

COMMUNITY SECURITY IS THE KEY TO SUSTAINABLE GOVERNANCE: METHODS AND FUNCTIONS OF CRIME HOTSPOT PREDICTIONS

Tien-Chin Wang^{*}, Bi-Chao Lee^{**}

^{*} Department of International Business, National Kaohsiung University of Science and Technology, Kaohsiung City, Taiwan

^{**} *Corresponding author*, Department of International Business, National Kaohsiung University of Science and Technology, Kaohsiung City, Taiwan
Contact details: National Kaohsiung University of Science and Technology No. 415, Jiangong Rd., Sanmin Dist., 80778 Kaohsiung City, Taiwan



Abstract

How to cite this paper: Wang, T.-C., & Lee, B.-C. (2021). Community security is the key to sustainable governance: Methods and functions of crime hotspot predictions. *Corporate Governance and Sustainability Review*, 5(2), 57–72. <https://doi.org/10.22495/cgsrv5i2p5>

Copyright © 2021 The Authors

This work is licensed under a Creative Commons Attribution 4.0 International License (CC BY 4.0). <https://creativecommons.org/licenses/by/4.0/>

ISSN Online: 2519-898X
ISSN Print: 2519-8971

Received: 22.12.2020
Accepted: 21.05.2021

JEL Classification: A10, C54, Q56
DOI: 10.22495/cgsrv5i2p5

Forecasting is becoming increasingly important in corporate sustainability governance, as is government governance, and the prediction of police crime hotspots is related to human rights, so transparency is needed. There are many ways to predict hotspots of criminal activity in urban areas. Experts assume that if many crimes occur somewhere, even more, are likely to happen at subsequent times. Such predictions may rely on a state dependency model such as the Poisson distribution algorithm to formulate re-occurrence, its results can provide a visualized hotspot map with Q-GIS maps. Forecasting sets the threshold for re-occurrence and affects the distribution of the forecast. This paper studies the occurrence of criminal activity in urban areas, refers to the metrics set by the NIJ's crime prediction contest and focuses on the presentation of the results by accumulating different historical data. It was determined that when the amount of cumulative data is greater, its prediction measures by the prediction accuracy index (PAI) insures that accuracy is improved, but the prediction efficiency index (PEI) that efficiency level is worse. Because threshold setting directly affects the performance of the forecast, it can be used differently. Here sets four different indicators, hit rate, useful rate, waste rate, and missing rate. It was determined that the hit rate, missing rate, the PAI value, and the PEI value are directly proportional to the threshold value, while the trend of useful rate and waste rate are inversely related. Concerned policymakers can set different thresholds dependent up the number and budgetary constraints of police forces, and they can work towards achieving crime prevention in urban hotspots. Importantly, Poisson's approach can be simply implemented with Excel, be conducive to drive by the office practitioner, and elevate the transparency of crime prediction.

Keywords: Quantitative Methods, Data Collection, Regional Government, Research and Development Policy, State Dependency Model, Poisson Distribution, Sustainability

Authors' individual contribution: Conceptualization — T.-C.W. and B.-C.L.; Methodology — T.-C.W. and B.-C.L.; Investigation — T.-C.W. and B.-C.L.; Writing — Original Draft — T.-C.W. and B.-C.L.; Writing — Review & Editing — T.-C.W. and B.-C.L.

Declaration of conflicting interests: The Authors declare that there is no conflict of interest.

1. INTRODUCTION

Sustainability is the new approach of corporations of the world over which is catching a lot of attention due to its divergence from the short-term approach to the long-term horizon (Malik & Yadav, 2020); public security is an external factor in corporate sustainable governance. Public insecurity has long impeded effective community governance, for example, drugs, gangs, corruption, and violence (Rekow, 2016). Promoting a sustainable development mindset with officer's policy will relay social policy for advancing quality management (QM) (Yeung, 2019). The "good" administrative authorities' governance practices are influenced by national culture (Rahman & Marjerison, 2020). So, in order to establish a sustainable cultural awareness of law and order, high-quality crime prediction methods are essential for the sustainable development of community public security.

The law "Police Power Exercise Act" (2011) of The Republic of China (Taiwan), Article 6, states, "The police may verify the identity of the following people in public places or public-accessible places: people who pass through designated public places, road sections, and checkpoints" (1st paragraph). The designation stipulated in subparagraph 6 of the preceding paragraph shall be made only when considered necessary to prevent crimes or deal with events that may affect major public safety or social order. The designation shall be determined by the supervisors in charge (2nd paragraph). The designated "public places, road sections, and checkpoints" are crime hotspots. Transparency is particularly important (Matheus, Janssen, & Janowski, 2021) when police use stop-question-frisk tactics in hotspots, a tactic linked to excessive interference in the daily lives of people who are not involved in crime (Sullivan & O'Keeffe, 2017). It like the disclosure of information serves the accountability of the corporation. Publicly listed corporations have a higher obligation of transparency because they benefit from the stock markets in which the public has access to trade the shares (Euler, 2014). Crime hotspots prediction determines where stop-question-frisk can be made, so people must know how the predicted information is obtained and predicted, whereas the state dependence model meets this requirement, and Poisson is an effective and convenient way to operate (Lee, SooHyun, & Eck, 2020).

From an economic viewpoint, the amount of police force manpower and available man-hours are both limited resources. The question of how to use these finite resources to reduce the occurrence of crime is the focus of police administrators in planning their service allocations. Some studies point out that incidents of criminality have "spatial" or geographical elements, and they are frequently clustered in specific locations according to certain factors or identifiable driving forces. Therefore, to explore the spatial factors of criminal occurrence, and to identify these particular locations in advance, it is necessary to develop an effective crime prevention strategy and to arrange services that can help to put the police force in the right area to save resources (Wen, Liu, & Lin, 2010). A common strategy for most police forces is to raise the policing profile in given urban areas that are deemed crime

"hotspots". These so-called "hotspots" have an inordinate amount of criminal occurrences (usually felonies) compared to other locations with similar population and socio-demographic make-up.

The Chief Police Officer often asks the police units to raise the "police presence" in order to maintain public order in such areas. For example, the Kansas City Preventive Patrol Experiment (1974), found that three experimental patrol conditions (reactive, control, proactive) did not appear to affect crime, service delivery, and citizens' sense of security in ways that the public and the police often assume they do. Likewise, the so-called Minnesota's Minneapolis Hotspots Patrol Experiment (1992) added the concept of a "crime hotspot" to the lexicon of urban crime-fighting. A hotspot was considered for purposes of crime hotspot analysis, then it could be assigned additional patrol vehicles for coverage. Results indicated that frequent police patrols between crime hotspots were far more effective in reducing crime occurrence than delivering a higher police presence and a concomitant rapid response policy (TTRDA, 2016).

Traditional criminal scholars believe that crime is not evenly distributed in every corner of an urban area, that is, the place where crime occurs is not randomly distributed, but instead, it is aggregated. The proximity of known criminal offenders affects the distribution of the criminal occurrence in a temporal, spatial, and subjective manner. Therefore, the place of criminal event occurrence is an important element in crime pattern theory. It is logically not only necessary (the perpetrator must have committed the crime in a particular place), but it also affects the feature or attribute of the place and the likelihood of the crime to occur. Compstat policing, standing for "computer statistics" deals specifically with a crime based on the parameters of geographic locale. This form of policing uses statistical data referencing criminality taken from computer databases and organizes the crime "hotspots", then the police may carry out frequent and coordinated patrol-work between the determined crime hotspots. This methodology was developed in the 1990s at the behest of the New York Police Department to help reduce crime in certain areas of New York City (Mon, 2003).

Sherman, Gartin, and Buerger (1989) have found in various studies that about 60% of the urban population who call the police for services are concentrated in 10% of a city's geographic areas. Chainey and Ratcliffe (2005) studied how crime has an inherent geographical quality, in that crime takes place at some common location. It was also found that crime also does not occur on a random basis (Chainey, Tompson, & Uhlig, 2008). The study of crime hotspots has become a topic of concern for some time among urban police forces.

In 1998, the National Institute of Justice of USA (NIJ-USA) awarded grants for five inaugural studies on crime locale prediction, which resulted in the introduction of the first predictive geographic model for criminal occurrences. The purpose of this original grant was to support researchers' and scientists' efforts to develop practical models for use by police agencies, but it also allowed scholars to explore the feasibility of crime place prediction (Lee et al., 2020). Crime hotspots in Taiwan have been researched by counting the number and

location of historical crimes with a geographic information system (GIS) application to identify hotspot areas. This description allows reference by the police in detecting crimes. For example, Mon (2003) researched “crime hotspots”, Xie et al. (2007) studied “characteristics of a crime area”, and Wen et al. (2010) wrote a “Crime Mapping and Hotspot Analysis”. However, less research has been conducted regarding the predictive location of crime hotspots, which serves as the motivation of this paper.

The first section is an introduction. Taiwan’s law “Police Power Exercise Act” (2011) permitted the police supervisors could designate public places to stop-question-frisk the people who through there. Therefore, the transparency of designation is particularly important. Under the inspiration of the sustainable operation of corporate governance, the selecting crime hotspots must be transparent, that conduce to public security governance and sustainable development of the community. It is the motivation of this study, too. The second section describes that forecasting research has become an important field of enterprises and is applied in many ways. Since the NIJ-USA has offered bonuses to hold a prediction contest in 2014, various methods of studying crime prediction have emerged. The occurrence of criminal cases conforms to the state dependence model and the characteristics of Poisson in line with the nature of crime hotspot prediction. To predict results, a visualized hotspot map with Q-GIS maps is provided. The third section describes the source of the data collection, the application of the Poisson method, and the comparison with PAI and PEI, to build the research areas and the selection of historical data. Section 4 describes the practical operation, to write a program to put the data into the grid cells, to compare the probability of recurrence at Poisson with the actual probability of occurrence, and to set different observation indicators. Section 5 is a discussion of results, where the setting of thresholds affected the performance of predictions, and this paper creates four different observation indicators to count different results and discuss their significance. Section 6 is the conclusion. Different years of data accumulation, different threshold values have different results, and limitations of research of this paper, and recommendations to substantive units.

2. LITERATURE REVIEW

2.1. Poisson for forecasts

A forecast is a statement of what is expected to happen in the future, especially in relation to a particular event or situation (definition by Collins English Dictionary). Forecasts are prepared based on estimates, which in practice, correspond with point predictions (Abdul Aziz, Percy, & Mohamed Yusof, 2009). In practical applications, such as forecasting used for climate forecasting (Dantanarayana, Herath, & Weerakoon, 2021), fiscal forecast (Dietsch, 2019), car fuel economy simulation forecast (Lei et al., 2018), global economic real GDP growth (Baumeister & Guérin, 2021), daily natural gas consumption (Bai & Li, 2016) and so on, be used in many areas.

The Poisson distribution is a discrete distribution that measures the probability of a given number of events happening in a specified time period (Kissell & Poserina, 2017). Its process is in a given time interval (Mahmud, Hasan, Chakraborty, & Roy-Chowdhury, 2016). Suitable for use in forecasting, as long as it conforms to its two characteristics, first, it gives the probability of a number of events occurring in a fixed interval of time or space if these events happen with a known average rate; the second, the events are independent of the time since the last event (Holmes, Illowsky, & Dean, 2019). Whereas the occurrence of criminal cases is in line with the above two characteristics.

2.2. What is predictive policing?

Predictive policing harnesses the power of information technology, geospatial technologies, and evidence-based intervention models to prevent criminal deployment, thus reducing crime and improving public safety (NIJ, 2014a). The Brennan Center for Justice defined predictive policing to involve the use of algorithms to analyze massive amounts of information in order to predict and help prevent potential future crimes (Lau, 2020). Predictive policing uses data respective the times, locations, and nature of past crimes, to provide insight to police strategists concerning where, and at what times policing should take place, or should maintain a presence. This is done in order to make the best use of police resources or to have the greatest chance of deterring or preventing future crimes (Rienks, 2015).

For law enforcement purposes, predictive policing uses computer statistics models to predict how communal conditions or criminal trending will evolve over time, namely anticipating likely crime events and then informing actions to prevent crime (NIJ, 2014a). Such modeling has the possibility to grasp these future crimes and then to quickly react to any incidents that occur. This is fundamental to the potential impact and ultimate consequences related to public safety (Leigh, Dunnnett, & Jackson, 2019). The related concept of crime hotspot holds that crime often exists regularly and can be predicted, it is not random, and the research of crime hotspot can clearly show the spatial distribution of crime cases (Xie et al., 2007).

Predictive policing has two views in the practitioners’ discussion. Proponents argue that using computer algorithms will predict future crimes more accurately and objectively than by having police officers rely on instinct alone. Some would also argue that predictive policing can save limited police department resources by making crime reduction more efficient. On the other hand, critics warn that an apparent lack of transparency from agencies that administer predictive policing programs may exist. They also consider civil rights and civil liberties issues becoming paramount, pointing that the algorithms used may exacerbate racial bias (i.e., profiling) within the criminal justice system (Lau, 2020). The NIJ pointed out that a predictive policing approach cannot replace traditional policing. Instead, it enhances existing approaches or practices, such as problem-oriented policing, community policing, intelligence-led policing, and hotspot policing. Applying advanced

analytics to various data sets, in conjunction with intervention models — can move law enforcement from simply reacting to crimes into the realm of predicting what and where something is likely to happen and then deploying resources accordingly (NIJ, 2014a).

2.3. Predictive policing methods

Predictive policing methods fall into four general categories: methods for predicting crimes, methods for predicting offenders, methods for predicting perpetrators' identities, and methods for predicting the victims of crime (Perry, McInnis, Price, Smith, & Hollywood, 2013). Predictions can focus on variables such as places, people, groups, or incidents, and they may all affect crime rates in particular areas, included, as demographic trends show, parolee populations and economic conditions, and so on. Using models supported by prior crime and environmental data to inform different kinds of interventions can help police reduce the number of crime incidents from occurring (NIJ, 2014a). Place-based predictive policing, the most widely practiced method, typically uses pre-existing crime data to identify places and times that have a high-risk tendency towards criminal incidence. Person-based predictive policing, on the other hand, attempts to identify individuals or groups who are most likely to commit a crime — or to be the victim of one — by analyzing for risk factors such as past arrests or victimization patterns that may occur (Lau, 2020).

To achieve scientific predictions based on the composite process of spatio-temporal information, it is not only necessary to decompose multi-source complex factors, but also to reconfigure various decomposition modes to form a new overall pattern. It is thus feasible to infer the value of an unknown point that is in line with the geographic value of a known point or even to further infer the state of the entire region. Current trends in geographic data analysis based on the development of computer technology, in addition to the integration of prior information, combines the use of newly developed spatial statistical methods to improve the accuracy of spatial estimation (Xie et al., 2007). There is a chance for considerable future development of location information as a predictive tool.

2.4. Model of state dependency

Crime pattern theory (van Sleeuwen, Ruiter, & Steenbeek, 2021) points out that crime is most likely to occur in the intersection of the offender's "cognitive space" and proximity to the appropriate target, the theory explains how the distribution of the crime that most offenders is not randomly selected according to the location of the crime. Instead, target selection is influenced by the interaction of offenders and the environment, and each crime is influenced by the offenders' experience and future intentions (Xie et al., 2007). In Bowers, Johnson, and Pease (2004), a theoretical model of repeat and near-repeat victimization is posited. The authors found that if the risk intensity of a crime location is high during the most recent two-month period, the same place is more likely to experience crime during the following two months

(Lee et al., 2020). Bogucki, Milczek, and Miziula (2020) assume that if many crimes occur in a specific geographic location, they are more likely to happen again. They believe that this principle is both accurate enough and fast enough for use as a state dependence model. We use a state dependence model of the number of crimes in the time periods prior to the predicted month. This algorithm is implemented in Excel, making it extremely simple to apply and completely transparent.

Persons who have experienced a criminal event in the past have more likelihood to experience a similar event in the future than are persons who have not experienced such an event. The conditional probability that a person will experience an event in the future is a function of experience (Heckman, 1981). Similarly, areas, where crime events have been experienced in the past, are more likely to experience a crime event in the future than areas that have not experienced such an event. Areas with the highest crime rates are considered to be the most dangerous areas and referred to as hotspots (Bogucki et al., 2020). Additionally, the rate of future criminal event occurrence will be high.

From a perspective of maintaining and updating a crime prediction system, the use of only historical crime data seems to provide a good solution. It is hard to find any non-constant, external factor that can both influence future crimes and make it easier to predict than the crimes themselves (Bogucki et al., 2020).

2.5. Common predictive methods in criminology

By combining GIS with crime-related research, the basic elements of GIS, points, lines, and faces, are given criminal significance. From a criminal event point-of-view, a "dot map indication" can be regarded as a criminal case or serve as the offenders' (victims) distribution pattern. In an urban setting, a "line map" may be considered as a high crime road section, a "face map" can be regarded as a crime hotspot, and by means of GIS spatial overlap analysis, the intersection of points and lines may show a city's criminal population density or case distribution and migration activities mechanism.

Many academics have studied the inherent nature of predictive policing, and they have published results based on time series analysis, regression methods, kernel density estimation, self-exciting point processes (Bogucki et al., 2020), or the Poisson distribution method (Lee et al., 2020).

3. METHODOLOGY

3.1. The collection of data

3.1.1. Seasonal naïve method

In order to understand how such a predictive pattern system may be utilized to both historical track and then predict future criminal activity, it is possible to provide an example. To proceed, the location address of a crime, such as theft, is first provided by the local police units to a centralized database. Most of the performance statistics methods of Taiwan's Internal Police Departments are then compared with the same month in the last year.

The seasonal naïve method is used for highly seasonalized data. In this study, we set each prediction to be equal to the last observed value from the same month per year (e.g., the same month as in the previous year) (Hyndman & Athanasopoulos, 2018).

3.1.2. Geographical X-Y coordinates

Since the location of crimes is typically recorded by the address of occurrence, the first step in the location information analysis of crimes is to convert the text address description into X-Y geographic coordinates through an address matching mechanism, which, in turn, presents its spatial distribution in terms of point data (Wen et al., 2010) (see Figure B.1 in Appendix B).

The first step in crime location analysis is to obtain the X-Y geographic coordinates of the crime case location, which presents its spatial distribution of point data in the dataset. Address profiles can be transferred as text address descriptions into X-Y geographic coordinates using an address-matching mechanism, such as Google Earth Pro, which is available free of charge online.

Al Boni and Gerber (2016) argued hotspot mapping is appropriate as a tool useful to police departments in order to analyze historical crime records and to identify future areas of high risk. Hotspot mapping assumes that criminal activities are spatially stable over time, to the extent that this is true, hotspot methods can use historical crime incidents to generate predictions to determine future areas of high risk.

3.1.3. Creating the grid cells

The hotspots of crime prediction require the establishment of an area of analysis and comparison, commonly known as “a grid of cells”. Sherman (1995) defined a hotspot as a small place where the frequency of crime is relatively higher than in other places. In this vein, more recent crime hotspot forecasting studies have used smaller units, such as grid cells measuring 500 feet (152.5 meters) on a side, or even smaller (Lee et al., 2020). Gorr, Olligschlaeger, and Thompson (2003) showed that the size of geographic units of analysis is one of the critical factors influencing the accuracy of short-term forecasting.

Bogucki et al. (2020) examined four types of regular grids: parallelogram grids, triangular grids with 3 vertices at a point, triangular grids with 6 vertices at a point, and hexagonal grids. They were parameterized by cell height, width, translations, rotations, and bending. No shape proved noticeably better than other ones. Hence, we ultimately decided to only use unrotated, rectangular grids. These grids are created by means of longitudinal and latitudinal coordinates.

3.2. The method of prediction

3.2.1. The selection of the prediction method

The appropriate prediction methods are as follows:

1. *Qualitative prediction method*: If there are no data available, or if the data available are not relevant to the prediction, then this method must be used for predictive analysis.

2. *Quantitative prediction method*: It can be applied when two conditions are satisfied: a) numerical information about the past is available, and b) it is reasonable to assume that some aspects of the past patterns will be continued into the future (Hyndman & Athanasopoulos, 2018).

In this article, the quantitative prediction method has been selected.

3.2.2. Poisson distribution method

Binomial distribution

In probability theory and statistics, the binomial distribution is a discrete distribution of the number of successes in an independent *yes/no* experiment, where the probability of success in each trial is “p”. Such a single success/failure experiment is also known as a Bernoulli test (Pereira et al., 2017). Poisson distribution can be seen as a limited situation for a binomial distribution, and it is suitable for application to the occurrence or non-occurrence of criminal cases.

Poisson distribution

A Poisson distribution is the probability distribution that results from a Poisson experiment. A Poisson experiment is a statistical experiment that possesses the following properties:

- The experiment results in outcomes that may be classified as successes or as failures.
- The average number of successes (λ) that occur in a specified region is a known integer.
- The probability that success will occur is proportional to the size of the region.
- The probability that success will occur in an extremely small region is virtually nil.
- Note that the specified region could take many forms. For instance, it could be a length, an area, a volume, a period of time, etc. (The Posts of the Great Statisticians, 2012; Stat Trek Teach Yourself Statistics, 2020).

The attribute of crime occurrence conforms to the aforementioned “state dependence”, and the more cumulative the quantity presents itself, the more in line with Poisson distribution it becomes, so this paper uses Poisson distribution as the chosen predictive algorithm. Because of the Poisson distribution method here, only Microsoft Excel was used to calculate to forecast hotspots. The police practitioners should be able to implement this procedure with relative ease (Lee et al., 2020). So, this article adopts it.

Suppose a Poisson experiment is conducted in which the average number of successes within a given region is λ . Then, the Poisson probability is considered to be:

$$p(x; \lambda) = \frac{e^{-\lambda} \lambda^x}{x!} \quad x = 0, 1, 2, \dots \quad (1)$$

where, x is the actual number of successes that result from the experiment and e (called Euler’s number) is approximately equal to 2.71828182845....

3.3. Evaluate the forecasting model

To evaluate the forecasting model central to this study, we similarly used the prediction accuracy index (PAI) and the prediction efficiency index (PEI). These criteria were used as the NIJ's judging criteria for the 2014 *Real-Time Crime Forecasting Challenge* (NIJ, 2014b). PAI measures the effectiveness that the hit rate against the areas correlates where crimes are predicted to occur with respect to the size of the study area (Hunt, 2016). Effectiveness is defined as the percentage of crimes that occur in predicted hotspot areas, as compared to the percentage of the area that is predicted to be a hotspot (Hunt, 2016). PEI will be used to measure the efficiency of the prediction, with the efficiency defined as how effective a model is when compared to how effective it could have been (Hunt, 2016). The PAI is meant to measure how well a prediction does, compared to the PEI which measures how well it could have done.

Lee et al. (2020) pointed out that effectiveness and efficiency are negatively related. Increasing the effectiveness by forecasting more crimes occurs at the expense of including more areas that should not have been in the forecasted area, thereby reducing efficiency. But, Mohler and Porter (2018) argued that PAI and PEI are equivalent since they only diverge if the size of the hotspot region varies.

3.3.1. Prediction accuracy index (PAI)

PAI measures the effectiveness of the forecasts utilizing the following equation:

$$PAI = \frac{n}{N} \frac{a}{A} \quad (2)$$

where, n equals the number of crimes that occur in the forecasted area; N equals the total number of crimes; a equals the forecasted area, and A equals the area of the entire study area.

3.3.2. Prediction efficiency index (PEI*)

The PEI^* will measure the efficiency of the forecast with the following equation:

$$PEI^* = \frac{PAI}{PAI^*} \quad (3)$$

where, PEI^* equals the maximum obtainable PAI value for the amount of area forecasted, a . As such:

$$PEI^* = \frac{n}{n^*} \quad (4)$$

where, n^* equals the maximum obtainable n for the amount of area forecasted, a .

3.4. Creation of the database

3.4.1. Build the study area

The occurrence of a crime is not related to the study area, but to spatial and temporal vicinity. Therefore, in order to facilitate statistics and make a prediction that is in line with an urban pattern, a specific study area is thus recommended. Crime prediction needs a large number of occurrences. Crime cases of urban

areas are more than rural areas, in order to facilitate statistical analysis, therefore, this study is based on the urban areas of Ling-Ya District of Kaohsiung City. Be center on it we build a rectangular area with the same vertical longitude and horizontal latitude, the longitude between 120.288 and 120.356, and the latitude between 22.609 and 22.645 as the study area (see Figure B.2 in Appendix B).

3.4.2. Selection of historical data

The performance statistics and evaluation of the National Police Agency of the Ministry of the Interior of Taiwan are typically based on the relative seasonality or month of any given year. This paper is based on a relative month of the year to serve as the basis for comparison, rather than a continuous monthly pattern. For example, the data is based on the crime of theft (excluding vehicular theft). In this paper, historical data (2014–2017) are used to predict the subsequent occurrence rate of each month in the year 2018, and historical data (2014–2018) are used to predict the occurrence rate of each month in the year 2019.

3.4.3. Obtaining the X-Y coordinate data

The theft location is provided by the local police units afterwards it is transformed through a geocoding program (Google Earth Pro) into a geographic coordinate located as a point (i.e., longitude and latitude). This makes it possible to observe the spatial distribution status of theft crimes in the study area. The address data is converted into spatial X-Y coordinates (i.e., longitude and latitude) through an address-to-bit program (Google Earth Pro). Then, the study area is divided into 153 grid cells (9×17), where the per-grid, cell-side length with 0.004 degrees of longitude or latitude (longitude at 0.004 about 410 meters, latitude about 447 meters) (see Figure B.3 in Appendix B) is given. Therefore, a search for the number of thefts in the per-grid cell of the study area using spatial assign technology (created by Excel VBA program, using the scatter diagram component) (see Figure B.4 in Appendix B) may be made. It is possible to calculate the number of events of crime within the grid cells (e.g., Table A.1 in Appendix A), and to produce a high-density surface, show a visual judgment effect, and form the disposition of hotspots area for the crime of theft (e.g., Figure B.5 in Appendix B).

4. RESULTS

4.1. The algorithm that predicts the location of a crime in the grid

4.1.1. Google Earth get X-Y coordinates

The Google Earth Pro was used in this article for purposes of the address matching mechanism. To accomplish this, first export the Excel file (.xlsx) of the criminal database into a text format file that is saved as file.csv, then import it to Google Earth Pro¹ and through "Google addresses perform a lot of address targeting" convert to file.kst. This file is not used, but it is stored at the staging location on

¹ The upper limit of imported data is 2500 rows. Otherwise, it should be divided into more than two files.

the left side of this window dialog box. At this point, right-click and save the file as new file — file.kml. Then open the file.kml by using Microsoft Excel and grab the longitude and the latitude data (Figure B.6 in Appendix B). The X coordinates are longitude coordinates, the Y coordinates are latitude coordinates.

4.1.2. Data put into grid cells by Excel

Using the Excel program, the X-Y coordinates of each incident of crime data are read and placed into the corresponding grid cells for the rectangular area aforementioned (e.g., Table A.2 in Appendix A). To execute: the Excel command is Program 1 in Appendix C.

$$p(x; \lambda) = \frac{e^{-\lambda} \lambda^x}{x!} \quad x = 0, 1, 2 \dots$$

$p(0; \lambda) = \frac{e^{-\lambda} \lambda^0}{0!}$ expresses the probability that will not occur any crime again

$p(1; \lambda) = \frac{e^{-\lambda} \lambda^1}{1!}$ expresses the probability that will occur 1 incident of crime again

⋮

$p(n; \lambda) = \frac{e^{-\lambda} \lambda^n}{n!}$ expresses the probability that will occur n incidents of crime again

$$p(0; \lambda) + p(1; \lambda) + p(2; \lambda) + \dots + p(n; \lambda) + \dots = \sum_{x=0}^{\infty} p(x, \lambda) \approx 1$$

The total $p(x; \lambda)$, $x = 0, 1, 2 \dots n \dots$, is close to 1, so by 1 subtracts $p(0; \lambda)$, that is the probability

4.2. Poisson probability

This study uses the Poisson probability function in Microsoft Excel for the prediction of crime hotspots. It is based respectively on five and four years' worth of data, and it predicts crime hotspots in the same month of the following year. The prediction method analyzes the occurrence rate statistically using the Poisson method to explore how to determine its re-occurrence rate (Lee et al., 2020). The λ is the average number that occurs in a specified region is known. It is calculated by means of the equation (1):

that will occur again.

Excel function is Program 2 in Appendix C.

$$1 - p(0; \lambda) = \frac{e^{-\lambda} \lambda^0}{0!} = 1 - e^{-\lambda} \tag{5}$$

4.3. The setting of the indicator and the threshold value

The Poisson probability of experiencing crime in some studies uses a value greater than 0.5 (or 50% chance) for representation crimes that have a chance to occur again in the given forecast area and particular time (Lee et al., 2020). It is determined that the threshold value is set with the odds, and the hit rate is different from the different threshold values. To examine the relationship between them, this paper observes four different indicators and calculates the PAI and PEI according to NIJ standards.

| | |
|---|--|
| 1 | $Hit\ rate(Hr) = \frac{prediction\ occurs}{actually\ occurs} + \frac{prediction\ doesn't\ occur}{actually\ not\ occurred}$. |
| 2 | $Useful\ rate(Ur) = \frac{Prediction\ occurs}{actually\ occurs}$ "it can be arranged preventive services in advance". |
| 3 | $Waste\ rate(Wr) = \frac{Prediction\ occurs}{doesn't\ actually\ occurs}$ "because it's a waste of police force if it's orchestrated". |
| 4 | $Missing\ rate(Mr) = \frac{Prediction\ doesn't\ occur}{actually\ occurs}$ "because it can't be arranged preventive services in advance". |
| 5 | The PAI calculates with the equation (2), Excel function is Program 3 in Appendix C. |
| 6 | The PEI calculates with the equation (3), Excel function is Program 4 in Appendix C. |

5. DISCUSSION

5.1. Accumulates different years with a difference in forecast results

In this paper, the average of 5 years is the λ , and the threshold value is set to 0.6 to get the various indicators, respectively. Results show that the hit rate is 0.6955, the useful rate is 0.4132, the waste rate is 0.1733, the missing rate is 0.5868, the PAI value is 1.8330, and the PEI value is 0.6961 (Table A.3 in Appendix A); and, it compares with the average of 4 years as the λ , respectively, the hit rate is 0.6656, the useful rate is 0.4189, the waste rate is 0.1970, the missing rate is 0.5811, the PAI value is 1.7887, and the PEI value is 0.7192 (Table A.4 in Appendix A). Result indicators show that the hit rate and the PAI value based on the 5-year average are higher than the 4-year average, while the useful rate, the waste rate, the missing rate, and the PEI value are lower (Figure B.7 in Appendix B).

If 0.5 is used as the threshold, it is possible to get the various indicators, respectively, the hit rate is 0.6846, the useful rate is 0.5311, the waste rate is 0.2440, the missing rate is 0.4689, the PAI value is 1.6826, and the PEI value is 0.5541 (Table A.5 in Appendix A). This compares with the average of 4 years as the λ , respectively, so that the hit rate is 0.6443, the useful rate is 0.5282, the waste rate is 0.2899, the missing rate is 0.4718, the PAI value is 1.6211, and the PEI value is 0.5824 (Table 6 in Appendix A). The results indicators are similar, as mentioned above (Figure B.7 in Appendix B).

5.2. Different threshold values are set to get the difference in forecast results

Based on the average value of the five-year historical data used in the above study, the hit rate, the useful rate, and the PAI values of each prediction were higher, while the waste rate, the missing rate, and the PEI value were lower. Based on other historical data for a 5-year period, the trends of different threshold values (Table A.7 in Appendix A) showed that the hit rate, the missing rate, the PAI value, and the PEI value are all directly proportional to the threshold value (Figure B.8 in Appendix B), while the useful rate and the waste rate trended in an inverse ratio (Figure B.9 in Appendix B).

5.3. Different-oriented application

The study results find that crime prediction does not only focus on computational skills but also on reasoning and understanding. Therefore, this paper sets different indicators, when the different thresholds calculate different results, can do different-oriented interpretation, to achieve more diversified in the application.

6. CONCLUSION

Based on the comparison of historical data for different years, it may be shown that the hit rate, useful rate, and PAI value of the given 5 years are higher than of the 4 years, while the waste rate and missing rate are both lower. Therefore, it would serve as the basis of the forecast of the annual historical data, when the cumulative data is more, its prediction is measured by the PAI, so that accuracy is better, but the PEI providing efficiency is worse.

By calculating the prediction of different threshold values based on five-year cumulative values, it may be shown that the hit rate, missing rate, PAI value, and threshold value are directly and proportionally related; while the useful rate and waste rate are inversely related to the trend, and the waste rate and missing rate are inversely compared.

This event occurs because a selection of the threshold value is related to the use of the local and regional police force budget. If the fiscal budget is sufficient and the police force is large enough, the lower threshold should be selected. Conversely,

a higher threshold could be selected if the fiscal budget is insufficient, and the police force is too small.

This study has two limitations: first, the problem of the dark figure of crime (Buil-Gil, Medina, & Shlomo, 2021). There is no hiding the fact because most performance evaluations will have the number of occurrences as the basis for assessing performance, a few units will inevitably try to reduce the number of cases and hide the occurrence of crime cases. Second, the occurrence of a crime case original records is not set at longitude and latitude, needed converting longitude and latitude by address, part of the longitude and latitude will be inevitably distorted. About this, the Kaohsiung City Police Department in the handling of traffic accidents has adopted additional record latitude and longitude and recommended it can promote the crime case recording operation, and the distortion could be improved.

In corporate governance, the quality of corporate governance reporting depends on company characteristics, not company performance (Ceschinski, Freidank, & Handschumacher, 2020), the government too. This article is provided to those in power, the prediction of crime hotspots, can effectively grasp the trend of public security, but needed the correct crime case statistics to improve the accuracy of crime hotspots prediction. In the prevent-crime, crime hotspots prediction is conducive to the use of the most appropriate police force, and can accurately arrange the most appropriate position to avoid waste, not for the performance evaluation and hide the number of crimes. Because we only used Microsoft Excel to calculate Poisson probabilities, evaluate the state of risk, and forecast hotspots. Many of Taiwan's police practitioners should be able to implement this procedure with relative ease and contributes to the sustainable governance of community policing.

The prediction results of crime hotspots, providing the legitimacy of the police organs designate the places of stop-question-frisk that have a great impact on human's rights, and the method of crime hotspots prediction used in this paper has better transparency (Lee et al., 2020), which could improve people's trust in police organs effectively (Reich, 2018), and also contributes to the sustainable governance of community policing.

REFERENCES

1. Abdul Aziz, Percy, D. F., & Mohamed Yusof, F. (2009). Sustainability in management accounting: Modelling profit forecasting. *Corporate Ownership & Control*, 6(4-1), 201-209. <https://doi.org/10.22495/cocv6i4c1p4>
2. Al Boni, M. A., & Gerber, M. S. (2016). Automatic optimization of localized kernel density estimation for hotspot policing. In *2016 15th IEEE International Conference on Machine Learning and Applications (ICMLA)* (pp. 32-38). <https://doi.org/10.1109/ICMLA.2016.0015>
3. Bai, Y., & Li, C. (2016). Daily natural gas consumption forecasting based on a structure-calibrated support vector regression approach. *Energy and Buildings*, 127, 571-579. <https://doi.org/10.1016/j.enbuild.2016.06.020>
4. Baumeister, C., & Guérin, P. (in press). A comparison of monthly global indicators for forecasting growth. *International Journal of Forecasting*. <https://doi.org/10.1016/j.ijforecast.2021.02.008>
5. Bogucki, R., Milczek, J. K., & Miziula, P. (2020). A simple crime hotspot forecasting algorithm. In M. Ganzha, L. Maciaszek, & M. Paprzycki (Eds.), *Proceedings of the 2020 Federated Conference on Computer Science and Information Systems (ACSIS)*, Vol. 21, pp. 23-26. <https://doi.org/10.15439/2020F5>
6. Bowers, K. J., Johnson, S. D., & Pease, K. (2004). Prospective hot-spotting: The future of crime mapping? *British Journal of Criminology*, 44(5), 641-658. <https://doi.org/10.1093/bjc/azh036>

7. Buil-Gil, D., Medina, J., & Shlomo, N. (2021). Measuring the dark figure of crime in geographic areas: Small area estimation from the Crime Survey for England and Wales. *The British Journal of Criminology*, 61(2), 364-388. <https://doi.org/10.1093/bjc/azaa067>
8. Ceschinski, W., Freidank, C.-C., & Handschumacher, F. (2020). Which characteristics determine the quality of corporate governance reporting? Concepts, reporting practices and empirical evidence from Germany [Special issue]. *Corporate Ownership & Control*, 17(4), 279-291. <https://doi.org/10.22495/cocv17i4siart6>
9. Chainey, S. P., & Ratcliffe, J. H. (2005). *GIS and crime mapping*. London, England: Wiley & Sons, Inc.
10. Chainey, S., Tompson, L., & Uhlig, S. (2008). The utility of hotspot mapping for predicting spatial patterns of crime. *Security Journal*, 21, 4-28. <https://doi.org/10.1057/palgrave.sj.8350066>
11. Dantanarayana, M., Herath, S., & Weerakoon, S. B. (2021). Improving sub daily scale storm forecasting for Kelani River Basin based on temporal distribution of rain events. *Journal of Climatology & Weather Forecasting*, 9(1), No. 270, 1-9. Retrieved from <https://www.longdom.org/open-access/improving-sub-daily-scale-storm-forecasting-for-kelani-river-basin-based-on-temporal-distribution-of-rain-events.pdf>
12. Dietsch, J. (2019). How to brighten the governor's gloomy fiscal forecast: Economy. *New Hampshire Business Review*, 41(6), 19.
13. Euler, D. (2014). Standards on transparency of publicly listed corporations: Information owed to the public? *Corporate Ownership & Control*, 11(3-1), 184-192. <https://doi.org/10.22495/cocv11i3c1p5>
14. Gorr, W., Olligschlaeger, A., & Thompson, Y. (2003). Short-term forecasting of crime. *International Journal of Forecasting*, 19(4), 579-594. [https://doi.org/10.1016/S0169-2070\(03\)00092-X](https://doi.org/10.1016/S0169-2070(03)00092-X)
15. Heckman, J. J. (1981). Heterogeneity and state dependence. In S. Rosen (Ed.), *Studies in labor markets* (pp. 91-140). Retrieved from <https://www.nber.org/books-and-chapters/studies-labor-markets/heterogeneity-and-state-dependence>
16. Holmes, A., Illowsky, B., & Dean, S. (Eds.). (2019). Discrete random variables. In *Introductory business statistics* (Chapter 4, pp. 203-240). Retrieved from <https://openstax.org/details/books/introductory-business-statistics>
17. Hunt, J. (2016). *Do crime hotspots move? Exploring the effects of the modifiable areal unit problem and modifiable temporal unit problem on crime hot spot stability* (Doctoral dissertation, School of Public Affairs of American University). Retrieved from <https://www.ojp.gov/ncjrs/virtual-library/abstracts/do-crime-hot-spots-move-exploring-effects-modifiable-areal-unit>
18. Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: Principles and practice* (2nd ed.). Retrieved from <https://otexts.com/fpp2/>
19. Kissell, R., & Poserina, J. (2017). *Optimal sports math, statistics, and fantasy*. London, England: Academic Press.
20. Lau, T. (2020, April 1). Predictive policing explained. *Brennan Center for Justice*. Retrieved from <https://www.brennancenter.org/our-work/research-reports/predictive-policing-explained>
21. Lee, Y. J., SooHyun, O., & Eck, J. E. (2020). A theory-driven algorithm for real-time crime hot spot forecasting. *Police Quarterly*, 23(2), 174-201. <https://doi.org/10.1177/1098611119887809>
22. Lei, Y.-L., Jia, Y.-Z., Fu, Y., Liu, K., Zhang, Y., & Liu, Z.-J. (2018). Car fuel economy simulation forecast method based on CVT efficiencies measured from bench test. *Chinese Journal of Mechanical Engineering*, 31(1), 1-16. <https://doi.org/10.1186/s10033-018-0283-9>
23. Leigh, J., Dunnett, S., & Jackson, L. (2019). Predictive police patrolling to target hotspots and cover response demand. *Annals of Operations Research*, 283, 395-410. <https://doi.org/10.1007/s10479-017-2528-x>
24. Mahmud, T., Hasan, M., Chakraborty, A., & Roy-Chowdhury, A. (2016, August 19). A poisson process model for activity forecasting. In *2016 IEEE International Conference on Image Processing (ICIP)* (pp. 3339-3343). <https://doi.org/10.1109/ICIP.2016.7532978>
25. Malik, C., & Yadav, S. (2020). Forecasting and asymmetric volatility modeling of sustainability indexes in India. *Corporate Governance and Sustainability Review*, 4(1), 56-64. <https://doi.org/10.22495/cgsrv4i1p5>
26. Matheus, R., Janssen, M., & Janowski, T. (2021). Design principles for creating digital transparency in government. *Government Information Quarterly*, 38(1), 1-18. <https://doi.org/10.1016/j.giq.2020.101550>
27. Mohler, G., & Porter, M. D. (2018). Rotational grid PAI-maximizing crime forecasts. *Statistical Analysis and Data Mining*, 11(5), 227-236. <https://doi.org/10.1002/sam.11389>
28. Mon, W. T. (2003, September 9). *Research on crime hotspots. The focus of crime problem of Ministry of Justice of R.O.C.* Retrieved from <https://www.moj.gov.tw/cp-1033-45778-5ab39-001.html>
29. National Institute of Justice (NIJ). (2014a, June 9). *Overview of predictive policing*. Retrieved from <https://nij.ojp.gov/topics/articles/overview-predictive-policing>
30. National Institute of Justice (NIJ). (2014b, June 9). *Real-time crime forecasting challenge posting*. Retrieved from <https://nij.ojp.gov/funding/real-time-crime-forecasting-challenge-posting#note2>
31. Pereira, C. A. d. B., Nakano, E. Y., Fossaluza, V., Esteves, L. G., Gannon, M. A., & Polpo, A. (2017). Hypothesis tests for Bernoulli experiments: Ordering the sample space by bayes factors and using adaptive significance levels for decisions. *Entropy*, 19(12), 696. <https://doi.org/10.3390/e19120696>
32. Perry, W. L., McInnis, B., Price, C. C., Smith, S., & Hollywood, J. S. (2013). *Predictive policing: The role of crime forecasting in law enforcement operations* (1st ed.). <https://doi.org/10.7249/RR233>
33. Rahman, M. J., & Marjerison, R. K. (2020). Sustaining competitive advantage through good governance and fiscal controls: Risk determinants in internal controls. *Corporate Ownership & Control*, 18(1), 34-46. <https://doi.org/10.22495/cocv18i1art3>
34. Reich, M. R. (2018). The core roles of transparency and accountability in the governance of global health public-private partnerships. *Health Systems & Reform*, 4(3), 239-248. <https://doi.org/10.1080/23288604.2018.1465880>
35. Rekow, L. (2016). Pacification & mega-events in Rio de Janeiro: Urbanization, public security & accumulation by dispossession. *Journal of Human Security*, 12(1), 4-34. <https://doi.org/10.12924/johs2016.12010004>
36. Rienks, R. (2015). *Predictive policing: Taking a chance for a safer future* (1st ed.). Retrieved from https://issuu.com/rutgerrienks/docs/predictive_policing_rienks_uk
37. Sherman, L. W. (1995). Hot spots of crime and criminal careers of places. *Crime and Place*, 4, 35-52.
38. Sherman, L. W., Gartin, P. R., & Buerger, M. E. (1989). Hot spots of predatory crime: Routine activities and the criminology of place. *Criminology*, 27(1), 27-56. <https://doi.org/10.1111/j.1745-9125.1989.tb00862.x>

39. Stat Trek Teach Yourself Statistics. (2020). *Poisson distribution*. Retrieved from <https://stattrek.com/probability-distributions/poisson.aspx>

40. Sullivan, C. M., & O’Keeffe, Z. P. (2017). Evidence that curtailing proactive policing can reduce major crime. *Nature Human Behaviour*, 1, 730-737. <https://doi.org/10.1038/s41562-017-0211-5>

41. Taiwan Military and Police Tactical Research and Development Association (TTRDA). (2016, March). *In the face of new security threats, to improve the police presence is really a panacea?* Retrieved from <http://ttrda.org/>

42. The Posts of the Great Statisticians. (2012, June). *Lesson on poisson distribution and hypergeometric distribution*. Retrieved from <http://statsayment.blogspot.com/2012/06/une-20-2012-lesson-on-poisson.html>

43. van Sleeuwen, S. E. M., Ruiter, S., & Steenbeek, W. (2021). Right place, right time? Making crime pattern theory time-specific. *Crime Science*, 10(2), 1-10. <https://doi.org/10.1186/s40163-021-00139-8>

44. Wen, T. H., Liu, T. C., & Lin, M. H. (2010). Crime mapping and hotspot analysis: A case study of residential burglaries in Taipei City, 1998-2007. *Journal of Geographical Research*, 52, 43-63.

45. Xie, W. Y., Liao, Y. L., Dong, J. T., Liu, T. C., Jhang, S. H., Huang, Y. L., & Lin, A. L. (2007, December). *Study on the characteristics of the criminal area of scooter theft in crime basic map of community* (Department of Crime Prevention and Control of Central Police University, Commissioned study by the Criminal Investigation Bureau, TW).

46. Yeung, S. M. C. (2019). UNSDGs and future quality management — Social policy for developing sustainable development mindset. *Corporate Governance and Sustainability Review*, 3(2), 26-33. <https://doi.org/10.22495/cgsrv3i2p3>

APPENDIX A

Table A.1. Total crimes of theft in the 2019 year within the study area

| Col. Row | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 |
|-------------|---|---|----|----|----|----|---|----|----|----|----|----|----|----|----|----|----|
| 9 | 0 | 0 | 0 | 0 | 0 | 0 | 6 | 5 | 10 | 18 | 20 | 12 | 2 | 6 | 3 | 4 | 0 |
| 8 | 0 | 0 | 0 | 0 | 0 | 0 | 6 | 8 | 3 | 8 | 8 | 5 | 4 | 3 | 6 | 4 | 4 |
| 7 | 0 | 6 | 7 | 15 | 8 | 6 | 0 | 2 | 1 | 4 | 1 | 2 | 1 | 3 | 2 | 7 | 9 |
| 6 | 1 | 5 | 5 | 13 | 8 | 3 | 6 | 6 | 2 | 6 | 7 | 5 | 3 | 6 | 2 | 5 | 1 |
| 5 | 2 | 4 | 7 | 3 | 3 | 10 | 4 | 11 | 3 | 3 | 2 | 7 | 1 | 7 | 38 | 9 | 6 |
| 4 | 1 | 5 | 11 | 38 | 9 | 6 | 3 | 7 | 2 | 0 | 20 | 6 | 0 | 0 | 0 | 8 | 1 |
| 3 | 1 | 3 | 17 | 10 | 11 | 13 | 5 | 9 | 3 | 1 | 1 | 2 | 0 | 0 | 1 | 2 | 6 |
| 2 | 0 | 3 | 9 | 16 | 30 | 15 | 4 | 2 | 5 | 7 | 0 | 5 | 1 | 4 | 3 | 7 | 2 |
| 1 | 0 | 0 | 0 | 14 | 1 | 10 | 3 | 6 | 4 | 2 | 4 | 8 | 2 | 4 | 6 | 0 | 0 |

Note: Total number: 802 (number of theft crimes that occurred throughout 2019); Cell number: 125 (125 cells in 153 grids).
Source: Authors' elaboration.

Table A.2. Total number of incidents of a cell per January from 2014 to 2018

| Col. Row | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 |
|-------------|---|---|----|----|----|---|---|----|---|----|----|----|----|----|----|----|----|
| 9 | 0 | 0 | 0 | 0 | 1 | 1 | 3 | 4 | 5 | 9 | 9 | 17 | 2 | 6 | 4 | 0 | 0 |
| 8 | 0 | 0 | 0 | 1 | 1 | 1 | 2 | 9 | 1 | 5 | 9 | 4 | 5 | 2 | 1 | 0 | 0 |
| 7 | 2 | 2 | 6 | 9 | 4 | 7 | 3 | 1 | 2 | 3 | 2 | 0 | 0 | 2 | 3 | 1 | 1 |
| 6 | 6 | 8 | 11 | 7 | 7 | 7 | 5 | 5 | 1 | 5 | 4 | 6 | 2 | 0 | 0 | 0 | 1 |
| 5 | 2 | 4 | 5 | 9 | 1 | 6 | 7 | 6 | 2 | 7 | 6 | 6 | 2 | 5 | 1 | 1 | 0 |
| 4 | 1 | 4 | 11 | 21 | 10 | 4 | 5 | 13 | 1 | 1 | 7 | 7 | 1 | 0 | 0 | 1 | 0 |
| 3 | 0 | 4 | 8 | 7 | 1 | 4 | 1 | 6 | 4 | 2 | 3 | 2 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 4 | 8 | 6 | 10 | 7 | 0 | 2 | 1 | 4 | 0 | 1 | 1 | 0 | 0 | 1 | 0 |
| 1 | 0 | 0 | 2 | 15 | 3 | 3 | 2 | 5 | 0 | 3 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |

Note: Total number: 505 (number of theft crimes that occurred throughout January from 2014 to 2018); Cell number: 114 (114 cells in 153 grids).
Source: Authors' elaboration.

Table A.3. The values of each item at threshold 0.60 for an average of 5 years

| Month Item | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec | AVG |
|---------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| Hr | 0.7124 | 0.7190 | 0.6732 | 0.7059 | 0.6797 | 0.6405 | 0.6928 | 0.6536 | 0.7582 | 0.7059 | 0.6732 | 0.7320 | 0.6955 |
| Ur | 0.5273 | 0.3846 | 0.3200 | 0.4107 | 0.4828 | 0.3542 | 0.4490 | 0.3922 | 0.4390 | 0.4200 | 0.3696 | 0.4091 | 0.4132 |
| Wr | 0.1837 | 0.1667 | 0.1553 | 0.1237 | 0.2000 | 0.2286 | 0.1923 | 0.2157 | 0.1250 | 0.1553 | 0.1963 | 0.1376 | 0.1733 |
| Mr | 0.4727 | 0.6154 | 0.6800 | 0.5893 | 0.5172 | 0.6458 | 0.5510 | 0.6078 | 0.5610 | 0.5800 | 0.6304 | 0.5909 | 0.5868 |
| PAI | 1.9170 | 1.9180 | 1.8856 | 1.9170 | 1.9373 | 1.7412 | 1.5712 | 1.6653 | 1.7759 | 1.9847 | 2.0101 | 1.6725 | 1.8330 |
| PEI | 0.7564 | 0.5326 | 0.8255 | 0.9313 | 0.7569 | 0.5429 | 0.5926 | 0.6670 | 0.6406 | 0.8016 | 0.5734 | 0.7320 | 0.6961 |

Source: Authors' elaboration.

Table A.4. The values of each item at threshold 0.60 for an average of 4 years

| Month Item | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec | AVG |
|---------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| Hr | 0.6928 | 0.7320 | 0.6471 | 0.6209 | 0.6078 | 0.6667 | 0.6405 | 0.6667 | 0.6144 | 0.7582 | 0.7516 | 0.5882 | 0.6656 |
| Ur | 0.5385 | 0.4545 | 0.3208 | 0.3462 | 0.4237 | 0.4255 | 0.4127 | 0.4667 | 0.2787 | 0.5273 | 0.5682 | 0.2642 | 0.4189 |
| Wr | 0.1932 | 0.1560 | 0.1800 | 0.2376 | 0.2766 | 0.2264 | 0.2000 | 0.2043 | 0.1630 | 0.1122 | 0.1743 | 0.2400 | 0.1970 |
| Mr | 0.4615 | 0.5455 | 0.6792 | 0.6538 | 0.5763 | 0.5745 | 0.5873 | 0.5333 | 0.7213 | 0.4727 | 0.4318 | 0.7358 | 0.5811 |
| PAI | 1.8915 | 2.2605 | 1.4178 | 1.8915 | 1.6013 | 1.3820 | 1.5136 | 1.8628 | 1.7133 | 1.5353 | 2.3194 | 2.0760 | 1.7887 |
| PEI | 0.9091 | 0.7170 | 0.6490 | 0.6114 | 0.5856 | 0.4820 | 0.9238 | 0.7784 | 0.8340 | 0.9921 | 0.5970 | 0.5506 | 0.7192 |

Source: Authors' elaboration.

Table A.5. The values of each item at threshold with 0.50 for an average of 5 years

| Month Item | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec | AVG |
|---------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| Hr | 0.6928 | 0.6863 | 0.6471 | 0.7059 | 0.6471 | 0.6405 | 0.6732 | 0.6732 | 0.7582 | 0.6993 | 0.6405 | 0.7516 | 0.6846 |
| Ur | 0.6182 | 0.4615 | 0.4000 | 0.5536 | 0.5345 | 0.5000 | 0.5510 | 0.5686 | 0.6585 | 0.5000 | 0.4130 | 0.6136 | 0.5311 |
| Wr | 0.2653 | 0.2368 | 0.2330 | 0.2062 | 0.2842 | 0.2952 | 0.2692 | 0.2745 | 0.2054 | 0.2039 | 0.2617 | 0.1927 | 0.2440 |
| Mr | 0.3818 | 0.5385 | 0.6000 | 0.4464 | 0.4655 | 0.5000 | 0.4490 | 0.4314 | 0.3415 | 0.5000 | 0.5870 | 0.3864 | 0.4689 |
| PAI | 1.7000 | 1.7279 | 1.6162 | 1.7000 | 1.7386 | 1.5030 | 1.7203 | 1.5896 | 1.6441 | 1.9053 | 1.8940 | 1.4524 | 1.6826 |
| PEI | 0.6111 | 0.4404 | 0.5769 | 0.6747 | 0.5698 | 0.5397 | 0.5091 | 0.5480 | 0.5106 | 0.6554 | 0.4367 | 0.5766 | 0.5541 |

Source: Authors' elaboration.

Table A.6. The values of each item at threshold 0.50 for an average of 4 years

| Month Item | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec | AVG |
|---------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| Hr | 0.7124 | 0.6928 | 0.6471 | 0.5882 | 0.5752 | 0.6667 | 0.6013 | 0.6405 | 0.6209 | 0.7059 | 0.6993 | 0.5817 | 0.6443 |
| Ur | 0.6154 | 0.5909 | 0.4717 | 0.4423 | 0.5254 | 0.5957 | 0.4762 | 0.6000 | 0.4262 | 0.6182 | 0.6364 | 0.3396 | 0.5282 |
| Wr | 0.2159 | 0.2661 | 0.2600 | 0.3366 | 0.3936 | 0.3019 | 0.3111 | 0.3333 | 0.2500 | 0.2449 | 0.2752 | 0.2900 | 0.2899 |
| Mr | 0.3846 | 0.4091 | 0.5283 | 0.5577 | 0.4746 | 0.4043 | 0.5238 | 0.4000 | 0.5738 | 0.3818 | 0.3636 | 0.6604 | 0.4718 |
| PAI | 1.8060 | 1.8916 | 1.4189 | 1.8060 | 1.4748 | 1.3146 | 1.4700 | 1.5309 | 1.4903 | 1.5755 | 1.8241 | 1.8505 | 1.6211 |
| PEI | 0.8107 | 0.5440 | 0.5052 | 0.5013 | 0.5069 | 0.4516 | 0.6598 | 0.5844 | 0.7059 | 0.6557 | 0.5322 | 0.5307 | 0.5824 |

Source: Authors' elaboration.

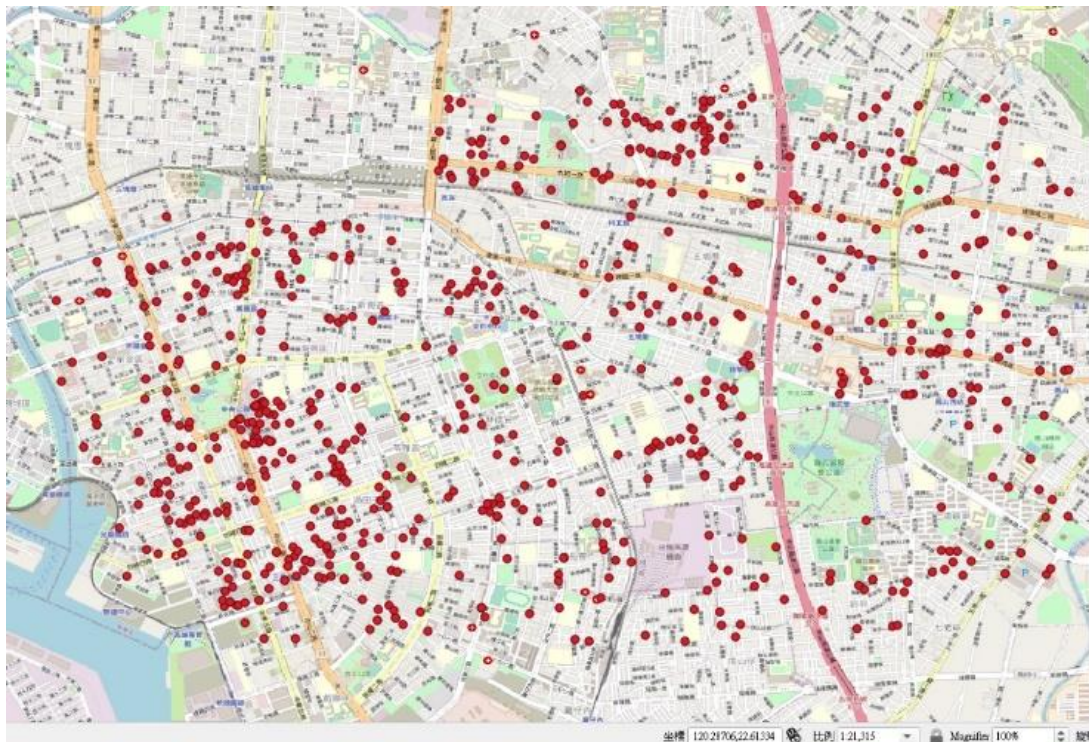
Table A.7. The indicators of different predictive threshold values for 5-year statistics

| Threshold Item | Hr | Ur | Wr | Mr | PAI | PEI |
|-------------------|--------|--------|--------|--------|--------|--------|
| 0.8 | 0.7004 | 0.1369 | 0.0346 | 0.8631 | 2.7396 | 2.3907 |
| 0.7 | 0.6999 | 0.2332 | 0.0812 | 0.7668 | 2.2185 | 1.2438 |
| 0.6 | 0.6955 | 0.4132 | 0.1733 | 0.5868 | 1.8330 | 0.6961 |
| 0.5 | 0.6846 | 0.5311 | 0.2440 | 0.4689 | 1.6826 | 0.5541 |
| 0.4 | 0.6487 | 0.6449 | 0.3507 | 0.3551 | 1.4904 | 0.4831 |
| 0.3 | 0.5910 | 0.7774 | 0.4964 | 0.2226 | 1.3410 | 0.4362 |

Source: Authors' elaboration.

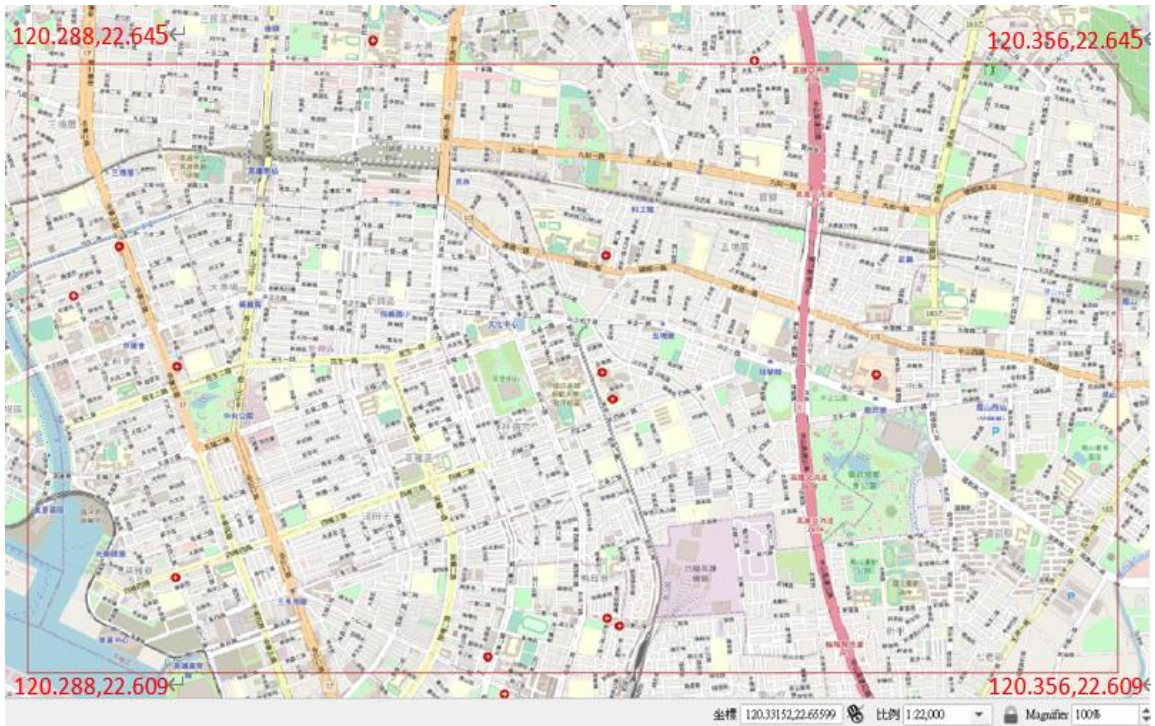
APPENDIX B

Figure B.1. The spatial distribution of the dot data of crime incidents on the Q-GIS (3.12.3)



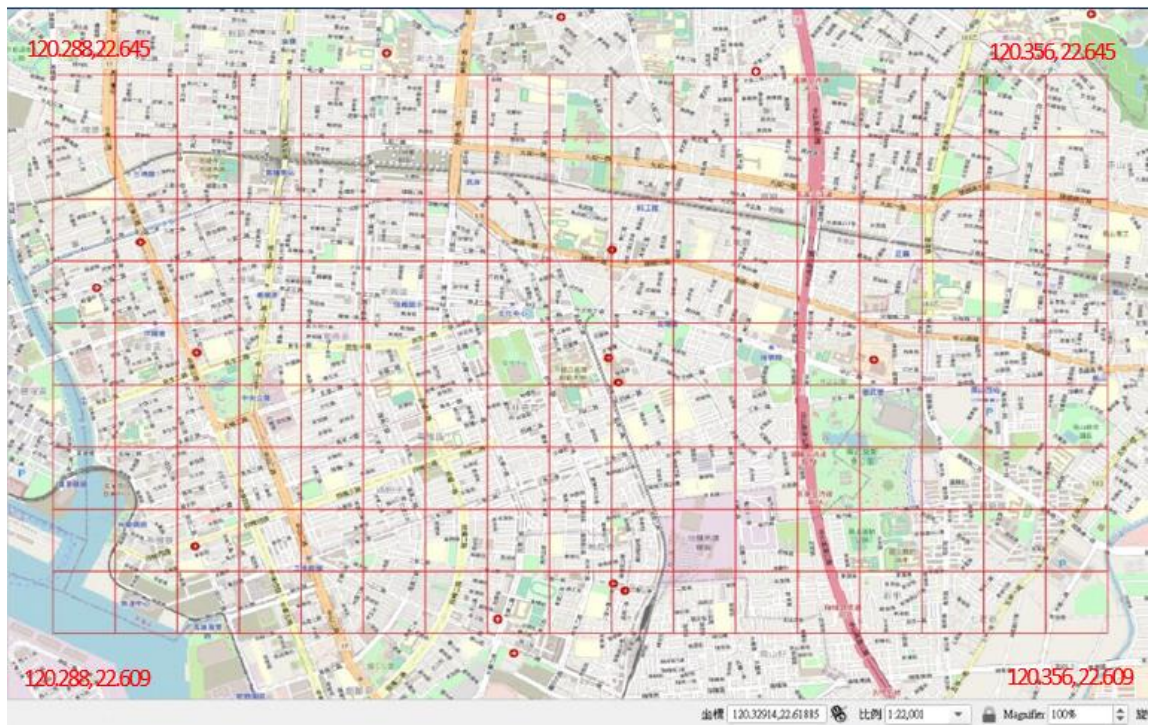
Source: Authors' elaboration.

Figure B.2. Study area (longitude 120.288-120.356, latitude 22.609-22.645) on the Q-GIS (3.12.3)



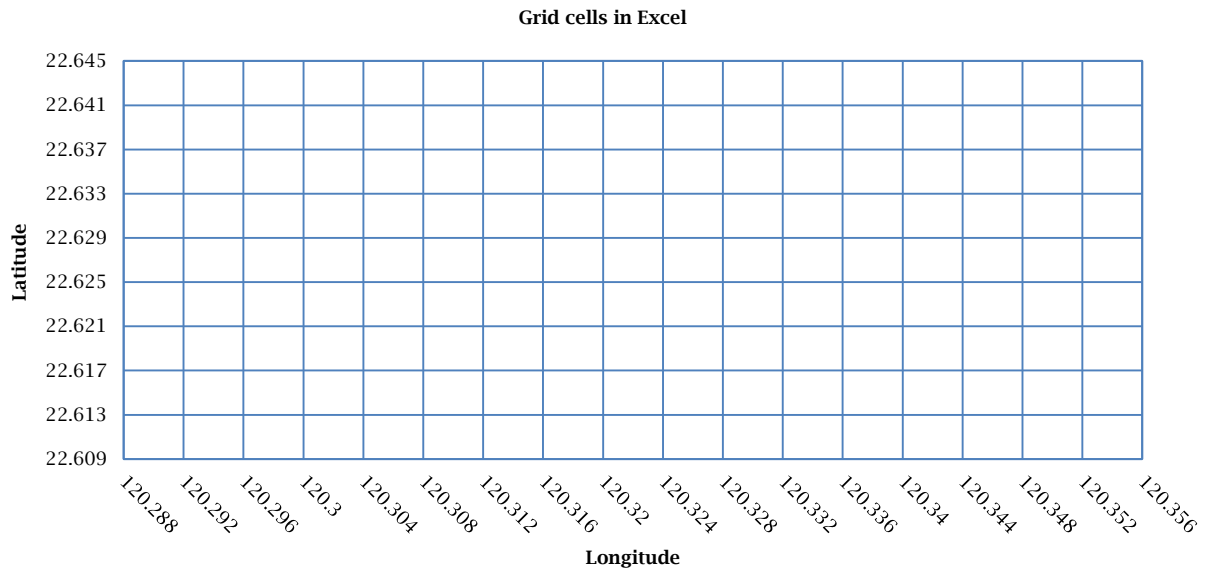
Source: Authors' elaboration.

Figure B.3. The study area is divided into 153 grid cells (9×17) on the Q-GIS (3.12.3)



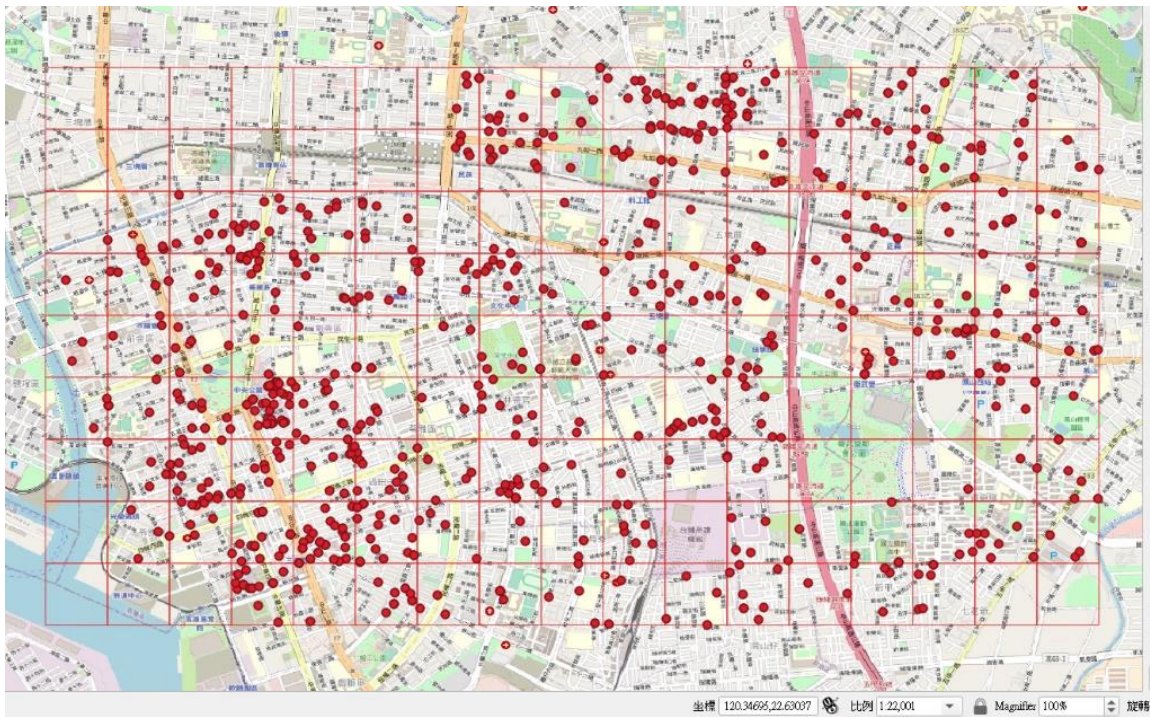
Source: Authors' elaboration.

Figure B.4. The study area is divided into 153 grid cells (9×17) by Excel



Source: Authors' elaboration.

Figure B.5. A visualization of theft crime in 2019 within the study area

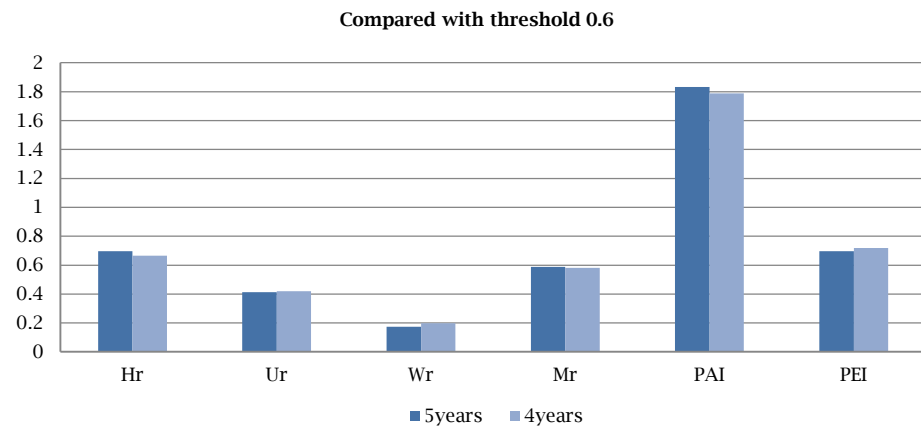


Source: Authors' elaboration.

Figure B.6. The Chinese address is converted into a longitude and latitude display (drawn by Google Earth Pro)

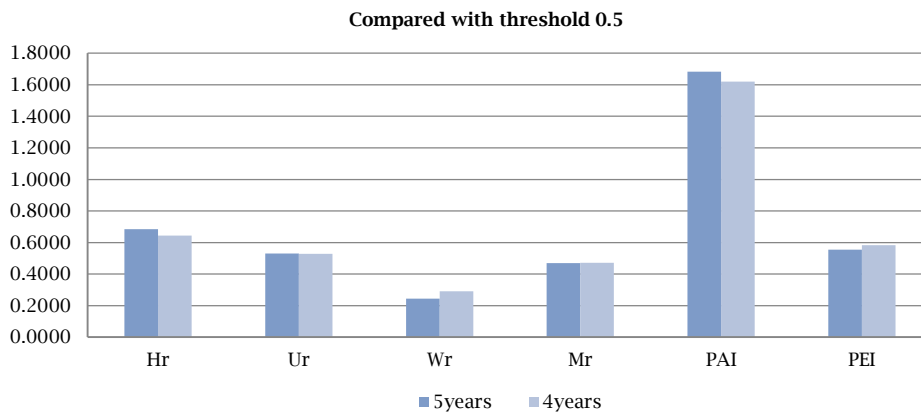
| ns1color12 | ns1colorModel3 | schemaUrl | ns1SimpleData | name14 | ns1coordinates |
|------------|----------------|-----------|----------------------|-------------------|---------------------------------------|
| 15 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 高雄市新興區海墘一路46號 | 發生_現_地點 120.3078965,22.62991500000010 |
| 16 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 1081012 0430 | 發生_現_時間 120.3033732,22.62076199999990 |
| 17 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 高雄市新興區新田路151號 | 發生_現_地點 120.3033732,22.62076199999990 |
| 18 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 1081009 2140 | 發生_現_時間 120.3038522,62551400000010 |
| 19 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 高雄市新興區可發街22巷81號 | 發生_現_地點 120.3038522,62551400000010 |
| 20 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 1081108 1740 | 發生_現_時間 120.3038231,22.62551399999990 |
| 21 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 高雄市新興區五福二路3號 | 發生_現_地點 120.3038231,22.62551399999990 |
| 22 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 1081113 1605 | 發生_現_時間 120.3027324,22.62340599999990 |
| 23 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 高雄市新興區文橫一路167巷87號 | 發生_現_地點 120.3027324,22.62340599999990 |
| 24 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 1081117 2140 | 發生_現_時間 120.3024649,22.62317800000010 |
| 25 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 高雄市新興區文化路8號 | 發生_現_地點 120.3024649,22.62317800000010 |
| 26 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 1081118 1300 | 發生_現_時間 120.3023915,22.62318499999990 |
| 27 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 高雄市新興區新田路9號 | 發生_現_地點 120.3023915,22.62318499999990 |
| 28 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 1081121 0000 | 發生_現_時間 120.3003493,22.62463800000000 |
| 29 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 高雄市新興區五福二路50號 | 發生_現_時間 120.3003493,22.62463800000000 |
| 30 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 1081122 0434 | 發生_現_時間 120.3003493,22.62463800000000 |
| 31 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 高雄市新興區新田路143號2樓 | 發生_現_時間 120.3004052,62221.4599999990 |
| 32 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 1081122 1730 | 發生_現_時間 120.2979009,22.63872000000010 |
| 33 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 高雄市前金區五福二路與自立 路 | 發生_現_地點 120.2979009,22.63872000000010 |
| 34 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 1081125 2050 | 發生_現_時間 120.2962243,22.63430199999990 |
| 35 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 高雄市前金區高成功 路209號2樓 | 發生_現_地點 120.2962243,22.63430199999990 |
| 36 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 1081125 2222 | 發生_現_時間 120.2954893,22.62834800000010 |
| 37 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 高雄市前金區高成功 路209號 | 發生_現_時間 120.2954893,22.62834800000010 |
| 38 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 1081125 0000 | 發生_現_時間 120.3017969,22.63253690 |
| 39 | ffa7e1ef | normal | #3 等德思德總發發生10812月_SS | 高雄市新興區中山一路153號B1室 | 發生_現_地點 120.3017969,22.63253690 |

Figure B.7. The λ of the average of 5 years and 4 years when compared with a threshold of 0.6

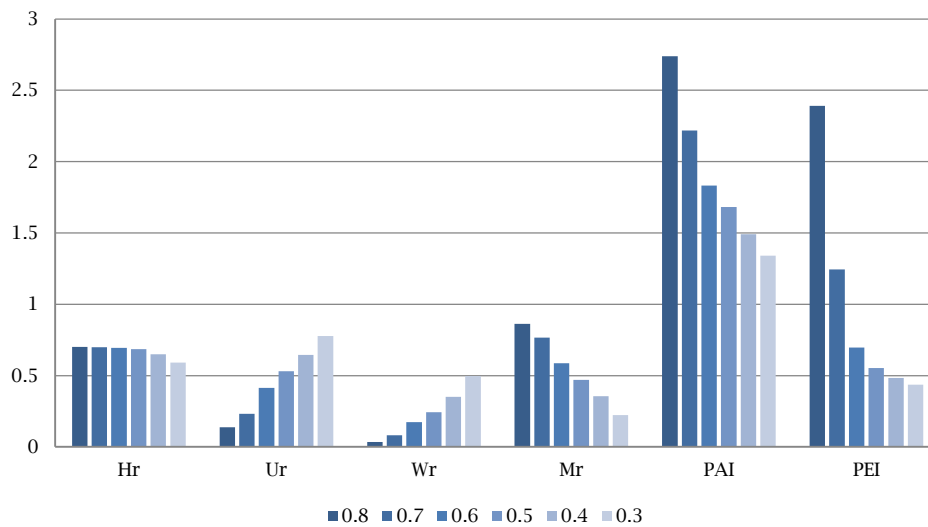


Source: Authors' elaboration.

Figure B.8. The λ of an average of 5 years and 4 years when compared with a threshold of 0.5



Source: Authors' elaboration.

Figure B.9. The trend chart with different predictive threshold values for 5-year statistics

Source: Authors' elaboration.

APPENDIX C

Program 1. Program for data put into grid cells. To execute: The Excel command is as follows:

```
Private Sub Get longitude and latitude _ Put into corresponding grid cell _ Click()
Dim Longitude, Latitude, YY, XX, StepValue As Single 'longitude, latitude, add values
StepValue = 0.004 ' increase values
'Range("C1").Value = ""
'Range("C2:XFD30000").ClearContents
'Vertical line: numbers are 17 in X-axis, longitude min-to-max
'Horizontal lines: numbers are 9 in the Y-axis, latitude, min-to-max
Dim X17, Y9 As Integer
Dim Month As Integer 'per Month of per year
Dim AA (1 To 12, 1 To 17, 1 To 9) As Integer 'Store the number of crime incidents per month.
'data set first row To data set last row, Start_Row = 2: Start_Col = 6
For Data_Row = 2 to 5516
    YY = Cells(Data_Row, 3).Value 'Longitude, vertical
    XX = Cells(Data_Row, 4).Value 'Latitude, horizontal
    '2 characters on the right side of the cell, month
    Month = Right (Cells (Data_Row, 1).Value, 2)
    X17 = 0: Y9 = 0 ' Set the initial value
    ' Vertical line-numbers are 17 in X-axis, longitude, min to max.
    For Longitude = 120.288 To 120.356 Step 0.004
        X17 = X17 + 1: Y9 = 0
        'Horizontal lines-numbers are 9 in the Y-axis, latitude, min to max.
        For Latitude = 22.609 To 22.645 Step 0.004
            Y9 = Y9 + 1
            If (YY > Longitude And YY < Longitude + StepValue) Then
                If (XX > Latitude And XX < Latitude + StepValue) Then
                    AA(Month, X17, Y9) = AA(Month, X17, Y9) + 1
                End If
            End If
        Next Latitude
    Next Longitude
Next Data_Row
'-----Display Results on Screen-----
Col = 7 'Display Results Position column number
Row = 7 'Display Results Position row number
For Month = 1 To 12
    Cells(Row, Col - 2).Value = Month 'horizontal axis.
    For Y = 9 To 1 Step -1
        Cells(Row, Col - 1).Value = Y 'Vertical axis.
        For X = 1 To 17
            Cells(Row, Col + X - 1).Value = AA(Month, X, Y)
        Next X
        Row = Row + 1
    Next Y
    Row = Row + 3 'Display next month
Next Month
End Sub
```

Source: Written by Tien-Chin Wang.

Program 2. Excel function is for Poisson

=1-EXP(-1×λ) 'λ =Average of 5 or 4 years,1-f(0).

Source: Written by Bi-Chao Lee.

Program 3. Excel function is for PAI

=(COUNTIF(DW7:EM15, ">0"))/(SUM(CI7:CY15))/((SUM(BO7:CE15)/153)
'DW7:EM15, CI7:CY15,BO7:CE15 are the extent of research; 153 is the total number of grids)

Source: Written by Bi-Chao Lee.

Program 4. Excel function is for PEI

(SUM(LARGE(CI7:CY15,ROW(INDIRECT("1:"&BM8)))))/(SUM(CI7:CY15))/(COUNTIF(CI7:CY15,">0"))/153
'SUM(LARGE(CI7:CY15,ROW(INDIRECT("1:"&BM8)))) is n*,("1:"&BM8) expresses the number of cells that predicted, and count down from the maximum to the number of predicted grids.
'(CI7:CY15) is the extent of research.

Source: Written by Bi-Chao Lee.