

Applying Crime Prediction Techniques to Japan: A Comparison Between Risk Terrain Modeling and Other Methods

Tomoya Ohyama¹  • Mamoru Amemiya²

Published online: 3 April 2018

© Springer Science+Business Media B.V., part of Springer Nature 2018

Abstract In recent years, the field of crime prediction has drawn increasing attention in Japan. However, predicting crime in Japan is especially challenging because the crime rate is considerably lower than that of other developed countries, making the development of a statistical model for crime prediction quite difficult. Risk terrain modeling (RTM) may be the most suitable method, as it depends mainly on the environmental factors associated with crime and does not require past crime data. In this study, we applied RTM to cases of theft from vehicles in Fukuoka, Japan, in 2014 and evaluated the predictive performance (hit rate and predictive accuracy index) in comparison to other crime prediction techniques, including KDE, ProMap, and SEPP, which use past crime occurrences to predict future crime. RTM was approximately twice as effective as the other techniques. Based on the results, we discuss the merits of and drawbacks to using RTM in Japan.

Keywords Crime prediction · Crime mapping · Risk terrain modeling · Self-exciting point process · Prospective mapping

Introduction

Many police forces in Western countries are now using computer-based crime prediction, the most well-known system being PredPol. Crime prediction attempts to forecast when and where crime will occur in the future by analyzing crime data and other statistical/

✉ Tomoya Ohyama
s1730128@s.tsukuba.ac.jp

Mamoru Amemiya
amemiya@sk.tsukuba.ac.jp

¹ Graduate School of Systems and Information Engineering, University of Tsukuba, 1-1-1, Tennodai, Tsukuba, Ibaraki 305-8573, Japan

² Faculty of Systems and Information Engineering, University of Tsukuba, Tsukuba, Japan

geographical data. There are several crime prediction techniques, such as risk terrain modeling (*RTM*: Caplan et al. 2011), self-exciting point process model (*SEPP*: Mohler et al. 2011), and prospective mapping (*ProMap*: Bowers et al. 2004; Johnson et al. 2007, 2009), which have been researched and developed in the United States or UK.

Crime prediction has begun receiving attention in Japan as well. The government has identified the analysis of spatiotemporal changes in criminal circumstances as an important area for development, and has promoted the utilization of crime data (Cabinet Secretariat 2014). Moreover, the Kyoto Prefectural Police Department introduced the use of crime prediction techniques last year, a move that will add momentum to the adoption of this methodology in other parts of Japan. The adoption of these techniques is largely driven by the need to optimize police activities using the new technology, and not because crime is a serious problem in Japan. Japan suffers from a loss of experienced law enforcement practitioners due to the mass retirement of “baby-boomer” police officers and a decreasing rate of candidate recruitment. In addition, the serious decline in the population will cause a reduction in the national budget in the future; thus it is possible that the police budget will be reduced as well. These factors contribute to a weakening of the police force across the nation. In the future, Japan will experience social changes such as an increase in the number of foreign workers and an increasing number of single-person households. Latent factors might lead to a deterioration in security, and social demands to optimize police activity based on crime prediction are likely to increase.

However, the application of crime prediction in Japan presents specific challenges. Crime incidents are much lower in Japan than in other countries (Roberts 2008; Roberts and LaFree 2004). Japan has the lowest crime rate among OECD [Organisation for Economic Co-operation and Development] countries (CIVITAS 2012). Depending on the type of offense, the rates of crime are as much as 50 times greater in the US than in Japan.¹ Prediction techniques which have been developed in Western countries assume a certain level of crime occurrence. The premise of the algorithms, such as crime concentration or interaction of crimes, may not be satisfied in Japan. Thus, the usability of current prediction techniques needs to be verified in the context of Japan.

Data availability is also a problem for the research environment in Japan. Unlike cities in the US, Japanese cities do not disclose detailed crime data. Researchers generally cannot access point-level crime data, which makes the research and development of crime prediction techniques difficult.

Risk terrain modeling (*RTM*), which was developed by Caplan et al. (2011), assesses future risk of crime through an analysis of the physical environment (bars, liquor stores, stations, parks, schools, etc.) and other crime correlates (e.g., drug arrests, prostitution, calls for service) of the city. *RTM* constructs risk layers from these features related to particular crimes and combines the layers by GIS. This results in a risk terrain map, which forecasts future crime occurrences. This predictive method was further developed as *RTM* diagnostics (*RTMDx*), and its utility software was implemented by Caplan et al. (2013). *RTM* methods have been used in Europe (Paris, Milan) and South America (Bogota), in addition to cities in the US such as New York, Chicago, and Atlantic City (Caplan and Kennedy 2016).

¹ According to United Nations Office on Drugs and Crime (UNODC) statistics (<https://data.unodc.org/>), the number of police-recorded offenses per 100,000 people in the US and Japan in 2014 are as follows: for theft, 1818.46 vs. 356.20; for burglary, 536.28 vs. 73.79; for assault, 228.86 vs. 21.02; for robbery, 101.08 vs. 2.41; for rape, 36.95 vs. 0.99; and for intentional homicide, 4.43 vs. 0.31.

Since the frequency of crimes in Japan is low, the pattern can be less specific, one that is nearly random. In such a situation, we are driven to use a method such as RTM, which focuses on the environment, rather than a method that depends on crime occurrence. Moreover, RTM is superior to other prediction methods in one respect: as Dugato (2013) indicated, it does not require real-time information or updated information on previous crime events. Thus, researchers who do not have such data can also utilize this method in Japan.

Even though RTM can be applied in Japan, crime-related social factors may differ between Japan and the US and UK. In Japan, there are few economically disadvantaged areas that draw crime and where it is concentrated. Thus, the mechanisms that cause crime also differ. Taking these factors into account, it is not possible to know whether RTM will be effective in Japan unless it is implemented on a trial basis.

The present study aims to clarify whether crime prediction will be effective in Japan, by applying several techniques to domestic data and evaluating the results. We focused particularly on the validity of RTM. The other techniques used were kernel density estimation (KDE), SEPP, ProMap, the Spatio-Temporal Generalized Additive Model (ST-GAM: Wang and Brown 2012), and prospective space–time scan statistics (PSTSS: Cheng and Adepeju 2013; Adepeju et al. 2016). The findings of this study will further our understanding of the types of crime prediction techniques that are effective in Japan, and will also be useful to other developed countries where crime rates are falling.

Literature Review

Various crime prediction methods (or predictive mapping techniques) have been developed by researchers. Anselin et al. (2000) and Groff and La Vigne (2002) were some of the early studies; more recently, Perry et al. (2013) comprehensively reviewed and organized crime prediction techniques. Ohyama et al. (2017) also reviewed existing research, clarified the origins of crime prediction study, and categorized prediction methods into four types: estimation of crime intensity based on space–time interaction (SEPP and ProMap); surveillance of space–time clusters of crime (PSTSS); prediction of crime risk based on environmental factors (RTM); and prediction of crime numbers/possibilities (ST-GAM).

We will now review each methodology. To start, an estimation of crime intensity based on space–time interaction can be described. This method utilizes past crime patterns and the space–time interaction of crime (repeat victimization and near-repeats: Townsley et al. 2003). Bowers et al. (2004) focused on near-repeats and applied this to crime mapping in a method referred to as ProMap. In this model, the risk of crime in any grid decreases with temporal distance as well as spatial distance. Although ProMap has been refined through further study (Johnson et al. 2007, 2009), and has recently even been extended to road networks (Rosser et al. 2017), the basic idea has not changed. SEPP also utilizes near-repeats for crime prediction. Mohler et al. (2011) built a model on the spatial–temporal clustering of crime with reference to epidemiology and seismology. Using the analogy of disease contagion and earthquake aftershocks, the authors separated crime risk into background and aftershock, then modeled the total risk as a sum of these two factors. The parameters of SEPP were estimated using the advanced maximum likelihood method, which was reported to have predictive accuracy superior to that of ProMap. One of the most famous crime prediction systems, PredPol, is based on the SEPP algorithm. The basis of ProMap and SEPP is a visualization of the spatial concentration of crime (Sherman et al. 1989; Sherman 1995), similar to the classical, retrospective method of KDE, although KDE

itself has been applied to crime prediction study (Caplan et al. 2011; Chainey et al. 2008; Dugato 2013; Kennedy et al. 2011).² These methods have the advantage that they require only crime data. When the data are available, the methods can be applied relatively easily. However, the accuracy of these crime data prediction methods can be lower when continuity or relevance among crimes is weak, or when crimes occur independently of each other.

Another method for crime prediction using crime data is the clustering/surveillance of events. This method includes nearest-neighbor hierarchical clustering and standard deviation ellipses (see Chainey 2005). Geographical Analysis Machine (GAM: Openshaw et al. 1987; Openshaw 1995) and Spatial and Temporal Analysis of Crime (STAC: Block 1995; Block and Block 1995) are techniques that utilize standard deviation ellipses. In recent years, Kulldorff's space-time scan statistics (Kulldorff et al. 1998) and prospective scan statistics (Kulldorff et al. 2005) have been used for crime prediction (Adepeju et al. 2016; Cheng and Adepeju 2013; Shiode 2011; Shiode and Shiode 2014). The STSS or PSTSS methods avoid the problem of multiple testing. Unlike KDE, ProMap, and SEPP, STSS detects clusters of crime that exceed the statistical threshold. These clusters are thus said to be statistically significant. Adepeju et al. (2016) revealed that the prediction accuracy of PSTSS is not higher than SEPP, ProMap, or KDE, although it did predict crimes that could not be forecast by other methods.

The prediction techniques mentioned above analyze the crimes themselves; other types of crime prediction are based on analysis of the environmental factors associated with the crime or crime correlates. These include the "environmental backcloth" (Brantingham and Brantingham 1995), a term used to describe the social and physical elements of a city that can be considered risk factors for crime. Caplan et al.'s (2011) RTM estimated the kernel densities of particular facilities or floating events as risk layers and summed them; the authors then generated a risk terrain map. The variables are selected using empirical studies and crime theories. RTM largely depends on features of a site that persist over time; therefore, it assesses the potential and longer-term risk levels of an area. As mentioned above, RTM is useful in that it does not require crime data. However, it is difficult to apply it to crimes for which environmental correlates are uncertain.

Another approach that uses environmental factors is the forecasting of crime numbers or possibilities using regression analysis. An early study conducted by Gorr and Harries (2003) applied several time-series analyses to five types of crime in Pittsburgh, PA. In recent years, Fox and Brown (2012) used a generalized linear model to forecast the probability of crime occurrence, utilizing features of a grid cell that relates the crime and spatial lag of crime. Similarly, Wang and Brown (2012) modeled crime possibility based on the social and physical features of an area using a generalized additive model. The method, which they call the Spatio-Temporal Generalized Additive Model (ST-GAM), estimates the smoothing function with each variable. These methods are quite familiar to researchers who use regression analysis, which is understood as a method for estimating the probability of crime occurrence using predictor variables. Nonetheless, the extrapolation of current data using parameters obtained by past estimation requires attention, since it assumes that the relationship between predictor variables and dependent variables remains unchanged, although that is not true in many cases.

Some studies compare several crime prediction techniques (Adepeju et al. 2016; Chainey et al. 2008; Hart and Zandbergen 2012; Levine 2008; Van Patten et al. 2009). The prediction

² While we do not discuss them here, we can find important studies that discuss the complexities of and tips for operationalizing hotspots in GIS (e.g., Chainey and Ratcliffe 2013; Eck et al. 2005). Other research discusses various techniques available for operationalization of hotspots (e.g., Haberman 2017). Crime prediction studies rely on this research, and thus the two are closely related.

accuracy of the RTM method has been compared against that of KDE (Caplan et al. 2011; Dugato 2013; Kennedy et al. 2011), STAC, and nearest neighbor hierarchical clustering (Drawve 2014). However, no study has compared RTM with ProMap and SEPP. This may be because of the difference in the forecast horizon for which predictions are made (Rosser et al. 2017): ProMap and SEPP are intended for shorter intervals of prediction than RTM. However, RTM has also been applied to shorter periods, such as 3 months (Kennedy et al. 2011), 1 month, 1 week, and 2 days (Drawve 2014). Since the number of crimes is relatively low in Japan, a comparison between RTM, ProMap, and SEPP is possible if we set the appropriate prediction period.

Outside the US, RTM has been studied only in Italy (Dugato 2013), Turkey (Onat and Gul 2018), and several maritime areas including Arabia and Southeast Asia (Moreto and Caplan 2010), but no study has been conducted in East Asia. The current research is the first RTM application trial in East Asia and in a country with a low level of crime. Since there is a social background gap between the US, UK, and other countries, the results will also differ. It is, therefore, of tremendous significance to validate this prediction method.

Methods and Data

We tested six prediction methods, including RTM, ST-GAM, KDE, SEPP, ProMap, and PSTSS, as described in the previous section. These methods were applied and tested as described below.

Research Setting and Variables

The current study was carried out in the Central Business District of Hakata and Chuo wards in Fukuoka City, Kyushu, Japan. Fukuoka City is one of the 20 major cities of Japan, with a population of 1.5 million, which is the sixth largest in the country. Since this city has the Sea of Japan to its north, it attracts many Asian tourists from China and South Korea. The crime occurrence in this city is higher than in other Japanese cities and is almost equal to the 23 central wards in Tokyo, though it is still much lower than that of major US cities (Table 1).³ The study area comprises the central districts of Fukuoka City: Hakata terminal station, the business districts, and the downtown areas. The area is approximately 5.5 km², with a population of approximately 54,789 residents.

The dependent variable was the occurrence of vehicle load theft and parts theft (henceforth, VLT/PT) in the study area from July to December 2014. VLT/PT are crimes whose risk factors (i.e., the locations where VLT/PT will occur) are easily assumed, and clustering in both space and time has been confirmed to some extent (Johnson et al. 2006). Thus, they could be suitable for the current test. The data were collected from the Fukuoka City police department⁴ and were geocoded into each parcel (surrounded by the street segments) level. Each record

³ Original data were downloaded from Fukuoka Prefectural Police Department's homepage (<http://www.police.pref.fukuoka.jp/data/open/cnt/3/1469/1/H27City.pdf>), Tokyo Metropolitan Police Department's homepage (http://www.keishicho.metro.tokyo.jp/about_mpd/jokyo_tokei/jokyo/ninchikensu.html) and the FBI's Uniform Crime Reporting website (<https://ucr.fbi.gov/crime-in-the-u.s./2015/crime-in-the-u.s.-2015/resource-pages/downloads/download-printable-files>); the rates were then calculated.

⁴ We should be cautious when dealing with crime data since under-reported occurrences are always present. Although we cannot know whether current data from Fukuoka city omit these potential victimizations, we can show how much underreporting is present in Japan. According to the fourth National Crime Victimization Survey (https://www.npa.go.jp/hanzaihigai/whitepaper/w-2013/html/gaiyou/part2/s2_4c5.html), in Japan in 2014, 29.5% of VLT (excluding N.A.s) were not reported to the police.

Table 1 Police-recorded crime comparison

| | Population | Per 100,000 people | | |
|------------------|------------|--------------------|----------|-------|
| | | Robbery | Burglary | MVT |
| Fukuoka | 1,538,681 | 2.3 | 47.6 | 2.9 |
| Tokyo's 23 wards | 9,272,740 | 3.4 | 48.6 | 2.0 |
| New York City | 8,550,861 | 198.2 | 164.9 | 86.4 |
| Chicago | 2,728,695 | 353.6 | 482.0 | 374.6 |

MVT motor vehicle theft

contains the date of the event. The total number of cases was 47 (July: 4 cases, Aug.: 5, Sept.: 11, Oct.: 8, Nov.: 9, and Dec.: 10).

The independent variables represent the risk factors for VLT/PT, and differed by prediction method. The RTM and ST-GAM models used the facility distribution data. Since we found little research that studies environmental risk factors for VLT/PT in Japan, we chose crime generators for these crimes such as roads, independent parking lots, and commercial facilities with parking lots as candidate variables. The following locations were selected as candidate variables: parking lots, convenience stores, department stores/supermarkets, family restaurants/fast-food restaurants, chain coffee shops, parks, and roads. Previous research on RTM has focused on other variables such as bars, liquor stores, libraries, hotels, or foreclosed properties. However, we selected candidate variables that are assumed to correlate with VLT/PT occurrences in a procedure that is detailed in the following section. In order to narrow the selection to variables that actually relate to this crime, we conducted a negative binomial regression analysis and ultimately chose parking lots, convenience stores, and roads as independent variables. All data were extracted from Zmap AREA II (version 3-2014; Zenrin Co., Ltd., Kitakyushu, Japan). The data, which are widely used in studies in Japan, were obtained by the entire field survey by Zenrin Co., Ltd.

Prediction methods that use crime data, i.e., KDE, SEPP, ProMap, and PSTSS, were analyzed using the date and location of the VLT/PT that occurred 6 months before the prediction target period in 2014 in the study area. The data were geocoded in the same manner as the dependent variables.

The cell size was set to 25 m × 25 m square, according to Ratcliffe's (1999) methodology, which suggested that the length of the grid square side should be the result of dividing the shorter side of the minimum bounding rectangle by 150. Each prediction method predicted its risk value in these cells.

Crime Forecasting Scenarios

As described above, we conducted a negative binomial regression analysis in order to identify the risk factors for VLT/PT when applying RTM and ST-GAM. Prior to this analysis, for each neighborhood unit ("*chome*"), the presence of facilities (point data) were counted and the length of road lines (line data) was totaled. The *chome* units approximately correspond to former communities and were not built systematically; thus, their shapes and sizes are not uniform. The current study area consists of 53 *chomes*. The average size of each *chome* is about 0.1 km². The dependent variable for the regression was the number of VLT/PT occurrences in each *chome* from January 2008 to June 2014. Standardized values were used

for the number of facility locations and total road extension. As the offset term, the logarithm of the size of each *chome* unit was introduced. After analyzing all independent variables (Model 1), a second analysis was conducted using variables with significant coefficients (Model 2). Finally, parking lots, convenience stores, and roads were adopted as predictor variables, and their incidence rate ratios in Model 2 were utilized for calculating the weight values of RTM (Table 2). We followed the procedure used by Moreto et al. (2014), who conducted a negative binomial regression analysis and selected factors that should be included in RTM, although that procedure is different from recent RTM studies in which regression analysis and variable selection were automated by the *RTMDx* utility. IBM SPSS software (version 22; IBM Corp., Armonk, NY, USA) was used for this analysis.

In order to construct RTM, KDE for each selected variable in each 25-m-side length cell was conducted using ArcGIS software (version 10.3; Environmental Systems Research Institute, Inc. [Esri], Redlands, CA, USA). The bandwidth was set to 250 m. The estimated risk values were re-converted to discrete values from 0 to 3, depending on the magnitude of the deviation from the average (0: less than average; 1: < average + 1 SD; 2: < average + 2 SD; 3: average + 2 SD or more); the weighted sum was calculated using the incidence rate ratios, which were obtained through a regression analysis as weight values. RTM was executed using ArcGIS.

For ST-GAM, we used VLT/PT as a dependent variable and three predictor variables, in the same manner as for RTM. Crime numbers for 2008 were counted on a per-cell basis; 1 was assigned to a cell for which at least one incident occurred per year; otherwise 0 was assigned. For each predictor variable, kernel density was estimated (its bandwidth was the same as RTM, 250 m), and a value was assigned for each cell. Next, a logistic additive model was constructed using the R ‘mgcv’ package. Generalized cross validation (GCV) was used to estimate the parameters. The occurrence of VLT/PT in 2014 was then predicted using estimated parameters and predictor variables that had been measured in 2014.

An analysis of KDE was conducted with ArcGIS, using the default quartic kernel function. A bandwidth of 250 m was selected based on the results of an examination of the

Table 2 Negative binomial regression for variable selection for RTM

| | Model 1 | | | | Model 2 | | | |
|------------------------------|----------|------------------------------|--------|-------------------|----------|------------------------------|-------|-------------------|
| | <i>B</i> | 95% Wald confidence interval | | Exp. (<i>B</i>) | <i>B</i> | 95% Wald confidence interval | | Exp. (<i>B</i>) |
| | | Lower | Upper | | | Lower | Upper | |
| Parking lot | 0.208* | 0.092 | 0.324 | 1.231 | 0.221* | 0.067 | 0.374 | 1.247 |
| Park | 0.048 | -0.044 | 0.140 | 1.049 | - | - | - | - |
| Family/Fast-food restaurant | -0.009 | -0.230 | 0.211 | 0.991 | - | - | - | - |
| Convenience store | 0.127*** | -0.006 | 0.261 | 1.136 | 0.196* | 0.098 | 0.294 | 1.217 |
| Coffee shop chain store | 0.119 | -0.048 | 0.285 | 1.126 | - | - | - | - |
| Department store/Supermarket | -0.103 | -0.244 | 0.037 | 0.901 | - | - | - | - |
| Total street length | -0.226* | -0.358 | -0.094 | 0.798 | 0.147** | 0.001 | 0.293 | 1.159 |
| (Intercept) | 0.874 | 0.759 | 0.989 | 2.396 | 3.088 | 2.969 | 3.206 | 21.926 |

BIC Model 1: 417.839

BIC Model 2: 408.336

p* < 0.01, *p* < 0.05, ****p* < 0.1

spatiotemporal concentration of VLT by Kikuchi et al. (2010) (namely, near-repeat victimization was assumed to exist). The estimated intensity (i.e., the risk value) was calculated for each cell, and was the same for all of the following methods.

For ProMap, the bandwidth was set similarly to KDE. We estimated the intensity of crime with the equation used by Johnson et al. (2009). The model counts the number of cells from each cell center to crime incidents within the bandwidth and provides values of 0 to 10 from the nearest. As in previous studies (Bowers et al. 2004; Johnson et al. 2007, 2009), the number of weeks since the date of occurrence was used. The number of days was divided by 7, and no rounding up was done. Further details are shown in the Appendix.

We constructed the SEPP model by referring to Mohler's previous studies (Mohler et al. 2011; Mohler 2014, 2015). The intensity of crime is represented as a summation by background function and triggering function. The parameters were estimated using an expectation-maximization (EM) algorithm. Calculations were carried out in the R statistical programming environment. Further details are shown in the Appendix.

For PSTSS, we used *spatiotemporal permutation scan statistics* (Kulldorff et al. 2005). The threshold of spatial accumulation (the maximum value of the circular area to be scanned) was 250 m; the time range for temporal accumulation to be considered as the emerging cluster on the 60th day was set at the most recent month. The number of random data points for the Monte Carlo test was set to 999 times. We used SaTScan, a specialized software program for executing spatial scan statistics (V9.4.4, provided by Prof. Martin Kulldorff).

Evaluation Methodology

We validated the prediction methods by repeating the forecasting and evaluating the accuracy. We constructed predictions for the next month by using the last 6 months' data, and calculated the prediction accuracy six times (July was forecast using January–June data; August was forecast using February–July data, etc.); we then took the average of these to verify the results.

For evaluation metrics, we adopted the *hit rate* and *prediction accuracy index* (PAI: Chainey et al. 2008). For hit rate, we calculated n as the number of crime occurrence spots that overlapped with the predicted high-risk area, and then divided it by N (total number of crimes in each target period). This rate (n/N) is the most basic and frequently used metric for crime prediction. It takes a value from 0 to 1. Although this is a basic crime prediction evaluation index, it can be 1 when the predicted area is extended to the entire region. Such a prediction map is quite useless. Therefore, we applied another index to evaluate the methods. We calculate PAI, which divides the hit rate by the ratio of a (size of predicted high-risk area) to A (total area size)—in other words, the *hit rate* is divided by a/A . This is useful for evaluating the efficiency of prediction and the volume of crime that could be predicted in a narrow area. It takes a value from 0 to ∞ .

Results

A Comparison of the Prediction Maps

Here, we show the prediction map for each method, along with the prediction accuracy for each. First, the prediction results by RTM and ST-GAM are shown in Fig. 1. In all prediction maps, the risk values estimated by each method are classified into 10 equal levels, then divided

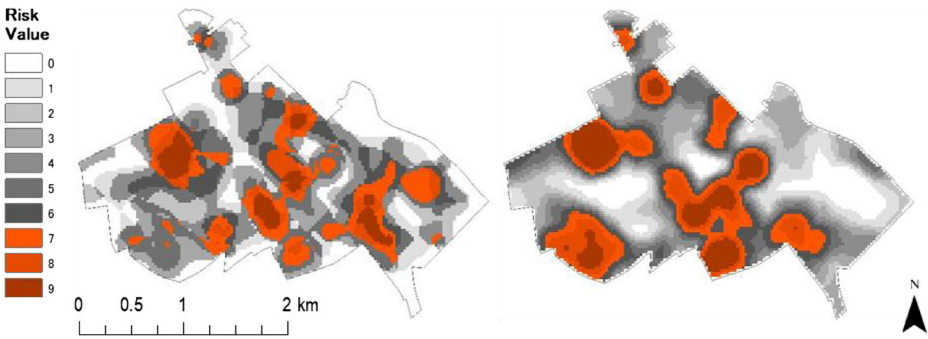


Fig. 1 Prediction maps using RTM (left) and ST-GAM (right)

into ranks of 0 to 9 from the lowest. The top three ranks (7–9) are highlighted in red. In this study, we regard these top three ranks as *predicted high-risk areas*. Figure 2 shows the prediction results for KDE, ProMap, and SEPP in July as examples. Results for all 6 months are shown in the Appendix, Fig. 5. For PSTSS, no significant emerging clusters were detected. This result suggests that prediction with the current data using PSTSS is difficult.

The prediction maps differ according to the method used. However, there are similarities between RTM and ST-GAM, both of which depend on the physical structure of a city. There are also some similarities among KDE, ProMap, and SEPP, which depend on crime data.

The concentration of predicted high-risk areas using RTM is observed in the northwest, southeast, and central parts of the region; ST-GAM also identifies the northwest and central areas as high-risk. However, in the ST-GAM analysis, risk is also predicted in the southwest (which is not predicted using RTM), and the eastern part is estimated as being relatively low-risk.

KDE, which is based only on the spatial information from crime data, predicted many high-risk areas in the western part and relatively few in the eastern part of the target area for July. As the prediction target period shifted, the high-risk area extending in a north–south direction in the western region (confirmed through the July prediction result) was divided after August. Conversely, KDE predicted high-risk areas in the eastern region as the months progressed (see Appendix, Fig. 5).

With ProMap, which predicts risk areas using the time information from crime data, the predicted distribution of high-risk areas and patterns of change were similar to those of KDE. However, we found that with ProMap, from July to September, the concentration seemed to be denser in the southwest region (identified by the deeper red color on the map) than it was for KDE. We also observed subtle differences between the two, such as a more prominent shift from west to east after September with ProMap than with KDE (see Appendix, Fig. 5).



Fig. 2 Prediction maps using KDE (left), ProMap (center), and SEPP (right) in July

For SEPP, the shape of the predicted risk areas is more extensive and continuous than with KDE or ProMap. Further, relatively smaller circle patterns are observable in the SEPP map.

On using RTM, we found that the predicted high-risk areas were different from those predicted using KDE, ProMap, and SEPP. In particular, the continuous north–south and central areas were not highlighted as high-risk in the predictions using the latter three methods. However, high-risk areas using RTM were confirmed in both the western and eastern regions; these areas were also flagged as high-risk using the three methods.

Evaluation of Predictive Accuracy

Table 3 compares the hit rate and PAI for each prediction method and shows the mean/standard deviation for 6 months of predictions. The analysis using RTM and ST-GAM resulted in only one prediction map each, because their variables were collected only once. However, we calculated the hit rate and PAI according to one-month predictions and calculated the mean/SD for 6 months. We excluded PSTSS here, since no significant clusters were found.

Table 3 demonstrates that RTM yields the best results among the five methods used. Both hit rate (40.9%) and PAI (1.87) are the highest for RTM, and they are almost twice as high as those for KDE, ProMap, and SEPP. ST-GAM, which uses the same data as RTM, is the second best. These results suggest that prediction methods based on environmental characteristics outperform methods that use past crime occurrences, in both predictive accuracy and efficiency.

For prediction methods that use past crime occurrence data, no PAI is above 1, which means that the prediction accuracy per area ratio is low. For instance, in the case of ProMap, in order to predict 17% of crimes, a prediction area larger than 17% of the total area would be required. Comparing the three methods, the hit rates for KDE and ProMap are almost equal, but ProMap has the highest PAI. In addition, ProMap’s SD for hit rate and PAI are lower than those of KDE and SEPP, which means that ProMap’s performance is more stable than that of other methods. Although SEPP surpassed KDE and ProMap in the hit rate, its PAI is the lowest among all the methods.

Comparing hit rate and PAI, RTM’s hit rate is about 2.3 times that of KDE and ProMap; RTM’s PAI is also about twice as high as that of KDE and ProMap. This indicates that the high-risk areas as predicted by RTM are more spread out.

Figure 3 shows a/A and n/N simultaneously. The horizontal axis shows the ratio to the total area when each cell is arranged in descending order of risk. The vertical axis shows the ratio to

Table 3 Hit rate and PAI for the prediction methods

| | Hit rate (%) | | | | | PAI | | | | | Actual no. of crimes |
|-----------|--------------|--------|--------|------|------|------|--------|--------|------|------|----------------------|
| | RTM | ST-GAM | ProMap | SEPP | KDE | RTM | ST-GAM | ProMap | SEPP | KDE | |
| July | 25.0 | 75.0 | 25.0 | 25.0 | 50.0 | 1.14 | 2.75 | 1.18 | 0.83 | 2.44 | 4 |
| August | 40.0 | 40.0 | 20.0 | 0.0 | 0.0 | 1.83 | 1.47 | 1.21 | 0.00 | 0.00 | 5 |
| September | 27.3 | 36.4 | 27.3 | 18.2 | 9.1 | 1.25 | 1.33 | 1.47 | 0.61 | 0.47 | 11 |
| October | 37.5 | 12.5 | 12.5 | 12.5 | 12.5 | 1.72 | 0.46 | 0.70 | 0.42 | 0.64 | 8 |
| November | 55.6 | 22.2 | 12.5 | 66.7 | 25.0 | 2.54 | 0.81 | 0.65 | 2.22 | 1.23 | 9 |
| December | 60.0 | 30.0 | 9.1 | 10.0 | 9.1 | 2.75 | 1.10 | 0.47 | 0.33 | 0.46 | 10 |
| Mean | 40.9 | 36.0 | 17.7 | 22.1 | 17.6 | 1.87 | 1.32 | 0.95 | 0.73 | 0.87 | |
| SD | 13.1 | 19.6 | 6.8 | 21.4 | 16.3 | 0.60 | 0.72 | 0.36 | 0.71 | 0.79 | |

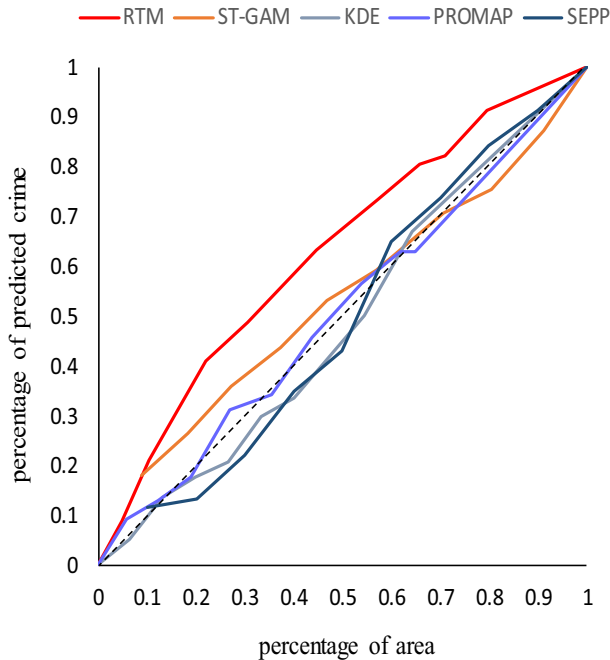


Fig. 3 Hit rates with area coverage for prediction methods

the total area in order to compare the prediction efficiency in all areas. Where the graph expands upward, it means that the prediction efficiency is high. The black dotted line represents the prediction efficiency when a/A and n/N are proportionate.

From this figure, it is clear that RTM performed better than random prediction in all regions. In addition, prediction efficiency is stable under RTM. With the exception of ProMap, the results for all prediction methods that use past crime occurrence data are below the dotted line.

Discussion

We now examine in detail the results outlined in the previous section and discuss the applicability and limitations of each method in a Japanese context. RTM showed the highest hit rate and PAI among all methods. Moreover, only the PAI of RTM surpassed 1.00 in all months. The variables used for RTM were parking lots, convenience stores, and street length, which are considered “crime generators” (Brantingham and Brantingham 1995) of VLT/PT, since the cars are parked and unattended. Although it is a relatively simple method of prediction with overlaying of crime generators, RTM outperformed all the other methods used in this study.

In contrast to a study by Adepeju et al. (2016), in which the authors found that SEPP had consistently higher accuracy when compared to KDE, ProMap, and PSTSS, in the current study, it is worth noting that the average prediction accuracy of SEPP was the lowest. This is likely because the triggering effect was not functioning sufficiently. Such a situation can occur when the relevance and continuity between past and present crime occurrences is extremely low. Kikuchi et al. (2010) investigated whether the near-repeat effect could be confirmed by studying various crimes in Japan; verification performed using the K-function revealed that

spatial relevance is recognized to some extent between crime occurrences. However, the temporal relevance of VLT is weaker than that of other types of offenses. The low performance of SEPP in this analysis may be the result of such a trend.

We believe that there is another reason for the low performance of crime data-based methods. In Japan, where the crime rate is low, the amount of available information on crime occurrence that could aid in crime prediction is less than the amount of information on environmental factors. In the work by Chainey et al. (2008), which reports crime prediction in the UK, the size of the target area is about eight times that of the current study's target area, with over 10,000 cases of VLT occurring annually compared to 87 for the current study. Such a difference in frequency greatly influences the prediction result. The lack of information on crime occurrence makes it difficult to predict future crimes in Japan using crime data itself. The low incidence of crime in Japan is also likely because crime risk is not actualized, or does not become visible, instantly. Thus, the risk is considered "implicit." We can, therefore, consider actualized crime occurrences as chance occurrences in such a situation. The merits of RTM are thus evident, as this method utilizes the environmental risk factors and assesses the potential crime risks for a site. This information may be more plentiful than crime itself in Japan.

In countries like Japan where crime occurrence is low, it is possible that a few individuals or groups are responsible for the crimes committed, and there are situations where the majority of crimes are committed by fewer people. In this case, a change in crime occurrence pattern, such as crime stops or hotspot moves, is likely to occur due to the circumstances surrounding the crimes (e.g., deterrence of crime through crime prevention measures or a change in target area). RTM is a stable and accurate method because it does not depend on such information. In countries with circumstances similar to those in Japan, relying on methods that are greatly influenced by temporal information on the occurrence of crime may lead to unstable predictive results.

Among the methods that use environmental factors, the performance of RTM and ST-GAM differed in this study, though they use the same variables. According to the prediction map using RTM, the eastern part of the area was predicted as high-risk, while this was not the case using ST-GAM. Hakata terminal station is located in this area and is surrounded by many businesses. When we look at the PAI from October to December, RTM outperforms ST-GAM; the opposite is true for the prior 3 months. This means that RTM could capture crime occurrence around the station in those 3 months. Although the RTM algorithm is simpler than that of ST-GAM, such a method—overlaying risk layers—is superior to a nonparametric additive function.

We also compared the performance of RTM with the results of existing research. With regard to the value of PAI, in previous studies, Chainey et al. (2008) predicted theft from vehicle using KDE at a value of 2.29 to 3.66, and Adepeju et al. (2016) predicted motor vehicle theft using KDE, ProMap, SEPP, and PSTSS at values of 1.59 to 1.99. Although a simple comparison cannot be made, since the study period and conditions are different, the PAI of RTM in the present study is comparable to existing research.

Nonetheless, the evaluation methodology in the current study leaves room for consideration. Since the hit rate is obtained by the process of division, values fluctuate depending on the denominator. When the denominator is too small, the hit rate is at an extreme high. PAI has the same problem, since it is based on the hit rate. When the crime occurrence is low, the results are greatly affected. Although both hit rate and PAI are widely used in crime prediction studies (e.g., Adepeju et al. 2016; Drawve 2014; Dugato 2013; Hart and Zandbergen 2012; Thakali et al. 2015; Van Patten et al. 2009), we should exercise caution when referring to the results of studies conducted in Japan. Furthermore, we should develop alternative evaluation methodologies, and this need must be addressed in the future.

Conclusion

Using domestic data, we analyzed and verified the accuracy and efficiency of predictions from major crime prediction methods for an area in Japan. We found that RTM had the highest prediction accuracy and that a prediction method based on environmental factors can be effective, at least for crime prediction in urban and metropolitan areas in Japan. From these results, it appears that crime prediction in Japan should incorporate factors strongly related to crime into crime forecasts. The availability of crime data with high spatial and temporal resolution in Japan is poor, and the opportunities to rely on such techniques are likely to increase.

The current analysis was conducted in a specific area in one city in Japan. Moreover, the results were obtained with specific parameters, such as the 250-m bandwidth and the 25-m length of the grid cells. Although these parameters were chosen using theoretical or practical backgrounds, we can assume that different results could be derived using different parameters. The same can be said of the types of crime selected. Thus, we must be cautious about generalizing the results. We cannot, therefore, make conclusions about the effectiveness of a specific method and the applicability of the geographical crime prediction to all cities in Japan.

It remains highly significant that RTM was found to be efficient in a low-crime setting. The prediction accuracy achieved was comparable to that in previous studies, though the current study area has a low occurrence of crimes that are “popular” in Western countries, such as VLT/PT. This result also suggests that other developed countries may also have less crime in the future. Meanwhile, we still need to clarify why crime occurrence-dependent methods such as SEPP had poorer performance. We cannot conclude that this is a result of low crime occurrence or weak crime interaction (near-repeat). It is important that these methods be applied and tested under a variety of situations, such as low crime occurrence and strong crime interaction, or high crime occurrence and weak crime interaction.

In this analysis, the spatiotemporal resolution was predicted on a monthly basis and a 25 m × 25 m square cell unit. Regarding temporal resolution, given that the average number of crimes was less than 10 cases per month, predictions at a higher resolution, in units of weeks or days, would be difficult in Japan. However, we suggest that this is reasonable when the level of crime occurrence in Japan is considered. Displaying the results of the prediction at the neighborhood level can help to prompt vigilance by neighborhood associations.

This is the first study to compare RTM with crime data-based methods such as ProMap and SEPP. These two types of methods may be applied in different situations. For instance, the risks predicted by RTM are likely to remain for a span of several months to several years for a particular location due to the characteristics of the variables used. To cope with such risks, we should take measures to improve the environment, as prescribed by Crime Prevention Through Environmental Design (CPTED), and to increase defenses against crime at the specific location rather than establishing temporary crime prevention measures such as police patrols. On the contrary, predicting the near future using ProMap or SEPP would be more useful as a direct crime deterrent (such as early arrests); these methods can be used to determine monthly patrol routes and to indicate areas where crime is most likely to next occur. The results of the current study suggest that we should focus on environmental improvements—such as CPTED—in which RTM can be used to deter crime in Japan.

In methods that use environmental factors, such as RTM, the prediction result depends on what is adopted as predictor variables. In the current study, variables were selected through an

exploratory procedure of regression analysis, but variables should be set based on existing theories and research on VLT/PT. In Japan, with the exception of Nagasawa and Hosoe (1999), few studies have examined in detail the environment where VLT/PT occur. Thus, in order to develop RTM for Japan, basic research frameworks must be developed to explore factors related to relevant crimes prior to prediction.

Finally, future works on crime prediction in Japan should investigate the characteristics of relevant data and focus on building algorithms for use specifically in a Japanese context. Although this may require a novel approach, it is necessary for establishing a unique technique. This may also lead to new results on the topic at an international level.

Acknowledgements The data on crime was provided to us under the Fukuoka Prefectural Police's Crime Prevention Research Advisor framework; we would like to thank the Fukuoka Prefectural Police for their support. We would also like to thank Dr. Millar for English language editing.

Funding This study was funded by a grant from the Nikkoso Research Foundation for Safe Society in 2016 and JSPS Grant Number JP17H02046.

Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

Appendix

Description for ProMap

For ProMap, the bandwidth and cell size were set similarly to KDE. We estimated the intensity of crime in a location (s) on date (t), using Eq. 1.1, as formulated by Johnson et al. (2009).

$$\hat{\lambda}(t, s) = \sum_{c_i \leq \tau \cap e_i \leq \nu} \left(\frac{1}{(1 + c_i)} \right) \frac{1}{(1 + e_i)} \quad (1.1)$$

where τ is the spatial bandwidth, ν is the temporal bandwidth, c_i is the number of cells between each location of crime i within the spatial, e_i is the time elapsed for each occurrence time of crime i within the temporal bandwidth and the cell.

To obtain c_i in Eq. 1.1, as shown in Fig. 4, a plurality of concentric circles (radius 12.5 m + 25 m * n, where $n = 0, 1, 2, \dots, 10$) were drawn. Although the radius of the largest circle is 262.5 m at the maximum, 250 m was set as the upper limit in order to exclude points outside of it. Equal weighting was given to the points existing within the same distance range (as shown in Fig. 4, $X_1 = 0, X_2 = 1, X_3 = 2$). As in previous studies (Bowers et al. 2004; Johnson et al. 2007, 2009), the number of weeks from the date of occurrence was used for e_i . The number of days was divided by 7; no rounding was performed.

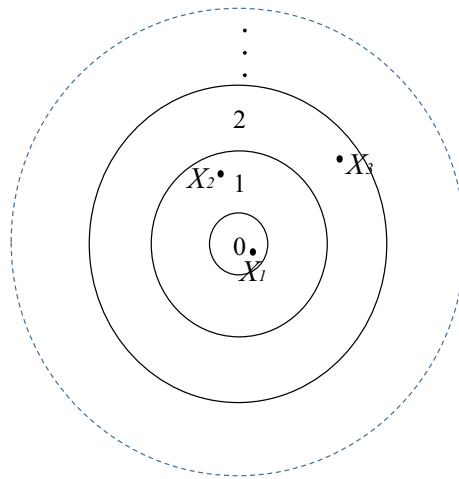


Fig. 4 Value of c_i of ProMap in the current study

Description for SEPP

For SEPP, the prediction was carried out using Eq. 1.2 with reference to a series of studies by Mohler (Mohler et al. 2011; Mohler 2014, 2015). The intensity of crime in a location (x,y) on date (t) is described as:

$$\lambda(t, x, y) = \sum_{\{k:t_k < t\}} \mu(x-x_k, y-y_k) + \sum_{\{k:t_k < t\}} g(t-t_k, x-x_k, y-y_k) \tag{1.2}$$

where $t-t_k$ is the numbers of dates between a prediction target period and each occurrence date of a crime event, $x-x_k, y-y_k$ are the instance between each target cell and each crime event.

We estimated μ and g using Eqs. 1.3 and 1.4.

$$\mu(x, y) = \frac{\alpha}{T} \sum_{t_i < t} \frac{1}{2\pi\eta^2} \times \exp\left(-\frac{(x-x_i)^2 + (y-y_i)^2}{2\eta^2}\right) \tag{1.3}$$

$$g(t, x, y) = \theta\omega \exp(-\omega(t-t_i)) \times \frac{1}{2\pi\sigma^2} \exp\left(-\frac{(x-x_i)^2 + (y-y_i)^2}{2\sigma^2}\right) \tag{1.4}$$

where:

$$\alpha = \frac{\sum_{i=1}^{N_i} \sum_{j=1}^{N_j} p_{ij}^b}{N_i} \tag{1.5}$$

$$\eta^2 = \frac{\sum_{i=1}^{N_i} \sum_{j=1}^{N_j} p_{ij}^b \left((x-x_i)^2 + (y-y_i)^2 \right)}{2\sum_{i=1}^{N_i} \sum_{j=1}^{N_j} p_{ij}^b} \tag{1.6}$$

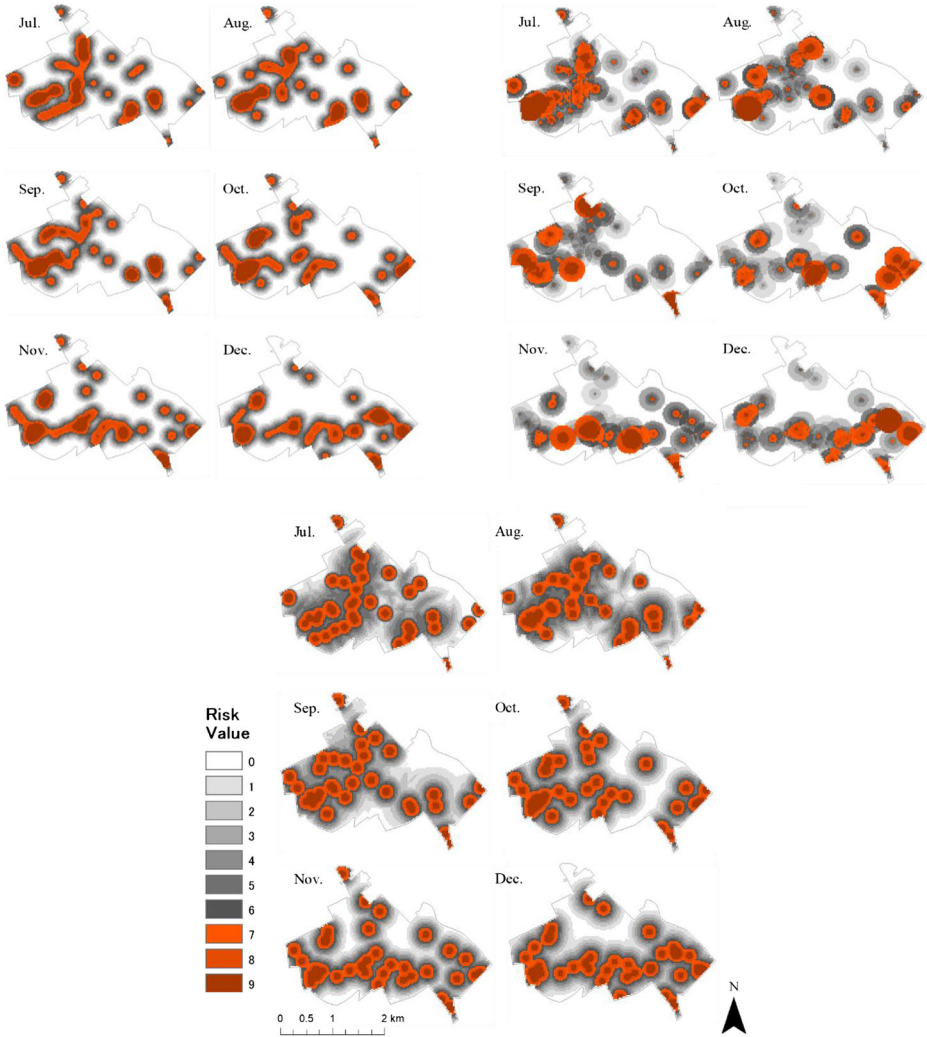


Fig. 5 Prediction maps using KDE (top left), ProMap (top right), and SEPP (bottom) from July to December

$$\theta = \frac{\sum_{i=1}^{N_i} \sum_{j=1}^{N_j} p_{ij} 1}{N_j - \sum_{j=1}^{N_j} \exp(-\omega(T-t_j)) 1} \tag{1.7}$$

$$\omega = \frac{\sum_{i < j} p_{ij}}{\sum_{i < j} (t_j - t_i) p_{ij}} \tag{1.8}$$

$$\sigma^2 = \frac{\sum_{i=1}^{N_i} \sum_{j=1}^{N_j} p_{ij} \left((x-x_i)^2 + (y-y_i)^2 \right)}{2 \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} p_{ij}} \tag{1.9}$$

In these equations, p_{ij} indicates the probability of event i (offspring) being triggered by another event j (parent). These i and j events are called triggering pairs. Additionally, p_{ij}^b is defined as the probability that event i occurs independently from other events. Thus, i is called a background event (equal to the parent events). We divided events into triggering pairs and background events using the EM algorithm described by Rosser and Cheng (2016). First, we set initial values of p_{ij} following Eq. 1.8 (here, we set α as 1.5 and β as 500) and obtained the probability matrix \mathbf{P}_0 (upper triangular matrix). Based on those values, we distinguished parents and their offspring.

$$p_{ij} = \exp(-\alpha(t_j - t_i)) \exp\left(-\frac{(x_j - x_i)^2 + (y_j - y_i)^2}{2\beta^2}\right) \quad (1.10)$$

We then calculated parameters following Eqs. 1.5–1.11. The ω and σ^2 were computed using triggering pairs. Once we obtained the parameters, we updated p_{ij} following Eq. 1.11 and repeated these steps until $\|\mathbf{P}_n - \mathbf{P}_{n-1}\|$ was smaller than 1×10^{-7} .

$$p_{ij} = \theta \omega \exp(-\alpha \omega (t_j - t_i)) \times \frac{1}{2\pi\sigma^2} \exp\left(-\frac{(x_j - x_i)^2 + (y_j - y_i)^2}{2\sigma^2}\right) \quad (1.11)$$

References

- Adepeju, M., Rosser, G., & Cheng, T. (2016). Novel evaluation metrics for sparse spatio-temporal point process hotspot predictions—a crime case study. *International Journal of Geographical Information Science*, 30(11), 1–22.
- Anselin, L., Cohen, J., Cook, D., Gorr, W., & Tita, G. (2000). Spatial analyses of crime. *Criminal Justice*, 4(2), 213–262.
- Block, C. (1995). STAC hot-spot areas: A statistical tool for law enforcement decisions. In *Crime analysis through computer mapping* (pp. 15–32). Washington, DC: Police Executive Research Forum.
- Block, R., & Block, C. (1995). Space, place and crime: Hot spot areas and hot places of liquor-related crime. In J. Eck & D. Weisburd (Eds.), *Crime and place* (pp. 145–183). Monsey: Criminal Justice Press.
- Bowers, K., Johnson, S., & Pease, K. (2004). Prospective hot-spotting: the future of crime mapping? *British Journal of Criminology*, 44(5), 641–658.
- Brantingham, P., & Brantingham, P. (1995). Criminology of place: Crime generators and crime attractors. *European Journal on Criminal Policy and Research*, 3(3), 1–26.
- Cabinet Secretariat (2014). Action Plan on Promoting Utilization of Geospatial Information: Summary by Measures (G-Space Action Plan), Geospatial Information Utilization Promotion Meeting. <http://www.cas.go.jp/jp/seisaku/sokuitiri/260617/gaiyou03.pdf>. Accessed 16 February 2017. (In Japanese).
- Caplan, J., & Kennedy, L. (2016). *Risk terrain modeling: Crime prediction and risk reduction*. Oakland: University of California Press.
- Caplan, J., Kennedy, L., & Miller, J. (2011). Risk terrain modeling: Brokering criminological theory and GIS methods for crime forecasting. *Justice Quarterly*, 28(2), 360–381.
- Caplan, J., Kennedy, L., & Piza, E. (2013). *Risk terrain modeling diagnostics utility (version 1.0)*. Newark: Rutgers Center on Public Security.
- Chainey, S. (2005). Methods and techniques for understanding crime hot spots. In *Mapping crime: Understanding hot spots* (pp. 15–34). US Department of Justice.
- Chainey, S., & Ratcliffe, J. (2013). *GIS and crime mapping*. Chichester: Wiley.
- Chainey, S., Tompson, L., & Uhlig, S. (2008). The utility of hotspot mapping for predicting spatial patterns of crime. *Security Journal*, 21(1), 4–28.

- Cheng, T., & Adepeju, M. (2013). Detecting emerging space-time crime patterns by prospective STSS. In *Proceedings of the 12th international conference on geocomputation*. <http://www.geocomputation.org/2013/papers/77.pdf>. Accessed 22 August 2017.
- CIVITAS. (2012). *Comparisons of Crime in OECD Countries*. http://www.civitas.org.uk/content/files/crime_stats_oecdjan2012.pdf. Accessed 22 August 2017.
- Dugato, M. (2013). Assessing the validity of risk terrain modeling in a European city: Preventing robberies in the city of Milan. *Crime Mapping*, 5(1), 63–89.
- Drawve, G. (2014). A metric comparison of predictive hot spot techniques and RTM. *Justice Quarterly*, 33(3), 369–397.
- Eck, J., Chainey, S., Cameron, J., & Wilson, R. (2005). *Mapping crime: Understanding hotspots*. Washington, D.C.: National Institute of Justice.
- Fox, J., & Brown, D. (2012). Using temporal indicator functions with generalized linear models for spatial-temporal event prediction. *Procedia Computer Science*, 8, 106–111.
- Gorr, W., & Harries, R. (2003). Introduction to crime forecasting. *International Journal of Forecasting*, 19(4), 551–555.
- Groff, E., & La Vigne, N. (2002). Forecasting the future of predictive crime mapping. *Crime Prevention Studies*, 13, 29–57.
- Haberman, C. (2017). Overlapping Hot Spots? *Criminology & Public Policy*, 16(2), 633–660.
- Hart, T., & Zandbergen, P. (2012). *Effects of data quality on predictive hotspot mapping: Final technical report (doc. #239861)*. Washington, D.C.: National Institute of Justice.
- Johnson, S., Birks, D., McLaughlin, L., Bowers, K., & Pease, K. (2007). *Prospective crime mapping in operational context, final report*. London: Home Office.
- Johnson, S., Bowers, K., Birks, D., & Pease, K. (2009). Predictive mapping of crime by ProMap: Accuracy, units of analysis, and the environmental backcloth. In D. Weisburd, W. Bernasco, & G. J. N. Bruinsma (Eds.), *Putting crime in its place* (pp. 171–198). New York: Springer.
- Johnson, S., Summers, L., & Pease, K. (2006). *Vehicle crime: Communicating spatial and temporal patterns, final report*. London: Home Office.
- Kennedy, L., Caplan, J., & Piza, E. (2011). Risk clusters, hotspots, and spatial intelligence: Risk terrain modeling as an algorithm for police resource allocation strategies. *Journal of Quantitative Criminology*, 27(3), 339–362.
- Kikuchi, G., Amemiya, M., Shimada, T., Saito, T., & Harada, Y. (2010). An analysis of near repeat victimization patterns across crime types—an application of Spatio-temporal K function—. *Theory and Applications of GIS*, 18(2), 129–138 (In Japanese).
- Kulldorff, M., Athas, W., Feurer, E., Miller, B., & Key, C. (1998). Evaluating cluster alarms: A space-time scan statistic and brain cancer in Los Alamos, New Mexico. *American Journal of Public Health*, 88(9), 1377–1380.
- Kulldorff, M., Heffernan, R., Hartman, J., Assunção, R., & Mostashari, F. (2005). A space-time permutation scan statistic for disease outbreak detection. *PLoS Medicine*, 2(3), 216–224.
- Levine, N. (2008). The “hottest” part of a hotspot: Comments on “the utility of hotspot mapping for predicting spatial patterns of crime”. *Security Journal*, 21(4), 295–302.
- Mohler, G. (2014). Marked point process hotspot maps for homicide and gun crime prediction in Chicago. *International Journal of Forecasting*, 30(3), 491–497.
- Mohler, G. (2015). Event forecasting system. U. S. Patent 13,676,358. 3 February 2015.
- Mohler, G., Short, M., Brantingham, P., Schoenberg, F., & Tita, G. (2011). Self-exciting point process modeling of crime. *Journal of the American Statistical Association*, 106(493), 100–108.
- Moreto, W., & Caplan, J. M. (2010). Forecasting global maritime piracy utilizing the risk terrain modeling (rtm) approach. *Rutgers center on public security brief*.
- Moreto, W. D., Piza, E. L., & Caplan, J. M. (2014). “A plague on both your houses?”: Risks, repeats and reconsiderations of urban residential burglary. *Justice Quarterly*, 31(6), 1102–1126.
- Nagasawa, H., & Hosoe, T. (1999). A study on the factors of criminal situations of thefts from cars. *Bulletin of the Faculty of Social Welfare, Iwate Prefectural University*, 61–72. (In Japanese).
- Ohyama, T., Amemiya, M., Shimada, T., & Nakaya, T. (2017). Recent research trends on geographical crime prediction. *Theory and Applications of GIS*, 25(1), 33–43 (In Japanese).
- Onat, I., & Gul, Z. (2018). Terrorism Risk Forecasting by Ideology. *European Journal on Criminal Policy and Research*, 1–17.
- Openshaw, S. (1995). Developing automated and smart spatial pattern exploration tools for geographical information systems applications. *Journal of the Royal Statistical Society: Series D (The Statistician)*, 44(1), 3–16.
- Openshaw, S., Charlton, M., Wymer, C., & Craft, A. (1987). A mark 1 geographical analysis machine for the automated analysis of point data sets. *International Journal of Geographical Information System*, 1(4), 335–358.
- Perry, W., McInnis, B., Price, C., Smith, S., & Hollywood, J. (2013). *Predictive policing: The role of crime forecasting in law enforcement operations*. Santa Monica: Rand Corporation.

- Ratcliffe J. (1999). *Hotspot detective for MapInfo helpfile version 1.0*.
- Roberts, A. (2008). The influences of incident and contextual characteristics on crime clearance of nonlethal violence: A multilevel event history analysis. *Journal of Criminal Justice*, 36(1), 61–71.
- Roberts, A., & LaFree, G. (2004). Explaining Japan's postwar violent crime trends. *Criminology*, 42(1), 179–210.
- Rosser, G., & Cheng, T. (2016). Improving the robustness and accuracy of crime prediction with the self-exciting point process through isotropic triggering. *Applied Spatial Analysis and Policy*, 1–21.
- Rosser, G., Davies, T., Bowers, K. J., Johnson, S., & Cheng, T. (2017). Predictive crime mapping: Arbitrary grids or street networks? *Journal of Quantitative Criminology*, 33(3), 569–594.
- Sherman, L. (1995). Hot spots of crime and criminal careers of places. In J. Eck & D. Weisburd (Eds.), *Crime and place: Crime prevention studies* (pp. 35–52). Monsey: Criminal Justice Press.
- Sherman, L., Gartin, P., & Buerger, M. (1989). Hot spots of predatory crime: Routine activities and the criminology of place. *Criminology*, 27(1), 27–56.
- Shiode, S. (2011). Street-level spatial scan statistic and STAC for Analysing street crime concentrations. *Transactions in GIS*, 15(3), 365–383.
- Shiode, S., & Shiode, N. (2014). Microscale prediction of near-future crime concentrations with street-level Geosurveillance. *Geographical Analysis*, 46(4), 435–455.
- Thakali, L., Kwon, T. J., & Fu, L. (2015). Identification of crash hotspots using kernel density estimation and kriging methods: A comparison. *Journal of Modern Transportation*, 23(2), 93–106.
- Townsley, M., Homel, R., & Chaseling, J. (2003). Infectious burglaries. A test of the near repeat hypothesis. *British Journal of Criminology*, 43(3), 615–633.
- Van Patten, I., McKeldin-Coner, J., & Cox, D. (2009). A Microspatial analysis of robbery: Prospective hot spotting in a Small City. *Crime Mapping: A Journal of Research and Practice*, 1(1), 7–32.
- Wang, X., & Brown, D. (2012). The spatio-temporal modeling for criminal incidents. *Security Informatics*, 1(1), 1–17.