Time's Effect on Crime Prediction Precision and Accuracy

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Abstract: Crime detection with high prediction and accuracy has become a focused issue in the process of crime investigation and prevention. The higher the accuracy or precision of a crime detection model the more efficient crime investigation and prevention becomes. The present research aims to examine the possible precision and accuracy differences of using two different test datasets (TD) to calculate the predictive accuracy index (PAI), and the recapture rate index (RRI) for kernel density estimation (KDE), risk terrain modeling (RTM) and the combined RTM–KDE model. The present study focuses on theft and robbery cases of between 1 December 2015 and 30 November 2018 in Budapest, Hungary. The novelty of the research lies in its first-time usage in Budapest, in a Central European evolutionary urban structure. The results show that there are differences in prediction performance and in each model using a Test Dataset (TD) more distant in time from the initial dataset resulted in a more accurate prediction. The research proved that datasets with different time distances can have an impact on the predictive accuracy and precision of crime detection.

Keywords: Evolutionary urban structure; Geoinformatics; Kernel density estimation; Predictive accuracy index; Recapture rate index; Risk terrain modelling; Spatial analysis

1 Introduction

Researchers have always been interested in understanding what motivates offenders and what underlying factors contribute to criminal behavior. To explain these phenomena, diverse theories with varying perspectives were developed. The most well-known theories are routine activities theory [1] and crime pattern theory [2]. The *routine activities theory* proposed that criminal opportunities are identified throughout peoples' daily activities [1], and three elements are necessary to crime incidents: a motivated offender, a suitable target, and a lack of capable protection. The *crime pattern theory* [2] later uses the location elements from the previous theory and extends it with the influence of the built physical environment. Environmental backcloth includes peoples' routine activities and the underlying network infrastructure, which can be influenced by crime generators and attractors. Crime generators can increase the likelihood of crime as they concentrate a large number of people to specific locations at the same time. Crime attractors are things that draw a lot of people to a specific location, where there is a relative lack of effective protection [2], [3]. These theories established the importance of analyzing the spatial distribution of crime incidents and resulted in the appearance of *hotspot policing.*

Hotspots are small areas with high crime concentration [4], often analyzed using retrospective techniques like hotspot mapping [5], which analyzes and predicts crime location and distribution based on historic crime incidents. Therefore, they rely on the assumption that past locations of crime are good predictors of future crime locations. When comparing the different types of hot spot mapping techniques, Drawve [6] found that the *Kernel Density Estimation (KDE)* was approximately one and a half to two times more accurate across six different hot spot techniques. KDE converts point data into a density surface by drawing circular neighborhoods around each point and calculating weighted values based on distance. Another tool, the *Risk Terrain Modeling (RTM)* is a regression-based analysis tool developed by Caplan and Kennedy [7], is used to calculate the risk assessment of a study area using a large number of physical and social risk factors. To analyze the accuracy of different types of tools in predicting future crime incidents, Chainey et al. [5] proposed metrics to measure the predictive accuracy (PAI) of different types of hotspot techniques [5]. Later, Levine [8] developed the Recapture Rate Index (RRI) to examine the precision of the model [8].

This research aims to accomplish two objectives. First, it seeks to evaluate the predictive accuracy of three spatial analysis models: KDE, RTM, and a combined RTM-KDE model, in the context of Budapest, Hungary, the first time. Second, it aims to examine the effect of using time-shifted TDs on the calculation of the PAI and RRI for hotspot identification. Specifically, the research will examine how the values of PAI and RRI change when calculated using datasets shifted by a quarter and a year compared to the original dataset. For instance, hotspots identified using June-August data will be evaluated using PAI and RRI calculated from September-November and the following year's June-August data, respectively.

The paper is structured as after some theoretical background the research design with the research questions, hypotheses, the literature review, and the research methodology is presented. The models and the indices are calculated, and the three models are compared in Section 5. The conclusion section summarizes the findings and gives recommendations for future research while including the research limitations.

2 Concepts and Literature Review

2.1. Risk Terrain Modeling (RTM) and Kernel Density Estimation (KDE)

Risk Terrain Modeling (RTM) is a promising methodology that relies on environmental factors associated with criminal activity rather than on historical crime data, making it an effective tool for forecasting and understanding crime patterns in various contexts. The literature on RTM demonstrates its widespread application in crime analysis, leveraging environmental factors to predict criminal occurrences. Using the Scopus database, a search was conducted with the query (risk AND terrain AND modelling AND crime PUBYEAR > 2009 AND PUBYEAR < 2025 AND rtmdx), which yielded 32 relevant papers. The original RTM framework was first introduced by Caplan et al. in 2011, marking the foundational work on the topic [9].

Since its introduction, RTM has been employed to study a variety of crime types across different locations, but the primary location of its usage resides in the USA. For instance, RTM was used to examine hate crimes in Columbus, Ohio [10], or in Los Angeles County [11]. Other studies applied the method to investigate violent crimes [12], gun violence in Newark, NJ [13], homicides concentrated near blighted properties and convenience stores in Baton Rouge, Louisiana [14], and in assessing robbery risks in Chicago, Newark, and Kansas City [15]. The flexibility of RTM is evident in its use across diverse geographic and criminological contexts. Wheeler and Steenbeek [16] used RTM and Random Forest for crime forecasts in Dallas, Texas, using 200–by–200–foot grid cells, while Szkola et al. [17] explored firearms–related risks in Baltimore, revealing that risk factors varied significantly over time. In Kansas City, Missouri, Caplan et al. [18] implemented a place-based crime intervention program using RTM combined with hotspot analysis and further demonstrated RTM's value through a comparative analysis of street robbery in Brooklyn, where an integrated approach using RTM and other methods yielded more accurate predictions [19]. This research underscores RTM's role in enhancing place–based policing through actionable intelligence derived from a deep understanding of environmental risks.

Internationally, RTM has gained traction beyond the United States. Andresen and Hodgkinson [20] investigated residential burglaries in Vancouver, Canada. Dugato et al. [21] focused on residential burglaries in Milan and explored the application of RTM to predict robberies [22]. Research has also highlighted RTM's use in Turkey [23] and in maritime contexts [24]. Giménez-Santana et al. [12] applied RTM to violent and appropriative crimes in Bogotá, Colombia, and later examined traffic accidents in Cadiz, Spain [12]. Ohyama and Amemiya [25] explored RTM's potential in Japan, where low crime rates posed challenges for traditional forecasting methods based on past data.

In Europe only a handful of studies could be found. Gerell [26] examined violent crime near bus stops in Malmö, Sweden. RTM has been extended beyond conventional crime types, as, for example, it was applied to predict violent dissident Irish Republican activity in Belfast, Northern Ireland [27]. Research by Kocher and Leitner [28] in Salzburg, Austria, tested the technique for forecasting various crimes, finding that predictive accuracy was highest for assaults and robberies but relatively low for burglaries and auto thefts.

Several comparative studies have reinforced RTM's effectiveness. For instance, Rummens and Hardyns [29] compared RTM with near-repeat and machine learning models using burglary data in a Belgian city, finding RTM to be a robust alternative for predictive policing. In Valencia, Spain, Briz-Redon et al. [30] analyzed 122 emergency calls and concluded that although a non-linear model proved more accurate in predicting property crime, robbery, and vandalism, RTM remained a valuable approach. Prior research also examined the predictive accuracy of KDE, RTM, and the integrated approach [5], [8], [22], [31], [32], [33], [34], [35]. For example, Dugato [22] found that KDE is less reliable, but more accurate than RTM [22], while Kennedy et al. found that RTM outperformed the density map [36].

Prior research calculating the predictive accuracy of different techniques mainly used a yearly time period [6], [34], [37], [38]. However, some studies use different time periods as Drawve [6] compared the PAI and RRI scores for eight consecutive months [6]. Chainey et al. [5] used data for a period before a date to generate hotspots and tested the predictive accuracy with the next time period [5]. Similarly, Caplan et al. [19] calculated the PAI score with the same logic, using one– or three month(s)'s crime data to predict the following one or three month(s)'s crimes [19].

2.2. City Structures

Settlements evolve like living organisms in space and time. Urban evolution is the evolutionary history of a settlement's changing operational models. As municipalities are constantly evolving systems, changes in operational models are inevitable. Bertaud [39] states that Central and Eastern European (CEE) cities experienced a centralized command economy for decades, resulting in spatial organizations distinct from Western cities [40], [41]. The absence of a real estate market significantly shaped socialist cities' development. Land use patterns and densities, particularly in industrial and residential zones, were determined by administrative decisions aiming at minimizing resource inputs rather than maximizing financial returns, not by market demand. These unique city structures require tailored methodologies to analyze phenomena like crime, traffic accidents [42], and visual pollution [43].

RTM, originally developed for the planned urban US cities has been applied successfully in Western Europe and Asia. However, given Central Europe's unique urban development, it is crucial to assess RTM's applicability in this context.

By examining its relevance and potential integration into Central European research, we can determine its viability in capturing the region's specific spatial dynamics.

3 Research Design, Questions and Hypotheses

Crime prediction, especially using methods like KDE and RTM, is becoming increasingly important. KDE bases its predictions on past crime occurrences, whereas RTM identifies crime-generating locations as integral elements of urban structures. While these methods are widely used by the police in the US, their application in Hungary is less common [44]. Given the unique urban development of Central Europe with its distinct structural and social environment, particularly its communist-era influence, it is crucial to assess how these models perform in this context. This research aims to fill this gap, as depicted in Figure 1.

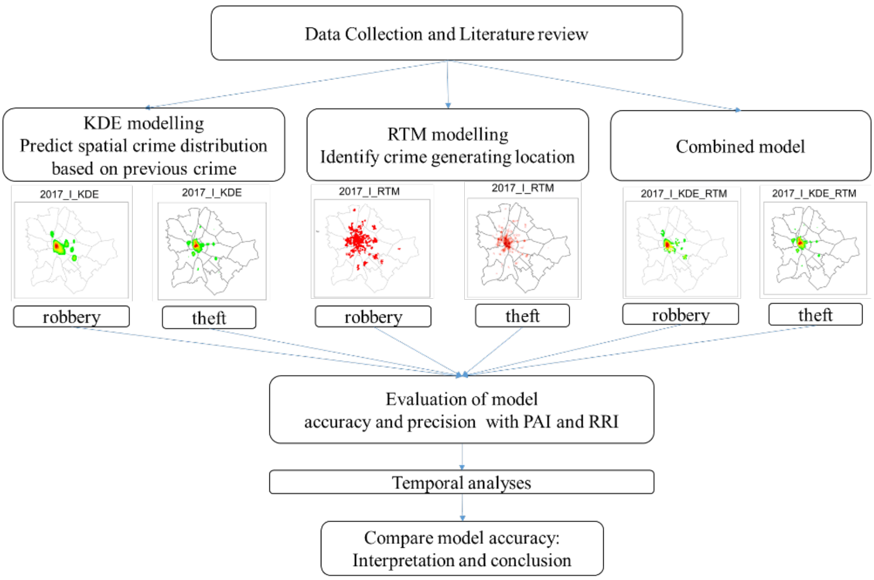

Figure 1

Research Design (developed by authors)

A literature review was conducted to identify relevant predictive crime models. Then, environmental (for RTM analysis) and crime (pertinent to KDE methodology) data were collected and prepared for model development and validation. KDE and RTM models were constructed and validated using different time periods. Model performance was evaluated using PAI and RRI. Finally, the models were compared to assess their effectiveness in CEE urban environments.

Based on the literature review and crime detection practices the following research questions were formulated:

RQ1: Does the RTM and KDE method work effectively within the urban structure of CEE?

RQ2: Which method provides a more accurate prediction? The first hypothesis (H1), therefore, is that RTM can be effectively used in CEE cities. The second hypothesis (H2) related to CEE urban structures is that the KDE model provides a more accurate prediction implementing the RTM model. As assumed, datasets from more distant time periods yield more precise predictions (H3).

4 Research Methodology

4.1. Risk Terrain Modeling (RTM)

The basis of RTM are the findings of *environmental criminology theories*, most precisely *crime pattern theory*. It uses the concept of crime generators and crime attractors to predict future crime incidents. Figure 2 describes the RTM model process applied in the present research.

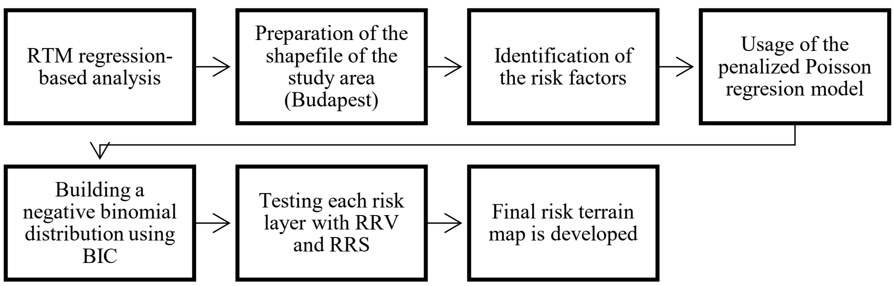

Figure 2

RTM process flow

The required parameters of the analysis besides the outcome event data are the shapefile of the study area, the block length, the cell size, and the model type. The average block length of Budapest was measured using ArcGIS Pro. The size of the raster cell is half of the block length size and results in 275 meters. The aggravating model [7] was used, which assumes that the factors are correlated with the outcome event. The model test for positive spatial affiliation between the risk factors and the outcome event.

The next step is to identify the pool of potential risk factors. Based on prior research 24 potential risk factors were included in the analysis [7]: ATMs, attractions, banks, bars, bus and trolleybus stops, CCTV cameras, colleges/universities, convenience store, electric car charging station, fast food restaurants, gas stations, grocery stores, hotels, nightclubs, parking lots/garages, parks, pawnshops, pubs, restaurants, secondary education, shopping centers, subway and train stations, tobacco shops, tram stops. The data was obtained from GeoX Information Kft., and BKK Centre for Budapest Transport.

To conduct the analysis, the RTMDx web-based software developed by Caplan and Kennedy [45] was used. After the operationalization of risk factors, RTMDx uses a penalized Poisson regression model, followed by cross-validation to reduce the large set of variables. At the same time, the software builds another model with a negative binomial distribution. The model uses the Bayesian Information Criteria (BIC) to select the best model, with the lowest BIC score [7]. Each risk layer is empirically tested and weighted. The utility produces the Relative Risk Value (RRV) as the weight of risk factors [7]. The Relative Risk Score (RRS) is calculated for each cell within the study area. Finally, all layers are combined into a final risk terrain map [7]. Places are considered high-risk places if the RRS were two standard deviations or higher above the mean.

4.2. Kernel Density Estimation (KDE)

Kernel Density Estimation (KDE) overlays a two-dimensional grid across the study area and draws a circular neighborhood around each crime incident. The method assigns more weights to nearby events than to distant ones. For each grid cell calculating the density value based on the distance from the center point of the grid cell. After this procedure, it summarizes the weighted incidents within the kernel [6], [19].

The analysis requires firstly the grid cell size, which is the same as in the RTM analysis, 275 by 275 meters. It will determine how the output of the analysis will be viewed. The search radius is computed specifically for the input dataset using a spatial variant of Silverman's Rule of Thumb [46], which is optimal when the underlying density being estimated is Gaussian. Places were considered hotspots if the kernel density values were two standard deviations or higher above the mean.

To assess the combined effects of the two methods, a Boolean approach was employed to develop an integrated measure of exposure and vulnerability. In ArcGIS, a single vector grid of cells with dimensions and cell sizes matching those of the raster grids used in the KDE and RTM analyses was created. In the attributes table of this grid, separate columns to indicate whether each cell was identified as a hotspot or a vulnerable location during each time period were included. For each period, then the ‘select by attributes’ function in ArcGIS to identify cells categorized as both hotspots and vulnerable locations was used.

4.3. Predictive Accuracy Index (PAI) and Recapture Rate Index (RRI)

In the research two accuracy and precision indices are applied and used for the crime detection models. The Predictive Accuracy Index (PAI) aims to evaluate the predictive accuracy of the different spatial analysis tools. It is derived from a hit rate to the area percentage:

$$PAI = ((\frac{n}{N}) * 100)/((\frac{a}{A}) * 100) \quad (1)$$

where n represents the number of crimes in the hot spot, N is the total number of crimes in the study area, a is the area of the hot spots, and A is the area of the study area. The numerator is known as the hit rate, while the denominator is the area percentage. The higher PAI score (unbounded) indicates better predictive accuracy [33], which is an objective measure of prediction accuracy to compare mapping techniques within a study area. It is one of the most widely used crime indices today and has been used in numerous studies to assess new hotspot mapping algorithms.

Levine developed RRI to further assess the predictive accuracy of different spatial analysis tools and defined it as “the ratio of crime density in 2006 to crime density in 2005, standardized by the ratio of total area density from 2006 to 2005” [8, p. 299]. Essentially, RRI can be understood as a measure of the treatment effect resulting from changes between two time periods on the frequency of a specific event type, it reflects the variation in occurrences (such as calls for service, arrests, or stops) within designated areas (like hotspots or treatment zones) in relation to the overall change in the number of events across the entire area. It compares the rate of change from one period to a future period [8]. The index can be calculated by dividing the ratio of high-risk places (hotspots) crime counts by the ratio of the total number of crimes each period:

$$RRI = \frac{n_1}{n_2} / \frac{N_1}{N_2} \quad (2)$$

where n_1 is the number of incidents in the historic hotspot, n_2 is the number of incidents in the predicted hotspot, N_1 is the total number of incidents of the historic area, and N_2 is the total number of incidents of the predicted area. The ideal value for RRI is 1, RRI value higher than 1 means more crimes in a hotspot, and RRI value lower than 1 means fewer crimes in a hotspot. PAI examines the predictive accuracy of a model, while RRI examines the precision of a model.

4.4. The Training and Test Datasets (TD)

In order to understand the seasonal changes of crime quarterly data and periods are considered to capture variations between different time periods and to understand the possible seasonal differences in theft. The seasons differ slightly from the early division as the 1st season includes the last month of the previous year (i.e. December) and ends with 28 or 29 February of the following year (denoted by Q1):

The 2nd season (spring) is between 1 March and 31 May (Q2); the 3rd season (summer) is between 1 June and 31 August (Q3), and finally, the 4th season (fall) is between 1 September and 30 November (Q4). To calculate the PAI for each period, two different TDs with different time periods were used. TD1 evaluates the hotspots of a quarter following the base quarter (the analyzed period) while TD2 includes the following year same period data. Data was available from 1 December 2015 to 30 November 2018. The seasonal division resulted in a total of eight quarters for which the PAI and the RRI indices are calculated and compared for KDE, RTM, and the combined RTM-KDE models.

In the calculation of a six-month period for each year for robbery, the periods are the first and second half years of an observed year. Data were available for the years 2016, 2017 and 2018. To calculate the PAI value TD1 evaluates the hotspots using the six–month period following the analyzed and observed half year, while TD2 includes next year same period data. The half yearly division resulted in a total of four periods for which the PAI and RRI scores are calculated and compared for KDE, RTM, and the combined RTM-KDE models.

4.5. Study Area and Data

This study focuses on Budapest, the capital and largest city of Hungary, with an area of 525 square kilometers and a population of 1 741 601 in 2015, 1 737570 in 2016, and 1 723033 in 2018 [47]. Data with geographic locations for every reported theft and robbery instance from the 1 December 2015 to 31 December 2018 were provided by the Hungarian National Police Headquarters. Each theft and robbery record consisted of an offense date and time and X/Y coordinate for geolocation. In order to examine the effects of using two different TDs, theft incidents were divided by quarters, and half-year data of robbery incidents were prepared. Figure 3 shows the distribution of thefts divided by quarters between 2016 and 2018.

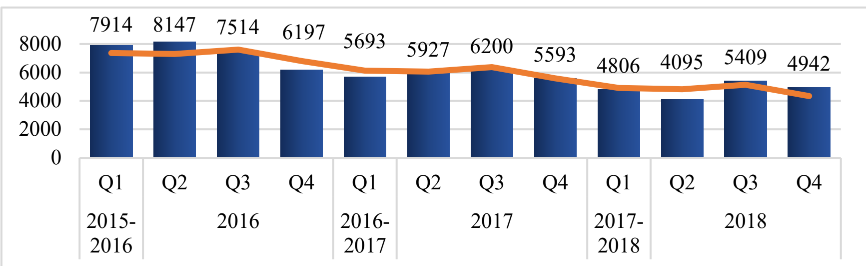

Figure 3

The distribution of thefts incidents between 2016 and 2018 split by seasons (quarters)

The incidents showed a downward trend in general. After the summer of 2016 (Q3), the number of thefts decreased gradually until the summer of 2017 (Q3), when after a slight increase to 6200 the decrease between the summer of 2017 (Q3) and spring of 2018 (Q2) continued, followed by a significant increase in the summer of 2018

(Q3) to 5409 theft issues, and a decline in the fall of 2018 (Q4). Seasonality was also detected; however, the inclusion of seasonality is subject to future research.

Figure 4 shows the half-year figures of robberies between 2016 and 2018. Like the trend in theft issues, it shows a downward trend, except in the second half of 2017, when a slight increase could be detected to 152 cases, followed by a decrease.

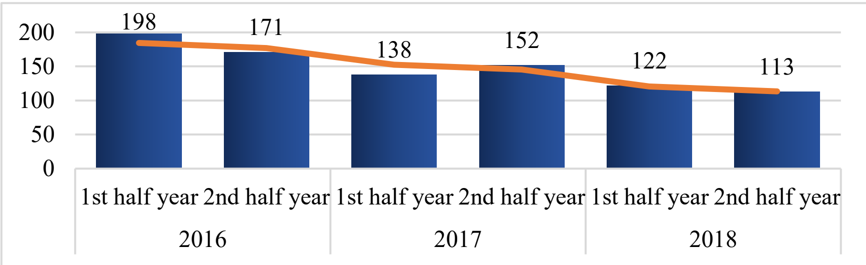

Figure 4
The distribution of robberies incidents between 2016 and 2018 divided by half-year terms

5 Results and Findings

The analysis was conducted for theft and robbery incidents, both the PAI and RRI indices have been calculated and applied for KDE, RTM, and the combined RTM-KDE model. Based on the results, the models are evaluated and an optimal solution is recommended for efficient crime detection.

5.1. Model Evaluation for Theft Incidents

Analyzing the distribution of theft for each time periods the PAI and RRI indices were calculated using TD1 and TD2 containing data of the quarter following the observed period and data of the same quarter of the following year, respectively.

5.1.1. KDE Model Evaluation

The distribution of the PAI and RRI scores for KDE analysis using two TDs are displayed in Table 1. The average PAI value for KDE in the case of TD1 (the quarter following the observed period) and TD2 (the same period next year) equaled 7.168 and 7.332, respectively. The difference between the two PAI scores is modest, and statistically not significant (p=0.81, assuming equal variances (p=0.47)). The statistical non-significance does not necessarily imply the absence of meaningful patterns, especially in exploratory or spatial perception research, where small effect sizes can still reflect systematic perceptual biases or tendencies within the urban environment. However, where TD1 gave a higher PAI the difference between the two TD scores equaled 0.151 on average, while in the case of TD2 having higher PAI the difference was 0.383. It means that when TD2 had a higher PAI score the prediction is more accurate. When TD1 had higher PAI score the difference was not that significant, meaning that using next year's same period data as TD in KDE indicates a slightly higher PAI score.

Table 1
PAI and RRI values for KDE analysis using two TDs in the case of theft incidents

Time periods		KDE - PAI		KDE-RRI	
		TD1.	**TD2.**	**TD1.**	**TD2.**
2015-2016	***Q1***	7.682	**8.439**	1.139	**1.037**
2016	***Q2***	7.818	**7.872**	1.082	**1.075**
	Q3	7.08	7.051	1.065	1.069
	Q4	8.525	8.484	1.039	1.044
2016-2017	***Q1***	7.528	**8.249**	1.045	**0.954**
2017	***Q2***	4.423	4.35	1.071	1.089
	Q3	6.199	**6.582**	1.059	**0.997**
	Q4	8.089	7.629	0.962	1.02
Average		*7.168*	***7.332***	*1.058*	***1.036***

Looking at the RRI values for KDE four of the eight time periods analyzed resulted in a better prediction for TD2 (see Table 1). The average RRI for KDE using TD1 and TD2 data equaled 1.058 and 1.036, respectively, where the difference is statistically not significant ($p=0.36$, assuming equal variances ($p=0.4$)), but, using same period next year data the results give a more accurate prediction (1 is the ideal RRI). The average distance from 1 for TD1 and TD2 is 0.067 and 0.048, respectively, which is smaller than for TD1. It demonstrates that using TD2 to evaluate the KDE analysis results in a slightly more accurate prediction for theft.

5.1.2. RTM Model Evaluation

The PAI and RRI scores for RTM analysis using two TDs shows that for the time periods Q2 2016, and Q3 2017 none of the risk factors tested in this analysis appeared to be geographically related, and no significant risk terrain model could be found. Consequently, that only half-year data can be used for the evaluation and the calculation of the PAI and RRI indices (Table 2). TD2 had a higher PAI only in two periods (2015-2016 1st half year and 2016-2017 1st half year). Looking at the average values for the datasets, TD1 had an average 3.456 PAI score and the TD2 reached an average 3.694 PAI score. When TD1 had higher PAI scores the average difference between the two TD values equaled 0.135, and when TD2 had higher PA values the difference averaged at 0.983. Despite its non–significant nature ($p=0.38$, unequal variances assumed ($p=0.01$)), the result implies that using TD2 gives a way more accurate prediction than using a dataset closer in time to the analyzed period.

Examining the RRI values TD2 outperformed TD1 only in two periods, in 2015-2016 Q1 and 2016-2017 Q1 (see Table 2). The average RRI value for KDE using TD1 equaled 1.023, while for TD2 it is 1.022. The average distance from 1 for TD1 is 0.042, and for TD2 it is 0.039. It demonstrates that using the TD2 results in a slightly better accurate prediction, but not significantly different ($p=0.98$ assuming equal variances ($p=0.32$)).

Table 2

PAI and RRI scores for RTM analysis using two TDs in the case of theft incidents

Time periods		RTM - PAI		RTM - RRI	
		TD1.	TD2.	TD 1.	TD 2.
2015-2016	*Q1*	3.168	**4.876**	1.107	**1.018**
2016	*Q2*	–	–	–	–
	Q3	3.548	3.405	1	1.042
	Q4	3.499	3.445	1.038	1.054
2016-2017	*Q1*	3.417	**3.674**	1.026	**0.954**
2017	*Q2*	3.442	3.293	1.024	1.07
	Q3	–	–	–	–
	Q4	3.663	3.471	0.943	0.996
Average		*3.456*	***3.694***	*1.023*	***1.022***

5.1.3. Combined RTM-KDE Model Evaluation

The PAI and RRI scores for the combined RTM–KDE model analysis using both TDs are displayed in Table 3. As mentioned above, no significant risk terrain models could be detected in the two periods. Similarly, to the RTM model analysis, only in two out of the six periods TD2 performed better (2015-2016 Q1 and 2016-2017 Q1) in both indices.

Table 3

PAI and RRI scores for the combined RTM-KDE model using two TDs in the case of theft incidents

Time periods		RTM-KDE PAI		RTM-KDE RRI	
		TD 1.	TD 2.	TD 1.	TD 2.
2015-2016	*Q1*	5.525	**6.095**	1.138	**1.032**
2016	*Q2*				
	Q3	8.044	7.852	1.044	1.069
	Q4	9.159	9.102	1.022	1.028
2016-2017	*Q1*	8.449	**9.286**	1.044	**0.950**
2017	*Q2*	4.080	3.909	1.045	1.091
	Q3				
	Q4	9.066	8.582	0.956	1.010
Average		*7.387*	***7.471***	*1.041*	***1.030***

When using next quarterly data as TD the average PAI value for RTM-KDE equaled 7.387, while, using the same period next year data the average PAI value equaled 7.471, giving a modest PAI difference. Despite not showing a significant difference ($p=0.95$ assuming equal variances ($p=0.5$)) when TD1 gave higher PAI scores the average difference between the two TDs' PAI values equaled 0.226, while, when TD2 had higher average PAI score the difference was 0.704, implying that TD2 gave a for better prediction. At the same time, when TD1 had higher value the difference was not considerably high (0.226) implying that using the same period next year data as a TD in RTM-KDE results in a higher PAI score.

Table 3 also shows the RRI values for the combined RTM-KDE model. In two out of the six periods TD2 performed better. The average RRI value for the combined model in the case of TD1 equals 1.041, while for TD2 it is 1.03. The average distance from 1 for TD1 is 0.056, while in the case of TD2 it is 0.047. It demonstrates that, despite again the non-significant nature (p=0.71 assuming equal variances (p=0.36)) TD2 performs better and gives a slightly more accurate prediction.

The highest average PAI score (=7.471) for theft was achieved with the combined RTM-KDE modeling with the help of TD2. Looking at the RRI scores, the closest average value to 1 was achieved in the case of RTM modeling using TD2 (1.022). The results demonstrate that for PAI and RRI the TDs taken from the same time period of the consecutive year resulted in a more accurate and precise prediction for theft prediction in Budapest. It is important to highlight that the seasonal effects of theft can be seen in the winter season, which are those seasons where TD2 was always outperformed by TD1 (Figure 5).

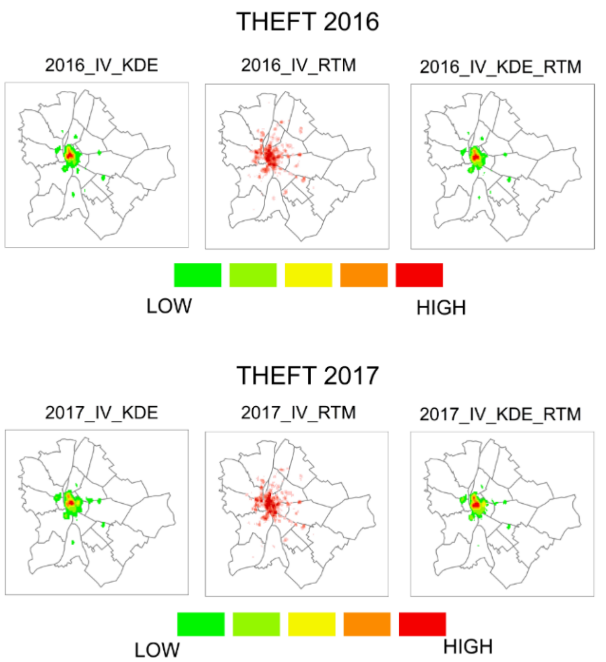

Figure 5

RTM, KDE and the combined model in case of Budapest in the fourth quarter in 2016 and 2017

5.2. Model Evaluation for Robbery Incidents

Analyzing the distribution of robbery incidents and finding the more accurate and precise prediction for each period the PAI and RRI indices are calculated for two different datasets again. TD1 contains data for the next half year of the observed period and TD2 has data of the same half year next year. The results are presented as follows.

5.2.1. KDE Model Evaluation

The PAI and RRI scores for the KDE analysis using two TDs are listed in Table 4. As data were divided in half-year periods, four half-year data were used for testing and prediction. Two out of the four half-year periods showed that TD2 gave a higher PAI score (2[nd] half year 2016 and 2017). TD1 average PAI value for the KDE model gave 5.536, and TD2 (same period next year) average PAI value equaled 5.735. Despite that the difference between the two PAI values is moderate (not statistically significant (p=0.844 assuming equal variances (p=0.19)), when TD1 gained higher PAI, the average difference equaled 0.653 while when TD2 achieved higher average PAI score, it equaled 1.052. Consequently, the TD2 that achieves a higher index value, gives a much better prediction.

Table 4
PAI and RRI values for KDE analysis using two TDs in the case of robbery incidents

	Jan-June 2016	July-Dec 2016	Jan-June 2017	July Dec 2017	Average
KDE - PAI					
TD1.	7.023	3.448	4.899	6.774	5.536
TD2.	5.960	**5.378**	4.656	**6.948**	5.735
KDE - RRI					
TD1.	1.136	1.697	1.344	1.465	1.410
TD2.	1.338	1.088	1.414	1.428	1.317

In the case of RRI calculations again two of the time periods showed that TD2 gave a better RRI value. The highest difference between the RRI values for the two TDs can be detected in 2[nd] half-year of 2016, where TD1 significantly outperformed the other one and TD2 reached the closest RRI value to 1 (RRI=1.088). The average RRI values for TD1and TD2 equaled 1.41, and 1.317, respectively. Despite the high RRI value for 2[nd] half-year of 2016, using TD2 on average resulted in a closer value to 1, thus resulting in higher precision.

5.2.2. RTM Model Evaluation

The values of the PAI and the RRI indices for the RTM analysis using two TDs as described earlier are given in Table 5. Three of the four periods of TD2 performed better, which indicates that using the following year same period results in a more accurate prediction (Table 5). The average PAI value for RTM equaled 4.284 and 4.897 for TD1 (next period data compared to the observed one), and TD2 (same period next year), respectively.

Table 5
AI and RRI values for RTM analysis using two TDs in the case of robbery incidents

	Jan-June 2016	July-Dec 2016	Jan-June 2017	July-Dec 2017	Average
RTM - PAI					
TD1.	4.161	2.832	4.323	5.818	4.284
TD2.	**4.420**	**4.964**	4.094	**6.112**	4.897
RTM - RRI					
TD1.	1.551	1.670	1.300	1.302	1.455
TD2.	**1.460**	**0.952**	1.373	**1.239**	1.256

When TD1 gained higher average PAI score the difference between the two TDs equaled 0.23, and when TD2 achieved higher average PAI scores the average difference equaled 0.895. Although not significantly (p=0.44 assuming equal variances (0.31), but the results imply that using dataset further away in time compared to the observed period results in a prediction way better than using a dataset close in time to the observed one.

Looking at the RRI values, similarly to the PAI scores, three out of the four periods of TD2 outperformed that of TD1. The average RRI for RTM using TD1 and TD2 is 1.455, and 1.256, respectively while the average distance from 1 for TD1 and TD2 is 0.455 and 0.256, respectively. It demonstrates that running the models on TD2 results in a slightly more accurate prediction, however, the difference could not be proved significant (p=0.21 assuming equal variances (p=0.39)).

5.2.3. Evaluation of the Combined RTM-KDE Modeling

The average PAI scores for the combined RTM–KDE model analysis is given in Table 6. In all four periods TD2 outperformed TD1, indicating that a dataset for the following year same period results in a more accurate prediction in the combined model's analysis. The average PAI score for TD1 and TD2 equaled 2.633 and 2.712, respectively. The difference between the two TDs was 0.079 on average, meaning that TD2 outperformed in all cases but not that significantly (p=0.7 assuming equal variances (p=0.39)).

Table 6
PAI and RRI values for the combined RTM-KDE model analysis using two TDs in the case of robbery incidents

	Jan-June 2016	July-Dec 2016	Jan-June 2017	July-Dec 2017	Average
Combined RTM-KDE - PAI					
TD1.	2.658	2.283	2.588	3.001	2.633
TD2.	**2.752**	**2.437**	**2.631**	**3.028**	2.712
Combined RTM-KDE - RRI					
TD1.	1.312	1.058	1.063	1.158	1.148
TD2.	**1.267**	**0.991**	**1.058**	**1.148**	1.116

Table 6 also shows the distribution of RRI scores for the combined model. In all time periods TD2 performed better. The average RRI for the combined model using TD1 and TD2 is 1.148 and 1.116, respectively. Although not statistically significant (p=0.72 assuming equal variances (p=0.5)), the average distance from 1 for TD1 is 0.148 meanwhile for TD2 it is smaller (0.121). It demonstrates that using TD2 results in a more accurate prediction.

The highest average PAI value for robbery was achieved with the KDE method using TD2 (PAI=5.735). On the other hand, looking at the RRI values the closest average value to 1 was achieved in the case of the combined RTM-KDE model using TD2 (RRI=1.116). The results demonstrate that for PAI and RRI next year's same period resulted in a more accurate and precise prediction for robbery in Budapest (Figure 6).

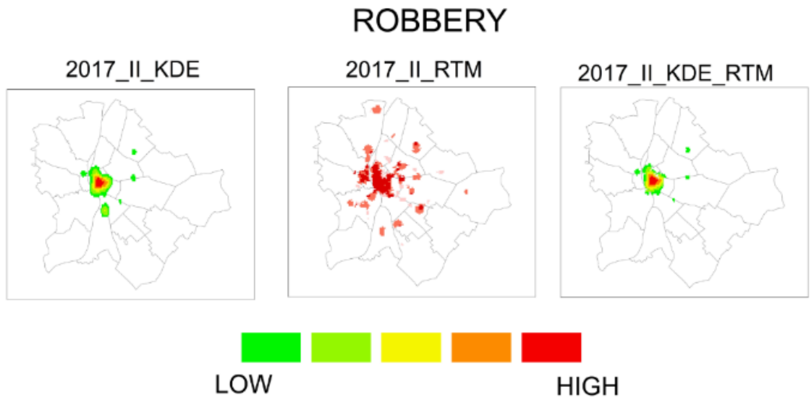

Figure 6

RTM, KDE and the combined models in case of robbery in Budapest in the second quarter of 2017

Conclusion

The present research tested the precision and the accuracy of two models, the RTM and the KDE with two precision indices. The aim of the research was to explore how precisely and accurately these models can work when test datasets are changed and they are moved further away in time from the initial observed dataset.

The analysis of theft and robbery incidents in Budapest had some interesting results. The research posed two research questions and three hypotheses. The results indicate that the most accurate analysis tool to reach high accuracy and precision was the combined RTM-KDE tool which was proven with the help of analyzing quarterly data and calculating the PAI scores similarly to the results of Caplan et al. [19]. On the other hand, RTM proved to be the most precise model when RRI scores were calculated for all three models, despite that PAI value for RTM was the lowest out of all the three models. Therefore, H1 is justified. In the case of robbery, the lowest PAI score was obtained in the case of the combined RTM-KDE model, and the highest PAI score was achieved in the case of the KDE modeling. However, the best RRI scores could be associated with the combined RTM-KDE model. Looking at the results, the combine RTM-KDE model proved to be the most reliable tool, potentially because KDE and RTM supplement each other. The reason could be that KDE can explain additional variance that is being picked up by RTM, which uses the potentially causal environmental features. Therefore, H2 has been justified.

The two TDs analysis showed that using a dataset further away in time from the observed data, i.e. the following year same quarterly data resulted in a better average PAI score for all three models. When RRI scores are considered, the average value was better in all cases. Some seasonal effects on the theft could be traced in the winter season, where in each case TD2 gave better PAI and RRI scores. When the period has been changed from quarter to half a year to analyze robbery incidents, more explanatory results were found. Using the TD for the same period the following year (half a year) a more accurate prediction could be conducted in all three model types. Overall, the analysis showed that the right choice of TD can highly influence the accuracy and precision of the models, implying that using datasets more distant in time from the observed dataset, it will results in a more precise model, despite the fact that all the previous research used the same year next time periods for testing [19], [30], [33]. Therefore, H3 is justified.

Further research is needed due to different reasons. On the one hand, the results show that higher PAI and RRI scores can be achieved when using TD further away in time from the observed period, the differences in PAI and RRI score did not prove significantly different, which calls for further research. On the other hand, testing with TDs even further away in time from the initial dataset is also the task of future research to understand the effects of using TDs from different time periods. Additional research on potential model refinements (e.g., incorporating machine learning techniques) would be valuable. The impact of socio-economic factors on crime prediction accuracy also could be explored further. The present research aimed to demonstrate in the context of theft and robbery incidents in Budapest, that more reliable predictions can be achieved when changing TDs and move further away in time from the observed and analyzed data. The models individually and in a combined way proved to be an effective method in predicting crime within the urban structure of CEE, namely in Budapest, Hungary (RQ1).

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