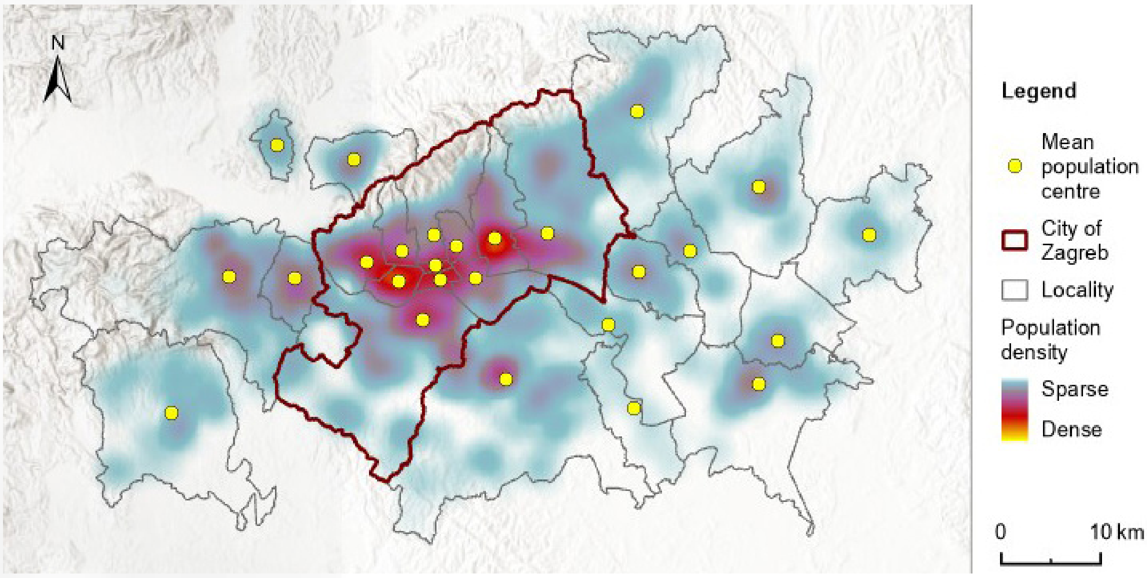

Figure 2. *The Population Density and the Mean Population Centroids for Each Neighbourhood*

FINDINGS AND DISCUSSION

Based on the analysis of available data, the means used for robberies and the primary targets of these crimes were highlighted. The relationship between the crime-related variables, such as the age of the offender and the means used, as well as the time of day of the crime and the travelled distance were examined. The study further analyses the frequency of robberies and the distance of criminal paths. The Street routing algorithm was employed to calculate criminal paths between the offender's residency and the target location. The distribution of criminal paths and the visualisation of all robberies in the study area are based on the performed analyses. Additionally, the study discusses the ratio of robberies per square kilometres and per population in the study area, as well as the use of a heat maps to identify higher crime areas.

CRIME SUMMARY ANALYSIS

In 2018, a total of 369 robbery incidents occurred in Zagreb. The most common mean of carrying out these robberies were the use of weapon, accounting for 49% of cases, followed by physical force at 31%, tools at 19%, and chemical substances at 2% (Figure 3). The primary targets of these robberies were individuals, accounting for 39% of cases, followed by stores at 26%, financial institutions at 9%, pharmacies at 7%, kiosks at 6%, gas stations at 5%, betting stores at 4%, hospitality facilities at 2%, and legal entities at 1% (Figure 4).

In 2018, a study was carried out on 180 solved robbery cases in Zagreb. The analysis revealed that the most common means used in these robberies were weapons, accounting for 45% of the cases. The physical force and tools were also frequently used, with percentages of 27% and 26% respectively, and chemical substances at 2% (Figure 3). The top targets for robbers are individuals (40%), stores (21%), pharmacies (11%), financial institutions (10%), kiosks (8%), betting stores (6%), gas stations (4%), and hospitality facilities (1%) (Figure 4).

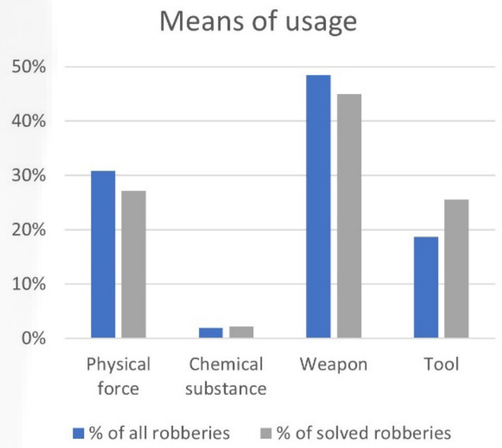

Figure 3. *Overview of Means Used for Robberies in the Study Area*

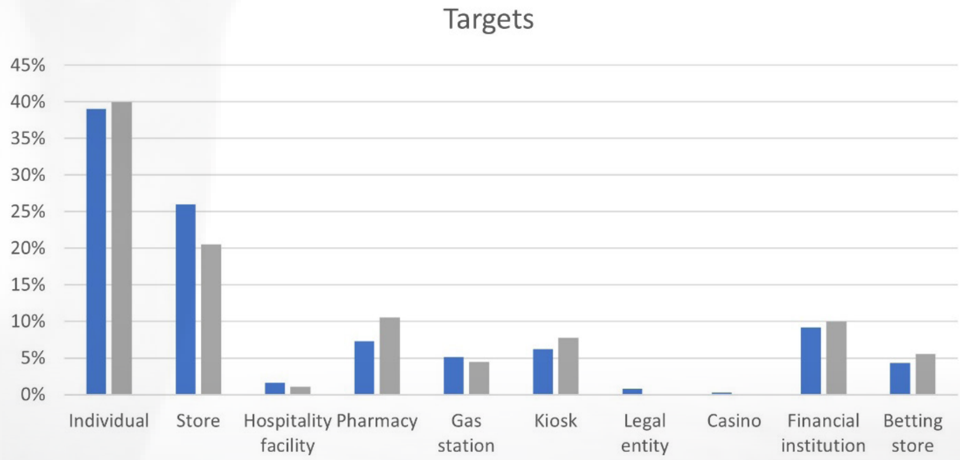

Figure 4. *Overview of Primary Targets of Robberies in the Study Area*

STREET ROUTING

The Street routing model was generated using Esri ArcGIS Pro 3.0. The model includes information about the road network, the locations of crimes, and offenders' residency. In reality the targets could be polygon shapes, but they are redefined as points for the purpose of generating paths (Iwanski et al., 2011). The model assumes that offenders travel in the direction of the target from their home location. As previously stated, offenders' home locations are geocoded as the mean centroids of population for each neighbourhood, due to the General Data Protection Regulation (GDPR), while the majority of target locations are geocoded to the exact location or street centroid, and the rest is geocoded as the mean centroids of population for each neighbourhood. Paths were simulated using only road network, assuming that offenders choose the shortest routes (Figure 5). The road network data are obtained from an OSM dataset and encoded as a feature class within ArcGIS Pro. The dataset includes information about the road segments, such as coordinates, direction of travel, length, and type of road. The input also includes the offenders' home locations, the crime locations, and the type of crime.

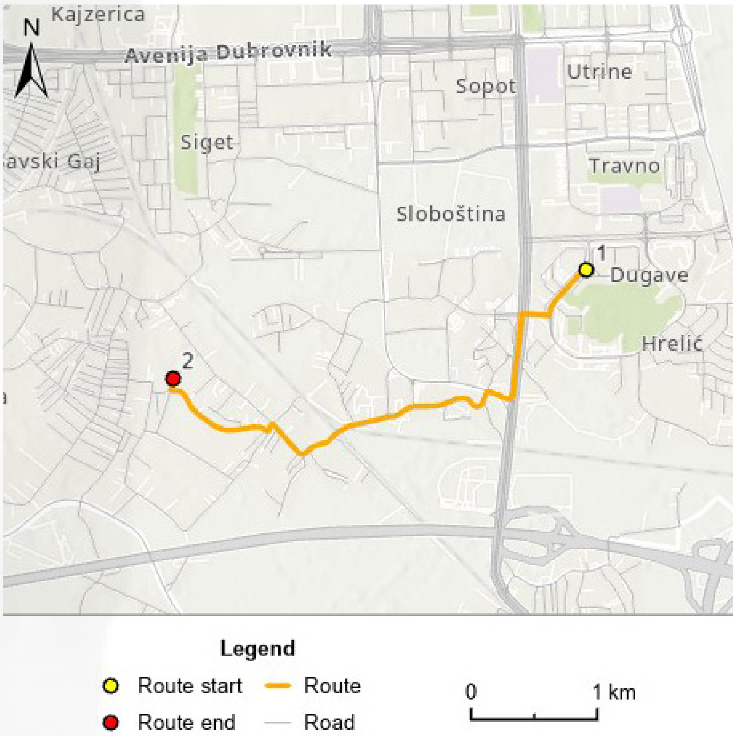

Figure 5. *Street Routing Example Between Offender's Residency (Point 1) and Target Location (Point 2)*

Figure 6. *The Distribution of Lengths of Criminal Paths*

The model focuses on crimes in the study area, with a total of 180 crimes. The presence of the distance decay effect was observed in the distance distribution of robberies committed by the offenders. Figure 6 shows that the frequency distribution of criminal path lengths decreases as the distance between the offender's residency and the target location increases. The median radius of all neighbourhoods in the City of Zagreb is 3 220 m, so the criminal paths are divided into classes of 3 000 m, as shown in Figure 6.

HEAT MAPS

This study used GIS methodology to analyse the distribution of robberies in different localities. Thematic maps were created to visually represent the number of robberies (Figure 7). Robbery density was calculated by dividing the total number of robberies by the area in square kilometres (Figure 8). Additionally, a robbery incidence rate was calculated by dividing the number of robberies by the population, expressed as % (Figure 9).

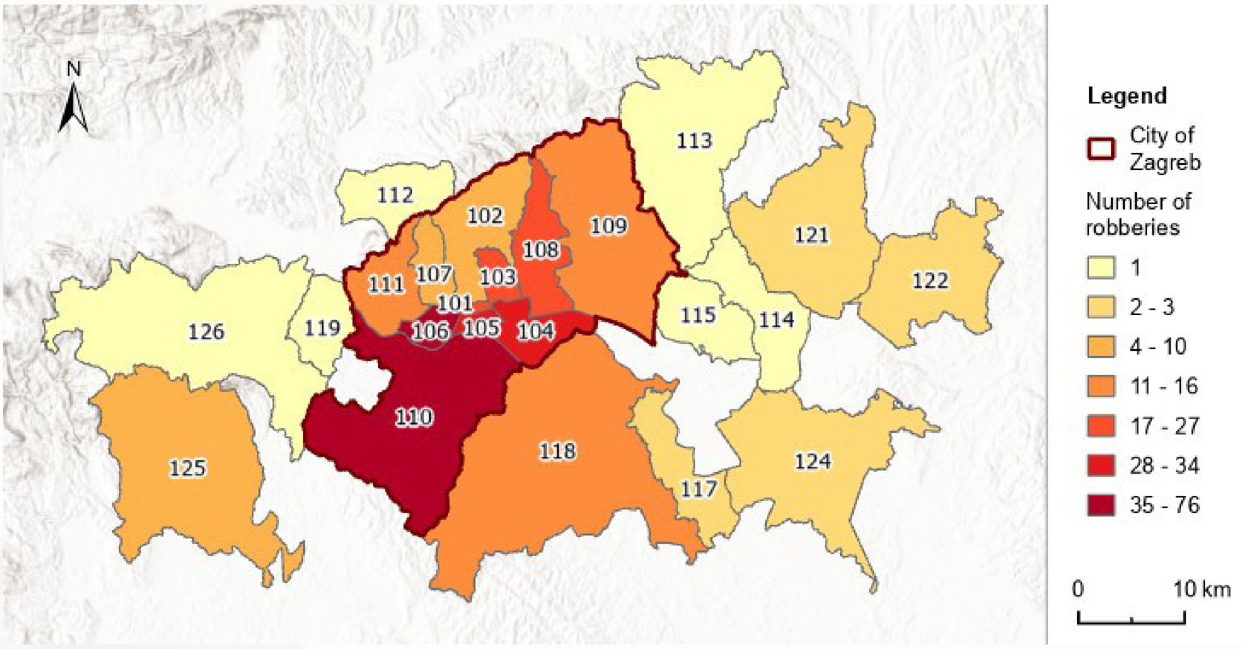

Figure 7. *Visualisation of All Robberies in the Study Area*

In 2018, there were a total of 369 robberies reported. The City of Zagreb had the highest number of robberies, with the majority occurring in the neighbourhoods of Novi Zagreb and Trešnjevka, following by neighbourhoods Trnje and Peščenica, as seen in Figure 7.

The density of robberies per locality can vary due to differences in the areas. Figure 8 shows the number of crime events per square kilometre, which indicates the density of robberies. The neighbourhood Centar has the highest density of robberies, which can be attributed to its status as the city centre and its economic, financial, commercial, and tourism activities. The neighbourhoods of Trešnjevka, Trnje, and Maksimir have a significant number of crime incidents and a high density. A study by Eman et al. (2013) found that robberies in Ljubljana and Maribor are also predominantly concentrated in the city centres and surrounding community districts.

Figure 9 displays the ratio of robberies per 1000 inhabitants in different localities. The Municipality Orle has the highest density of robberies, which can be attributed to its small population size compared to the other areas. The neighbourhoods of Trnje and Peščenica have a high crime density per population. They are followed by the neighbourhoods Trešnjevka, Novi Zagreb, and Centar.

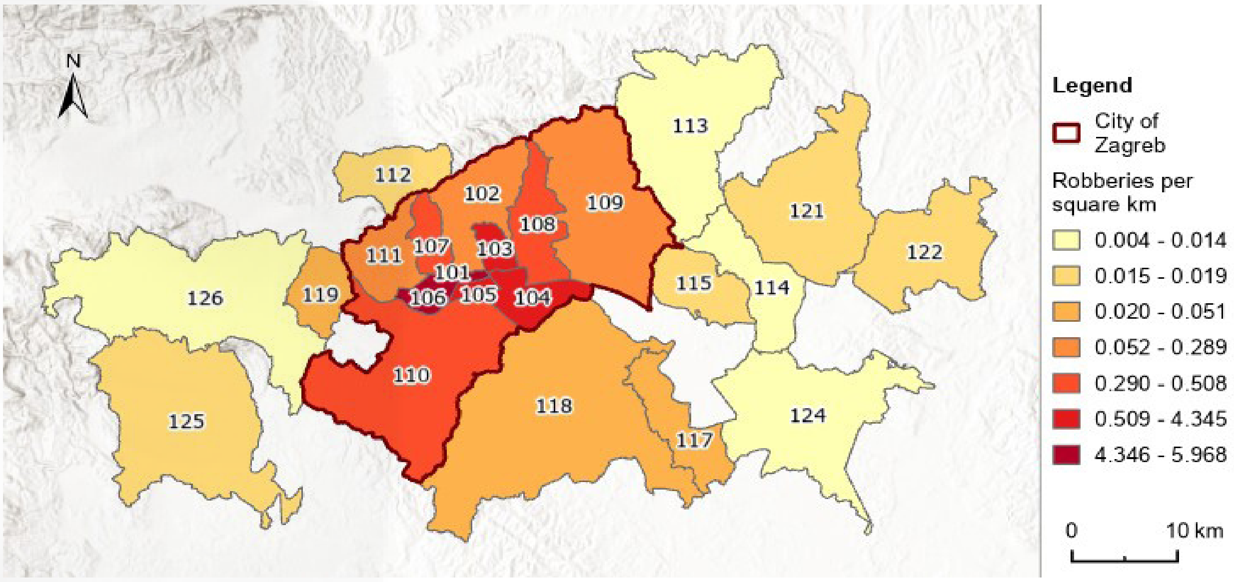

Figure 8. *Ratio of Total Number of Robberies per Square Kilometres in the Study Area*

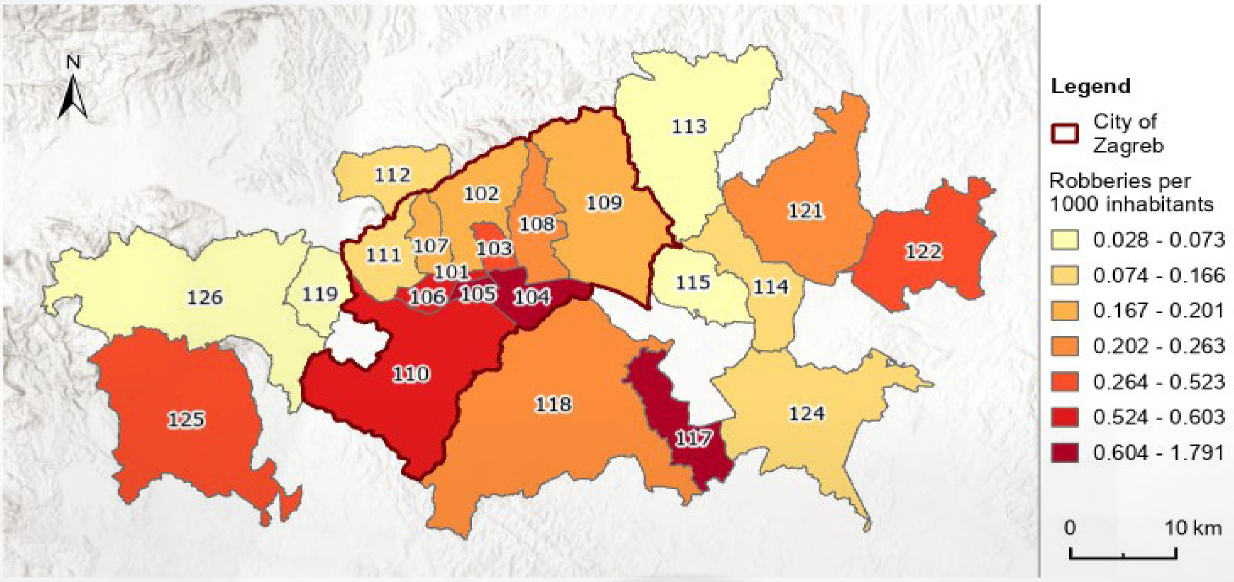

Figure 9. *Ratio of Total Number of Robberies per 1000 Inhabitants in the Study Area*

A heat map in Figure 10 displays the distribution of robbery locations in the City of Zagreb. The study found that the downtown area has the high number of robberies due to its economic, financial, commercial, and tourism activities. As seen from Figure 7 – Figure 10, there is a high robbery rate in the parts of neighbourhoods Novi Zagreb, Peščenica, Trnje, and Trešnjevka surrounding the downtown area. The data shows higher number and density of robberies in the neighbourhoods of the City of Zagreb, while the towns and municipalities in the Zagreb County has lower numbers of robberies.

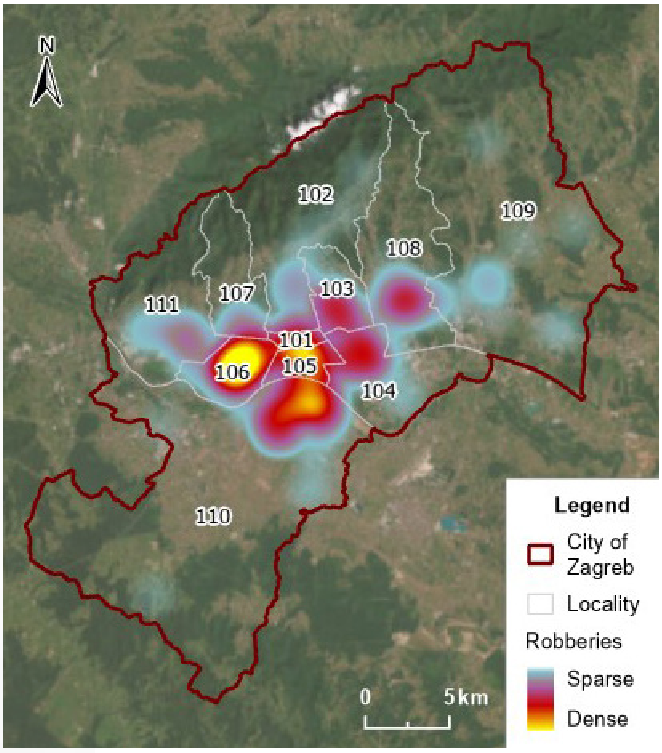

Figure 10. *A Heat Map Showing the Locations of Robberies in the City of Zagreb*

ROBBERY PATTERN ANALYSIS

The data collected on offenders include their age, sex, marriage status, education level, and resident location at neighbourhood level. However, there is missing information of the education level for about 30% of the offenders, and there are only 15 female offenders out of the total 180. Therefore, the analysis focuses on the age of the offenders. The data are divided into age groups, and the frequency of occurrence of the travelled distance (Figure 11), target (Figure 12), means of usage (Figure 13), and time of day of the crime (Figure 14) are analysed for each age group.

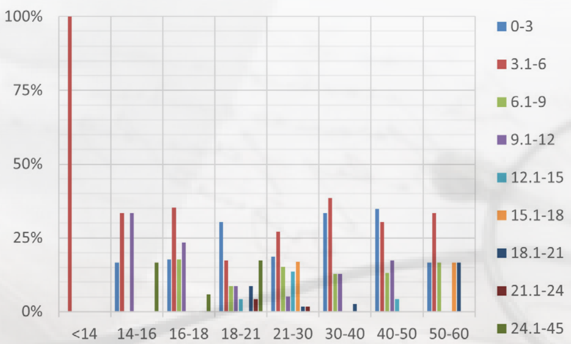

Figure 11. *Distribution of Robberies by Age Group of Offenders and the Travelled Distances (km)*

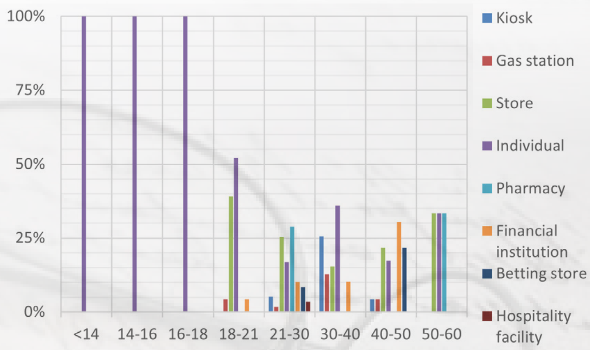

Figure 12. *Distribution of Robberies by Age Group of Offenders and Their Targets*

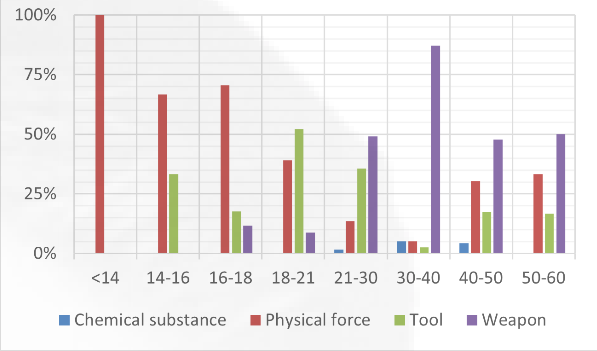

Figure 13. *Distribution of Robberies by Age Group of Offenders and the Means of Usage*

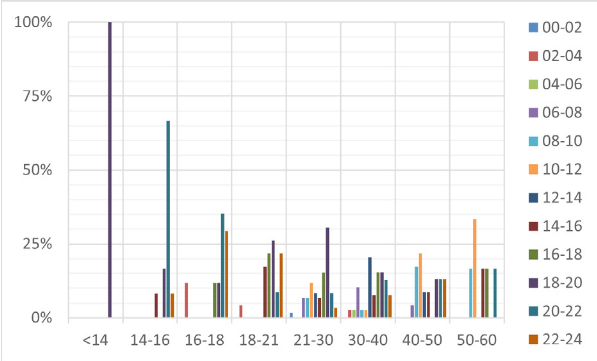

Figure 14. *Distribution of Robberies by Age Group of Offenders and the Time of Day*

The data indicate that the most common distance travelled by criminals of all age groups is between 0-3 km and 3,1 - 6 km (Figure 11 Distribution of robberies by age group of offenders and the travelled distances (km)). Specifically, for individuals aged 18-21 years and 40-50 years, the most frequent distance travelled is up to 3 km. However, for the other age groups, the most frequent distance is between 3,1 and 6 km.

The data show that 40% of all attacks are on individuals (Figure 12 Distribution of robberies by age group of offenders and their targets). The age group up to 18 years only uses physical force and targets individuals. The age groups from 18 to 21 years and from 30 to 40 years are the most likely to attack individuals, accounting for 52% and 36% of cases, respectively. The age group from 18 to 21 years also has a significant number of attacks on stores (39%), while the age group from 30 to 40 years targets kiosks in 26% of cases. The age group from 21 to 30 years primarily attacks pharmacies (29%) and stores (25%). In contrast, the age group from 40 to 50 years primarily targets financial institutions (30%), followed by stores and betting stores (both 22%). The oldest age group, from 50 to 60 years, evenly attacks individuals, pharmacies, and stores (all 33%).

The most commonly used means of attack are weapons, accounting for 45% of cases, followed by physical force at 27% and tools at 26% (Figure 13). Physical force is most commonly used by offenders up to 18 years of age. Between the age of 18 and 21, the majority of attacks involve the use of tools in 52% of cases. For offenders aged 21 an older, weapons are the most commonly used means of attack. In the 21 to 30 age group, 49% of attacks involve weapons, while tools are the second most commonly used means, accounting for 36% of cases. From 30 to 40 years old, weapons are used in 87% of cases. For the age group from 40 to 50 years, weapons are still the most commonly used means of attack, followed by physical force at 48% and 30%, respectively. In the age group of 50 to 60 years, weapons are most commonly used in 50% of cases, followed by physical force at 33%.

The majority of robberies occur between 18 and 22 hours (Figure 14). The research by Milojković and Petrović (2019) also found that the critical time for retail establishments is at night, near closing hours, when street activity is significantly lower. The specific time frames in which attacks are most common vary depending on the age group of the offenders. Offenders up to 14 years of age commit their attacks between 18 and 20 hours. Offenders between 14 and 16 years of age commit their attacks between 20 and 22 hours (67%). Offenders between 16 and 18 years of age primarily attack between 20 and 22 hours, as well as between 22 hours and midnight (35% and 29%, respectively). Offenders between 18 and 21 years of age mainly attack between 18 and 20 hours (26%), as well as between 16 and 18 hours (22%). Offenders between 21 and 30 years of age have a higher frequency of attacks between 18 and 20 hours (31%), followed by between 16 and 28 hours (15%). The age group between 30 and 40 years tends to commit robberies mostly between 12 and 14 hours (21%), as well as between 16 and 18 hours and 18 and 20 hours (15% each). The age group from 40 to 50 years tends to commit robberies mostly between 10 and 12 hours (22%) and 8 and 10 hours (17%). The age group from 50 to 60 years tends to commit robberies mostly between 10 and 12 hours (33%). Milić (2015) found that the robberies are most frequently committed during the morning hours, particularly between 9 and 11 a.m., in identified hotspots. It has been concluded that the criminal acts of robbery are most often committed by the perpetrators at the beginning and at the end of working hours, anticipating fewer people present.

The data are organized into targets, which are further categorized by type. The analysis focuses on three factors for each target: the distance the offender travels to reach the target (Figure 15), the time of day when the crime occurs (Figure 16), and the means used by the offender (Figure 17).

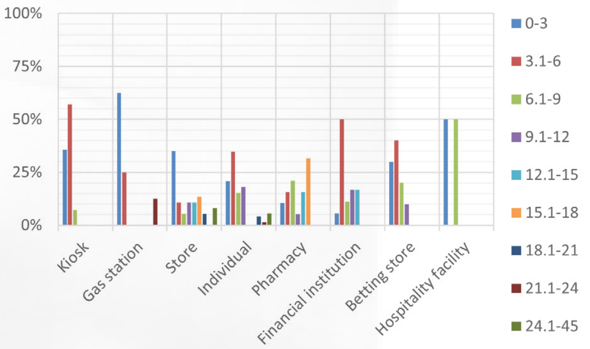

Figure 15. *Distribution of Robberies by the Target and the Travelled Distances (km)*

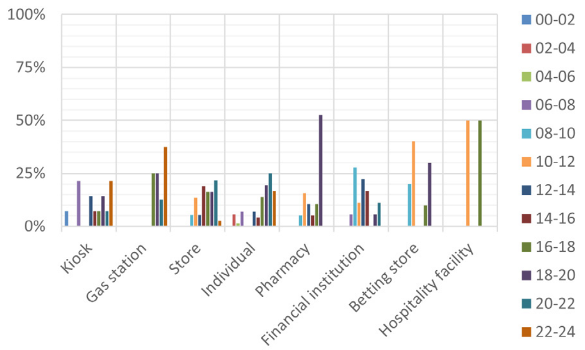

Figure 16. *Distribution of Robberies by the Target and the Time of Day*

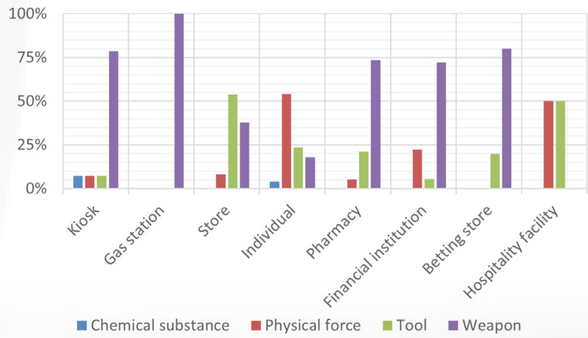

Figure 17. *Distribution of Robberies by the Target and the Means of Usage*

The data show that the most common length of the offenders' criminal path for the target is between 3,1-6 km in 31% of cases, followed by the distance range of 0-3 km in 25% of cases (Figure 15). The offenders travelled up to 3 km to gas stations in 63% of cases, to kiosks in 36% of cases, and to stores in 35% of cases. The most frequent length for kiosks is between 3,1-6 km in 57% of cases, for financial institutions in 50% of cases, and for betting stores in 40% of cases. When the target is a hospitality facility, the frequency of occurrence is divided between 0-3 km and 6,1-9 km, each accounting for 50% of cases.

The analysis reveals that the most frequent times of a day for different types of targets are between 16 and 22 hours (51% of all robberies) (Figure 16). For pharmacies, the majority of robberies occur between 18-20 hours, accounting for 53% of cases. For gas stations, the most common time of day for robberies is between 22 and midnight, representing 38% of cases. Additionally, 25% of cases occur between 16-18 and 18-20 hours. For betting stores, the highest frequency of robberies is observed between 10-12 hours, accounting for 40% of cases. This is followed by 30% of cases occurring between 18-20 hours and 20% of cases occurring between 8-10 hours. Robberies at stores are spread throughout the day, with the most frequent time of day being between 20-22 hours in 22% of cases. The attacks on individuals are also most frequent during this time, accounting for 25% of cases. The remaining cases are divided throughout the day, with the majority occurring between 14 and midnight. However, there are exceptions, with 6% of cases happening between 2-4 hours and 7% of cases occurring between 6-8 hours.

The most frequently used means of attack is a weapon (Figure 17), with 100% of cases involving gas stations, 80% involving betting stores, 79% involving kiosks, 74% involving pharmacies, 72% involving financial institutions, and 38% involving stores. When the target is an individual, the most frequently used means is a physical force in 54% of cases, followed by a tool in 24% of cases, and a weapon in 18% of cases. Physical force is used in 22% of cases for financial institutions, and in 50% of cases for hospitality facilities, where a tool is also used in 50% of cases.

ORIGINALITY/VALUE

This paper presents the results of the first research project on geographic profiling in Croatia. It emphasises the environmental features of the robberies and criminal behaviour characteristics of the robbers which are specific for the area of the City of Zagreb as an initial step of the model development. The research paper builds on the existing knowledge of the topic and addresses possible implications for future development of the spatial crime models in Croatia. The distance distribution covered by perpetrators of robberies shows the presence of the distance decay effect. There is also a certain positive relationship between both the crime-related and the offender-related variables such as the age of the offender and the means of usage, as well as the time of day of crime incident. The frequency of occurrence of the crime in relation to the distance and temporal component indicates a trend of shorter distances in the night and morning hours, while there is a greater variation in distance during the day, which may be connected to the mobility of the offenders, especially those who use public transportation. The data collected from the Croatian General police directorate for the study area have some limitations, particularly in terms of both insufficient spatial information and offenders' characteristics. For the more plausible results more accurate spatial data on the crime locations, as well as the locations of the offender's residence, and homogeneous socio-demographic data on offenders ought to be provided by the police.

Geospatial data processing technology is used to analyse crime patterns and connections between socio-demographic, spatial, and temporal features. The researchers used the street routing algorithm on road network to reconstruct the routes taken by the offenders to their crime locations. The research emphasises the significance of geostatistical methods in crime analysis, particularly in identifying crime occurrence through heat map analysis. The study suggests that understanding the relationship between the offenders' activity spaces and crime locations could help identify perpetrators and contribute to crime reduction. It is advisable to discuss potential improvements to the model and suggest extending the analysis to other cities and crime types. Likewise, the possibility of incorporating factors like public transport network into the model to account for the dynamic nature of a city road network should be discussed. Overall, the study aims to provide the relevant insights for criminologists, police, and policymakers to focus on the key areas frequented by the offenders. The crime analysis can enhance public safety, to identify trends, and plan crime-prevention strategies. Law enforcement can optimize resource allocation, solve cases, and implement effective crime-reduction strategies. The basis for geographic profiling is the study of criminal path.

A study by Strmečki and Majer (2022) carried out in Croatia found that despite the usefulness of GIS in the police work, 80% of the 266 police officers surveyed had no education in GIS. However, 74% of them recognized the value of geographic profiling in criminal investigation. This highlights the need for further research on the geography of crime in Croatia including the implementation of GIS. The study findings will be also beneficial for research, particularly in calibrating distance decay functions to understand offenders' movement by the example of the City of Zagreb and Zagreb County.

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