GEOSPATIAL-BASED DATA AND KNOWLEDGE DRIVEN APPROACHES FOR BURGLARY CRIME SUSCEPTIBILITY MAPPING IN URBAN AREAS

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DEDICATION

This thesis is dedicated to the awesome parent that I have:

Ayah, Noor Azmy Zainaabidin who never considered financial disabilities as an end to higher education. To Mama, Siti Zurina Mohd Zulkifli that always understands my difficulties by being there for Noah.

To my better half:

Ahmad Fakhruddin - for believing in me, and willingly becoming my shoulder to cry on. Thanks for all the emotional support and encouragement.

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ABSTRACT

The Damansara-Penchala region in Malaysia, is well-known for its high frequency of burglary crime and monetary loss based on the 2011-2016 geospatial burglary data provided by the Polis Diraja Malaysia (PDRM). As such, in order to have a better understanding of the components which influenced the burglary crime incidences in this area, this research aims at developing a geospatial-based burglary crime susceptibility mapping in this urban area. The spatial indicator maps was developed from the burglary data, census data and building footprint data. The initial phase of research focused on the development of the spatial indicators that influence the susceptibility of building towards the burglary crime. The indicators that formed the variable of susceptibility were first enlisted from the literature review. They were later narrowed down to the 18 indicators that were marked as important via the interview sessions with police officers and burglars. The burglary susceptibility mapping was done based on data-driven and knowledge-driven approaches. The data-driven burglary susceptibility maps were developed using bivariate statistics approach of Information Value Modelling (IVM), machine learning approach of Support Vector Machine (SVM) and Artificial Neural Network (ANN). Meanwhile, the knowledge-driven burglary susceptibility maps were developed using Relative Vulnerability Index (RVI) based on the input from experts. In order to obtain the best results, different parameter settings and indicators manipulation were established in the susceptibility modelling process. Both susceptibility modelling approaches were compared and validated with the same independent validation dataset using several accuracy assessment approaches of Area Under Curve - Receiver Operator Characteristic (AUC-ROC curve) and correlation matrix of True Positive and True Negative. The matrix is used to calculate the sensitivity, specificity and accuracy of the models. The performance of ANN and SVM were found to be close to one another with a sensitivity of 91.74% and 88.46%, respectively. However, in terms of specificity, SVM had a higher percentage than ANN at 57.59% and 40.46% respectively. In addition, the error term in classifying high frequency burglary building was also included as part of the measurements in order to decide on the best method. By comparing both classification results with the validation data, it was found that the ANN method has successfully classified buildings with high frequency of burglary cases to the high susceptibility class with no error at all, thus, proving it to be the best method. Meanwhile, the output from IVM had a very moderate percentage of sensitivity and specificity at 54.56% and 46.42% respectively. On the contrary, the knowledge-driven susceptibility map had a high percentage of sensitivity (86.51%) but a very low percentage of specificity (16.4%) which making it the least accurate model as it was not able to classify the high susceptible area correctly as compared to other modelling approaches. In conclusion, the results have indicated that the 18 indicators used in this research could be employed to successfully map the burglary susceptibility in the study area. Furthermore, it was also found that residential areas within the vicinity of Brickfields, Bangsar Baru, Hartamas and Bukit Pantai are consistent to be classified as high susceptible areas, meanwhile areas of Jalan Duta and Taman Tunku are both identified as the least susceptible areas across the modelling methods.

ABSTRAK

Kawasan Damansara-Penchala di Malaysia, diketahui dengan kekerapan jenayah pecah rumah berserta kerugian kewangan yang tinggi berdasarkan data geospatial pecah rumah yang diperolehi daripada Polis Diraja Malaysia (PDRM) untuk tahun 2011-2016. Dengan itu, dalam usaha untuk meningkatkan kefahaman tentang komponen yang mempengaruhi kejadian jenayah pecah rumah di kawasan ini, kajian ini bertujuan untuk membangunkan pemetaan kecenderungan jenayah pecah rumah dalam kawasan perbandaran. Peta penunjuk spatial telah dibangunkan daripada data pecah rumah, data banci dan data tapak bangunan. Peringkat awal kajian difokuskan kepada pembangunan penunjuk spatial yang mempengaruhi kecenderungan sesuatu bangunan kepada jenayah pecah rumah. Penunjuk yang membentuk pembolehubah kecenderungan diperolehi terlebih dahulu daripada kajian literatur. Ianya kemudian disenarai pendek kepada 18 jenis penunjuk yang ditandakan sebagai penting melalui proses temu bual bersama pegawai polis dan pelaku pecah rumah. Pemetaan kecenderungan ini telah dibangunkan berasaskan data dan pengetahuan. Peta berasaskan data telah dibangunkan menggunakan teknik statistik Pemodelan Nilai Maklumat (IVM) dan pendekatan pembelajaran mesin – Mesin Sokongan Vektor (SVM) dan Rangkaian Neural Buatan (ANN). Manakala, peta kecenderungan pecah rumah berasaskan pengetahuan dibangunkan menggunakan formula Indeks Kerentanan Relatif (RVI) berdasarkan input daripada pakar. Bagi memperoleh hasil terbaik, pelbagai tetapan parameter dan manipulasi penunjuk telah diwujudkan dalam proses pemodelan kecenderungan. Kedua-dua kaedah pemodelan dibandingkan dan disahkan dengan set data pengesahan bebas yang sama menggunakan beberapa kaedah penilaian daripada Luas dibawah Lengkung-Ciri Operator Penerima (AUC-ROC) dan matriks korelasi bagi Positif Benar dan Negatif Benar. Matriks ini digunakan untuk mengira kepekaan, ketentuan dan ketepatan setiap model. Prestasi bagi ANN dan SVM adalah lebih kurang sama iaitu dengan nilai kepekaan masing-masing sebanyak 91.74% dan 88.46%. Walaubagaimanapun, daripada segi ketentuan, SVM memperoleh peratusan yang lebih tinggi berbanding ANN iaitu masing-masing 57.59% dan 40.46%. Selain daripada itu, selisih dalam pengelasan kekerapan pecah rumah bangunan yang tinggi sebagai kecederungan tinggi juga dipertimbangkan dalam memilih kaedah terbaik. Melalui perbandingan hasil pengelasan dengan data daripada set data pengesahan, didapati kaedah ANN berjaya mengelaskan bangunan dengan kekerapan kes pecah rumah yang tinggi kepada kelas kecenderungan tinggi dengan tiada langsung selisih, lalu dipilih sebagai kaedah terbaik. Sementara itu, hasil daripada kaedah IVM berprestasi sederhana dengan nilai kepekaan dan ketentuan sebanyak 54.56% dan 46.42%. Sebaliknya, kaedah pemetaan menggunakan pendekatan berasaskan pengetahuan mempunyai kepekaan yang tinggi (86.51%), tetapi peratusan ketentuannya terlalu rendah (16.4%) yang menjadikannya model yang kurang tepat berikutan ianya gagal untuk mengkelaskan kawasan berkecenderungan tinggi dengan tepat berbanding kaedah pemodelan lain. Kesimpulannya, keputusan mendapati kesemua 18 penunjuk yang dikenal pasti dalam kajian ini boleh digunakan bagi memetakan kecenderungan jenayah pecah rumah dalam kawasan kajian. Seterusnya, kawasan perumahan di sekitar Brickfields, Bangsar Baru, Hartamas dan Bukit Pantai dikenal pasti secara konsisten sebagai kawasan berkecenderungan tinggi manakala perumahan di sekitar Jalan Duta dan Taman Tunku telah dikenal pasti sebagai kawasan berkecenderungan rendah melalui kesemua kaedah yang telah digunakan.

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LIST OF ABBREVIATIONS

AHP	-	Analytical Hierarchical Process
ANN	-	Artificial Neural Network
AUC	-	Area Under Curve
CON	-	Conventional Neighborhood
CPTED	-	Crime Prevention through Environmental Design
DBKL	-	Dewan Bandaraya Kuala Lumpur
DOSM	-	Department of Statistics Malaysia
FN	-	False Negative
FP	-	False Positive
GIS	-	Geographical Information System
GN	-	Guarded Neighbourhood
GTP	-	Government Transformation Plan
IVM	-	Information Value Modelling
JPJKK	-	Jabatan Pencegahan Jenayah dan Keselamatan Komuniti
MaCGDI	-	Malaysia Centre of Geospatial Data Infrastructure
MO	-	Modus Operandi
NKRA	-	National Key Results Area
PDRM	-	Polis Diraja Malaysia
POI	-	Point of Interest
RBF	-	Radial Basis Function
ROC	-	Receiver Operator Characteristics
SPBS	-	Sistem Pemantauan Bandar Selamat
SVM	-	Support Vector Machine
TN	-	True Negative
TNR	-	True Negative Rate
TP	-	True Positive
TPR	-	True Positive Rate

LIST OF SYMBOLS

Σ	-	Summation
exp	-	Exponential
ln	-	Natural Algorithm

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CHAPTER 1

INTRODUCTION

1.1 Background Study

Crime is a serious problem faced by every nation worldwide, regardless of the economic and political status. The unsettled crime issues entanglement with human life is critical that it is described as “a part of our way of living” by Brantingham and Brantingham (1995). Crime evolves through years, mostly with the economic revolution. This claim is supported by Zhong, Yin, Wu, Yao, Wang and Yu (2011) as they found that the crime rate in Shanghai, China has increased 50 times in 1970 compared to the crime rate in 1960 and 1950. The economic revolution has increased the population density and the concentration of human activities in Shanghai as the city centre (Zhong et al., 2011). The good economic condition has also added the attractiveness for the crime to be inflicted. Meanwhile, the highly concentrated population has created the instability of socioeconomic gaps which increases the motivation for crime to be committed. The same traits can be seen in the rapid development of urban cities in Malaysia. The rapidly growing city has higher crime offending due to high population density especially in the working-class neighbourhood (Marzbali, Abdullah, Razak and Tilaki, 2011b; Yaakob, Masron and Masami, 2012).

With the increasing number of crime committed annually, the authority has conducted many efforts to deter crime. The most primitive effort to prevent the occurrence of crime includes patrols by the neighbourhood watch at in places with frequent crime occurrence. The basic idea of crime prevention through environmental design was pitched by Enrico Ferri as early as 1899 commented on the character of spatial features which makes it prone to crime and outlines several features that discourage the crime offence (Nicotri, 1929). Later in 1971, the term “environmental criminology” was coined by Jeffery (1971) but were ignored by the authority since the early studies of crime tend to focus on three elements of crime that consists of the victim (what makes some people more susceptible to crime than others), the law (how laws affect crime) and offenders (what makes some people commit crime) (Jeffery, 1971). During this era, the theory of crime is being actively produced. Some of the examples of theories include Routine Activity Theory (Cohen and Felson, 1979) followed by Geometric Theory of Crime (Brantingham and Brantingham, 1993, 1995), Rational Choice Theory (Clarke and Cornish, 1985) and others. The underlying dynamics of crime occurrence location were proven empirically a long time ago by researches conducted by Quetelet (1831) and Mayhew (1861) as reported by Beirne (1986). Since then, the criminology research involving the elements of geography in crime has been expanded with the improvement of data scale, from county to census tract to smaller unit, and today, to individual level of data such as building unit or land parcel. The improvement of technology indeed has enhanced the human capability in collecting, gathering and analysing data in a more accurate manner.

Crime in Malaysia is not a heterodox problem. According to the index crime statistics by Numbeo (2016) as shown in Figure 1.1, Malaysia is ranked 15th place with a crime rate of 65.56 crimes per 100,000 population. To be placed between the highly populous countries such as Jamaica, Bangladesh and Brazil, this is not to be proud of since Malaysia's population is much smaller compared to the other listed countries. However, in the same webpage, Malaysia is surprisingly ranked third (3rd) place for the highest crime index in Asia region for the year 2016 after Bangladesh and Syria, beating Indonesia. This sort of information will outturn a negative connotation to people regarding safety, alas the potential tourist or business collaboration which will indirectly affect the economy of Malaysia.

In general, crime can be categorized into violent crime, property crime and cyber-crime (Brown, Gunderson and Evans, 2000). In Malaysia, property crimes are reported to make up about 90% of the crime's occurrence for 24 years dated from 1980 to 2004 (Johar, Hosni and Zulkarnain., 2005; Marzbali, Abdullah, Razak and Tilaki., 2012; Sidhu, 2005). Property crimes include those offences involving the loss of property has no engagement of violence by the perpetrators (Che Soh, 2012; Johar et al., 2005). Even though property crime primarily occurs with property loss without involving violence, it still put the risk on the presence victims. Burglary and robbery are another two different types of property crimes which usually mistakenly understood. Robbery is defined as “the taking of money and goods in the possession of another, from his or her person or immediate presence, by force and intimidation” by Gale Encyclopedia of American Law (2010). Robbery involves the threat of force or actual use of force in connection with a theft and with the presence of victim (Gale Encyclopedia of American Law, 2010). Meanwhile, burglary crime is defined as “the criminal offence of breaking and entering the building illegally for the purpose of committing a crime” (Gale Encyclopedia of American Law, 2010). Differs from robbery, in order for a burglary to occur, a victim does not have to be present. The unlawful entry can be any type of buildings including business office, personal home and even garden sheds can also be considered as breaking and entry (West’s Encyclopedia of American Law, n.d.)

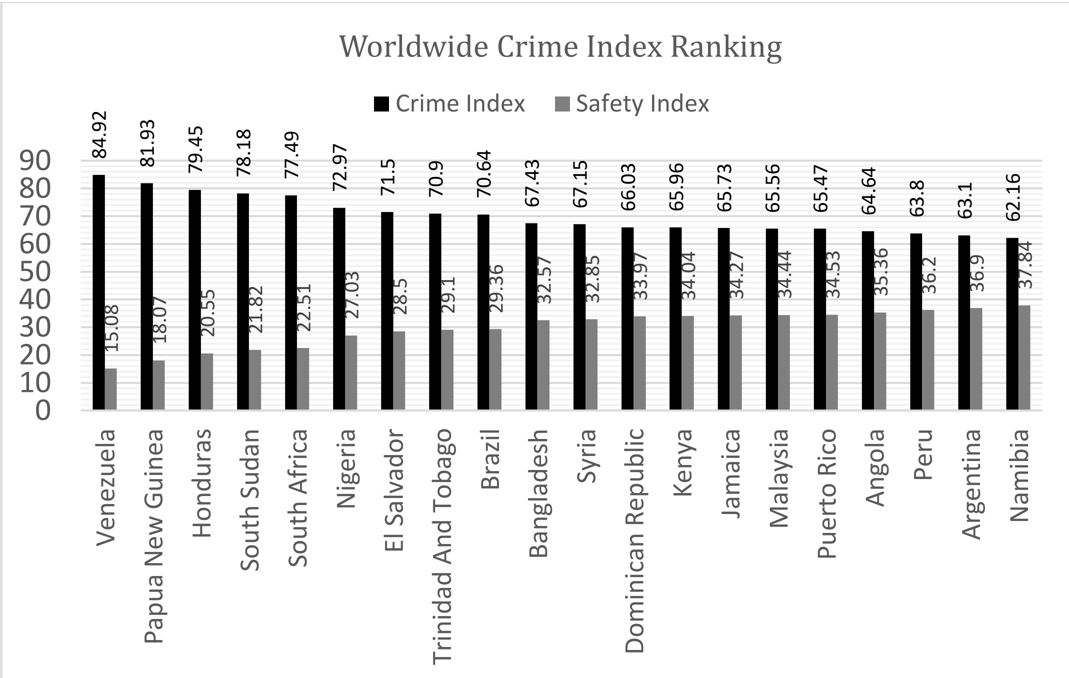

Figure 1.1: The Worldwide Crime Rate Ranking (After Numbeo, 2016)

Property crime in the Malaysian law context includes various theft cases such as robbery and burglary (night time and day time burglary) (PDRM, 2016). Burglary is a serious crime occurrence in Malaysia as it has been mentioned as one of the major security threats in Malaysia 2015 Crime and Safety Report by United States

Department of State Diplomatic Security (OSAC, 2015). Due to the seriousness of the burglary occurrence, various techniques of deterring crime have been designed. The designed techniques can be a straightforward solution to physically preventing the entrance of burglar or it can be a psychological solution to create the fear inside a motivated offender from committing burglary. The straightforward solution can be in form of the usage of deadbolt locks, grill and door bars. Meanwhile, the psychological solution includes the installation of surveillance cameras and the implementation of Crime Prevention through Environmental Design (CPTED) elements in the house design and neighbourhood. CPTED encourages natural surveillance to occur by placing the right element at the right place which is able to deter the occurrence of crime (Jeffery, 1971).

Burglary in Malaysia is a serious problem as the monetary loss from burglary has reached RM 17, 974 per premise on the average while the cost to manage the crime are estimated around RM 742 per convict (Goh, 2006). According to Goh (2006), alone, the total cost of property loss from burglary crime in 2004 alone is estimated at around 1,492 million *Ringgit* (RM 1,492,000,000). Whilst, in the United States, the government's expenditure on prison is six times higher than the expenditure for higher education (Mcmillon, Simon and Morenoff, 2014). To make the matter worst, the cost of crime is not only limited to monetary losses, but it also affected the social values of the local resident (Abdullah, Marzbali, Bahauddin and Tilaki, 2012; Sakip, Abdullah and Mohd Najib, 2013; Johar et al., 2005; Shihadeh, 2009; Sakip and Abdullah, 2008). The emotional impact on victims of modern-day residential burglary can reflect similar concerns about security, victims reporting fear, a sense of violation and no longer feeling safe in their own homes; it is this, rather than the scale of financial loss, that motivates judges to continue to pass relatively heavy sentences on burglars (Maguire, Wright and Bennet, 2010). High crime in the neighbourhood elevates the fear of crime and the feeling of safety among the resident and later lead to community isolation (Skogan, 1986). The community isolation will create a crime-concentrated zone such as ghetto area which will lead to other problems related to social disorganization (Shihadeh, 2009).

Supporting this burglary-deterrent plan, various field of researches have been conducted to understand the burglary crime better. Local studies conducted in Malaysia are also on board in defining the factors that contribute to crime in various approaches. Univariate forecasting based on 10-years of historical time series data has been conducted by Noor, Retnowardhani, Abd and Saman (2013); Talib, Sallehuddin and Hassan (2006) using ARIMA intent to predict the future occurrence of burglary. Considering the restrictive ability of univariate forecasting method, the studies on bivariate analysis have been ventured by researchers to find the dual correlation between factors and the crime. One example of such research was conducted by Mulok, Kogid, Lily and Asid (2016); Habibullah, Baharom, Din, Muhammad and Ishak (2014); and Baharom and Habibullah (2009). In addition to this, various statistical relationship studies have been established to find the significant factor encouraging burglary in local scale to enhance the knowledge of resident towards the burglary crime occurrence. Example of the local studies that majoring in defining the factors of crime are as conducted by Zakaria (2014); Zakaria and Rahman (2015); Zaki and Abdullah (2012a, 2012b) and Zulkifli, Razali, Masseran and Ismail (2015). Despite many researches that have been conducted previously, there are still gaps to fill in, such as in terms of model parameterization which involves multiple aspects contributing to burglary susceptibility, not limited to socioeconomy factors, and as modelled in geospatial approach. Besides that, the potential of improving the scale of burglary modelling using the individual occurrences of burglary cases located on each building is possible, compared to the utilization of the statistical or aggregated spatial boundary data as adapted by the previous studies.

The technique of deterring crime has improved greatly with the enhancement of technology and sufficient knowledge possession. The study to understand crime mechanisms has become the research focus and the relationship between the factors that possibly contribute to crime offence has been proven through mathematical, statistics and spatial approaches. Recently, the crime prevention agenda has moved to a new chapter, targeting to achieve the future crime prediction, based on vulnerability and temporal pattern of the spatial data (Almanie, Mirza and Lor, 2015; Lopez, 2015; Li, Haining, Richardson and Best, 2014; Wolff and Asche, 2009; Thornley, 2004; Sorensen, 2003; Townsley, Homel and Chaseling, 2000). The criminologist believes that the authority and community can deter the crime effectively by possessing some degree of understanding in the tactical strategies of the potential offender (D. Canter, 2004; P. Canter, 1994; Yokota and Canter, 2004). Parallels to this belief, this research is motivated to achieve the understanding of burglary crime occurrences by developing a model that comprises components that make up the crime such as the susceptibility factors and the preferences of the offender towards the target. The opportunity of crime can be in the form of guardianship absence and surveilability, lack of security or the perceptive wealth of the victim from the offender's point of view. Hence, this study targetting to model and classify the burglary crime susceptibility from the data, without neglecting the burglars' behaviour point of view in terms of target selection.

Burglary crime is chosen as the main focus of crime type due to its close relationship with spatial placement and derivative opportunity and attractiveness. With this security wariness, this research has been designed to aid the proposal of burglary crime prevention by the authority by identification of highly susceptible areas towards burglary occurrence, by using four mapping approaches which derived using two comparative approaches of data-driven and knowledge-driven. The indicators contributing to burglary occurrence in spatialsocio-demography setting was identified beforehand to develop the susceptibility map.

In this research, two approaches of data-driven and knowledge-driven has been adapted in developing the model. As shown in Figure 1.2, the list of all possible indicators was filtered and narrowed down after the process of interview with police officers and burglars. This finalization of indicators allows the preparation of spatial data as the template for both model development and further down to the preparation of data according to approach. The output of interviews with police officers and burglars has been used in designing the questionnaire for knowledge-driven data collection to yield the score and weightage of each indicator and sub-indicator from the expert's point of view. This scoring and weight values will be analyzed and become the input for knowledge-driven susceptibility map development. Meanwhile, for the data-driven, the spatial data were divided into portion of training and testing data which is elaborated in Section 3.5.3 for data-driven map development. All these maps were validated to compare their findings and performance.

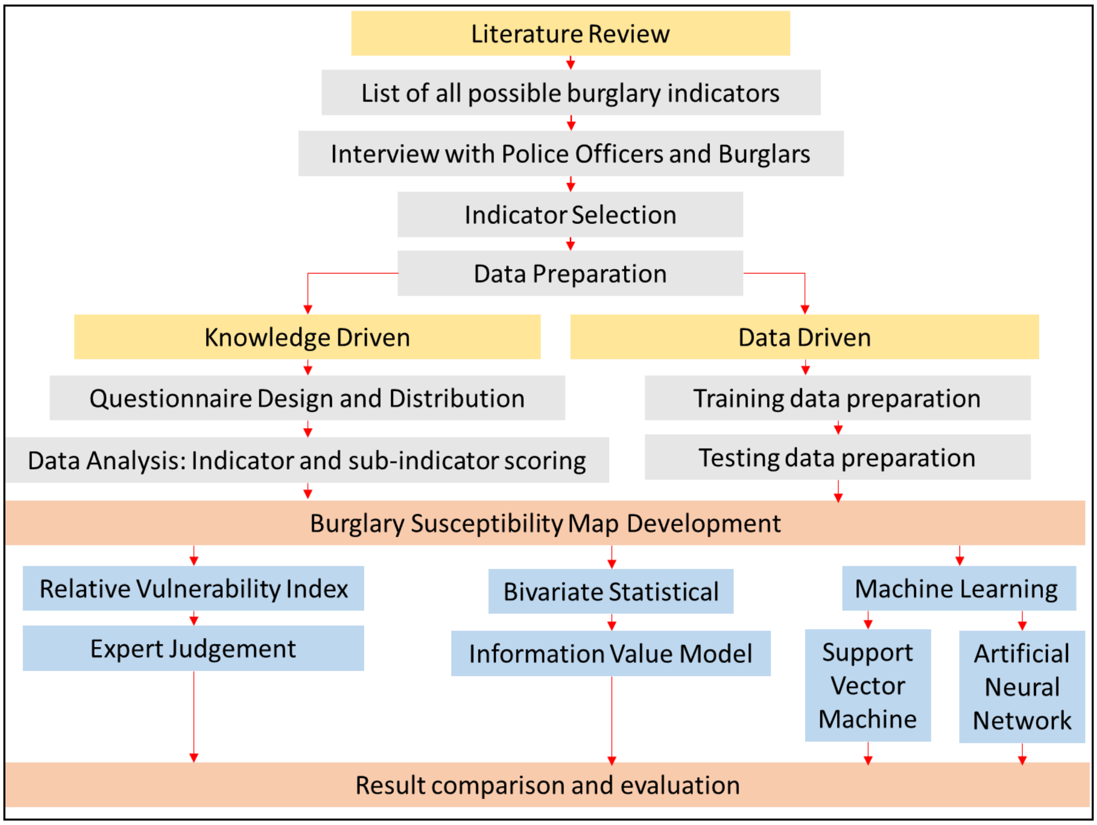

Figure 1.2: The simplification of the research component and aim

Building a model of areas with high crime concentration (hotspot) is the normal practice of common crime analysis. This research aims to develop a comprehensive model of burglary susceptibility modelling through the indicator establishment which comprises the physical building properties, the socio-demography factor, the element of surveillance and the adjacency to crime generators area. Apart from modelling the susceptibility based on data-driven approach, one of the research deliverables is adapting the knowledge-driven indicator scoring input to incorporate the "behavioural" element in susceptibility mapping techniques.

In general, the collected and gathered data in this research are in the form of qualitative and quantitative. The quantitative data is the reported burglary data (in form of spatial points) and questionnaire feedbacks, meanwhile the qualitative data is the thematic-extracted data of expert judgments which comprises of interview sessions with the burglars who are also former drug addict and the police officers from *Jabatan Pencegahan Jenayah dan Keselamatan Komuniti* (Department of Crime Prevention and Community Safety), JPJKK. Both sources of data collection are processed in geospatial setting to map and define burglary susceptibility of buildings inside the study area.

1.2 Problem Statement

As mentioned in Section 1.1, the main issues of burglary crime are monetary loss including the cost of personal loss, as well as the cost of managing the crime itself, and the degradation of social values that affect the perception of safety among the residents. Entails, there are variety crime deterring approaches has been developed, including the crime prevention agenda such as Defensible Space (Newman, 1996), CPTED (Jeffery, 1971) and UNHabitat initiative (Andersson et al., 2014). UNHabitat initiative combining the input from Defensible Space and CPTED, while improving other features accordingly to suit in becoming a nation-scale programme. These initiatives were accompanied with the physical implementation to enhance security features, along with the development of digital models, with intention to understand the crime dynamics better, and this information can be manipulated into the designing of crime prevention strategies.

Modelling of crime can be divided into mathematical model, geospatial model and knowledge-driven model. Mathematical model mostly focused on the establishment of empirical relationship/ bivariate relationship between the burglary crime incidences with the factors as mentioned in the works by Ajimotokin, Haskins and Wade (2015); Johnson and Summers (2015); Yearwood and Koinis (2011), Dritsakis and Gkanas (2009); Edmark (2003); Felson and Poulsen (2003); Fajnzylber, Lederman and Loayza (2002); Papps and Winkelmann (2000); Kapuscinski, Braithwaite and Chapman (1998); Rattner (1990). Mathematical model is the essence of knowledge of other advance model, but it is lacking in terms of local-based accuracy and has the tendency to generalize the relationship. It is important to note that one mathematical formula is insufficient to represent the burglary scenario for a state in the whole, instead it varies depending on the underlying characteristics of the local features.

With the technological advancement, this gap has been filled with the approach of geospatial integrated model. The geospatial based model provides a multifaceted view of crime modelling. The dynamics of relationship between the burglary and the parameters can be seen changing, moving from hotspot and coldspot, crime number can be seen varies with the characteristics of places, varies of location-based analysis and tools has been used to predict crime and many others. One of the example of geospatial-based burglary crime research are as cited in the works by Borg, Boldt, Lavesson, Melander and Boeva (2014); Chainey et al. (2008); Fitterer, Nelson and Nathoo (2016); Furtado, Melo, Coelho, Menezes and Perrone (2009); Kim and Shin (2014); Liu (2016); Malleson, Happenstall and See (2010a); Wang, Ding, Lo, Stepinski, Salazar and Morabito (2013). Seeing the data-driven mapping as one-dimensional output, some researchers incorporated the input from burglar and translate the thematic input into the geospatial parameters to develop the knowledge-driven model. The research that adapting this concept are Bernasco and Block (2013); Bernasco and Nieuwbeerta (2005); Vandeviver, Neutens, Daele, Van Geurts and Vander (2015).

Apart from modelling approach, another important features for developing a model is the parameter chosen to represent the phenomenon, in this case, the parameter that significantly contributes to burglary crime susceptibility. From the literature, the researcher will collectively use the parameters from the categories of socioeconomic (Ajimotokin et al., 2015; Baharom and Habibullah, 2009; Bernasco and Nieuwbeerta, 2005; Chiu and Madden, 1998; Choe, 2008; Dahlberg and Gustavsson, 2008; De Maio, 2007; Demombynes and Berk, 2005; Dritsakis and Gkanas, 2009; Edmark, 2003; Fajnzylber et al., 2002; Nilsson, 2004a; Zakaria, 2014; Zhong et al., 2011), demography (Chen, Kurland and Shi, 2019; Fajnzylber et al., 2002; Justus et al., 2015; Metz and Burdina, 2016; Peterson and Krivo, 2009; Pettiway, 1982; Shihadeh, 2009; Sidhu, 2005), Spatial features or POI (Mohd Shamsuddin et al., 2009; Marzbali et al., 2011; Kadar and Pletikosa, 2018; Lee, 2016; Nguyen, Hatua and Sung, 2017; Rummens, Hardyns and Pauwell, 2017; Bogomolov et al., 2014), temporal features (Lauritsen and White, 2014; Sorensen, 2003; Sakip and Abdullah, 2008) or the combination of each categories. In regards to the scale of model, most researcher use the scale of district, meanwhile others use the grid-base boundary to predict the burglary susceptibility.

To mitigate the burglary situation, it is crucial to find the contributing factors and the classification of susceptibility in spatial space of concern. An ideal burglary model supposedly comprises of the spatial criminogenic properties, the social factor, the demographic profile of the place and the behavioural element from the burglar actor itself (Malleson et al., 2010a; Entorf and Spengler, 2000). Western studies have far more advanced in dynamically modelling the burglary crime ranging from non-spatial mathematical model according to Ajimotokin et al. (2015); Johnson and Summers (2015); Yearwood and Koinis (2011), Dritsakis and Gkanas (2009); Edmark (2003); Felson and Poulsen (2003); Fajnzylber (2002); Papps and Winkelmann (1999); Kapuscinski et al. (1998); Rattner (1990); to geospatial element integration embedded in the model (Borg et al., 2014; Chainey et al., 2008; Fitterer et al., 2016; Furtado et al., 2009; Kim and Shin, 2014; Liu, 2016; Malleson et al., 2010a; D. Wang et al., 2013) as well as incorporating the knowledge-driven input from the burglar insight in order to produce a more sensible model (Bernasco and Nieuwbeerta, 2005; Block and Bernasco, 2009; Vandeviver et al., 2015).

Based on the literature review, a summary of the extent to which research has been conducted compared to the improvisation are tabulated in Table 1.1. Primarily, the improvements that have been made in this research focus on parameterization model tailored to local condition and combinations of several categories of indicators to represent comprehensibility in describing the criminogenic of burglary phenomenon, which previously has been modelled separately on a rather generalized scale in small-scale mapping.

Table 1.1: The thesis improvisation to the body of knowledge

No.	Features of previously conducted studies	Improvisation
1	The largest scale of model in representing the burglary prediction and susceptibility are only limited to scale of district, town or grid-based.	Instead defining susceptibility in form of hotspot or as a group of grids, this study represents the class of burglary susceptibility by the individuals building unit.

2	Previous researchers adapting and combining parameters from the category of sociodemography, Point of Interest (POI) or street layout as indicator to burglary susceptibility.	Apart from using parameters from the group of sociodemography, POI and street layout, this study also includes the building characteristics as one of the model components in contributing the crime susceptibility.
3	Previously, only the method of IVM was applied to classify the landslide vulnerability.	This research attempt on applying IVM to classify the building's burglary susceptibility.
4	Unavailability of knowledge-driven model for burglary susceptibility in Malaysia.	Developing the knowledge-driven model customized with the characteristics of urban areas in Malaysia

The first gap that has been improved in this study is in the form of the results' scale by defining the susceptibility according to the building individuals. Previous studies has only deduced the susceptibility to the extent of District / municipality level (Vandeviver et al. 2015; Poulsen and Kennedy, 2004; Zakaria and Rahman, 2016) and grid (Devia and Weber, 2013a; Lin, Yen and Yu, 2018; Rummens et al., 2017; Yu, Ding, Chen and Morabito, 2014). The susceptibility of the place has been found not only depending on its sociodemography features and the spatial features such as crime generators, but the vulnerability of a building based on physical characteristics also need to be considered (Agarbati et al., 2015). Representing the susceptibility custom to each building characteristics with other contextual factor is definitely improving the accuracy of the real-world representation.

Another improvement of burglary modelling component is in term of parameterization. Instead of using the socioeconomic and spatial feature (POI, crime generators, land-use) separately or as combination in model development, this research has also included the physical building characteristics which elevated the vulnerability towards burglary from the expert point of view as group of indicators. This element is important for areas with mixed building types whereby, even it is located on the same locality, it is not accurate to assume the susceptibility is similar due to adjacency factor alone. The risk of boost and flag undeniably exist, but the physical building characteristics is another factor which need to be considered during the target selection by burglars which defines the perception of easiness of entrance, accessibility and limited surveillance (Agarbati et al., 2015).

Apart from adapting the element of expert judgement as mapping methods, this study also developed a bivariate statistical model as one of the comparative methods. Comparing several methods for crime modelling is a common practice of experiment. However, for crime, usually the statistical method of logistic regression (Chen et al., 2019; Rummens et al., 2017) or Naïve Bayesian (Almanie et al., 2015; Boldt et al., 2018) are applied. For the sake of experimenting, the bivariate statistics method of IVM has been used in one of the model developments of this research. IVM method was selected for its performance in classifying the landslide susceptibility (Ba, Chen, Deng, Wu, Yang and Zhang, 2017; van Westen, 1997, 2016).

Last but not least, the unavailability of knowledge-driven model and sources for burglary tendency for Malaysia were seen as the biggest gap that have been fulfilled by this study. To date, there is no single study conducted found aims to record the burglar's point of view in target selection and vulnerability for burglary crime as conducted in other countries such works by Bernasco (2005), Y. Chun and Lee (2013b) and Nee and Taylor (1988). In this study, the output of interview with burglary offenders were reported with hope to become a pioneer to more similar resources in the future.

In accomplishing the objective and aims of this research, several contributions on research novelty have been achieved as listed below:

i. The establishment of local burglary factors and indicators for Malaysia.

ii. Inclusion of geospatial-based indicator in modelling development.

iii. The micro-scale model development, utilizing the functional spatial unit of the building individuals.

iv. Improving the crime prediction parameterization by including the physical building characteristics as the indicator describing the burglary susceptibility along with other factors such as crime generator area (spatial POI), the social-demography profile and the surveillance element.

In terms of methodology, this study compares the model output which developed using the knowledge-driven approach and the data-driven approach. The modelling techniques of bivariate statistics (Information Value Modelling, IVM) and machine learning (Support Vector Machine, SVM and Artificial Neural Network, ANN) will be adapted in data-driven model development. The experimental approach of modelling burglary using IVM has been attempted in this study, since this aforementioned method was previously used widely in landslide modelling, but not in any crime modelling. Meanwhile, machine learning techniques are known as a well-established method in its ability of improving the accuracy of burglary modelling compared to statistical method as proven by Kadar and Pletikosa (2018); Lin et al. (2018); Stalidis, Semertzidis and Daras (2018), however, for all its worth, currently there are still very limited studies applying this method for burglary modelling in Malaysian context.

1.3 Aims and Objectives

This research aims to develop a geospatial-based burglary crime susceptibility modelling in urban areas of Damansara - Penchala region. To achieve the aim, four objectives have been outlined to guide the phase of the study:

1. To identify and produce geospatial-based burglary crime indicator maps for urban areas in Malaysia, particularly in Damansara-Penchala region.
2. To develop the burglary susceptibility model based on knowledge-driven approach.

3. To develop the burglary susceptibility model based on data-driven bivariate statistics and machine learning approaches.

4. To evaluate the performance of data-driven and knowledge-driven approaches in modelling the burglary susceptibility.

1.4 Research Questions

Objective 1: To identify and produce geospatial-based burglary crime predictor maps for urban areas in Malaysia, particularly in Damansara-Penchala zone.

i. What are the indicators that contribute to burglary crime in the study area?

ii. What is the relevant method to be adapted in order to identify the indicators?

iii. How to produce the geospatial-based burglary crime indicator from the available data source?

Objective 2: To develop the burglary susceptibility model based on knowledge-driven approach.

i. How does burglary crime occur from the perspective of a burglar?

ii. What does the burglary preferences or cue on selecting the target?

iii. How much does the local preference differ to compare with the perspective of the burglar in Western's studies?

iv. What is the best approach in gathering the preference in a sufficient sample?

v. How to spatially model the burglar preference from the collected data?

Objective 3: To develop the burglary susceptibility model based on data-driven bivariate statistics and machine learning approach.

i. How to prepare the identified indicator of burglary crime into a spatial data format based on the available data?

ii. How to evaluate the accuracy of the developed model?

iii. Which is the best fit model in describing the susceptibility of burglary events based on the historical burglary records?

Objective 4: To evaluate the performance of data-driven and knowledge-driven approach in modelling the burglary susceptibility.

i. How to evaluate the output of susceptibility models?

ii. Which validation method that is relevant to compare the performance of both modelling approaches?

iii. Which is the most suitable modelling approaches to model the burglary susceptibility of the study area?

iv. How much the knowledge-driven model and data-driven model does reflect on the susceptibility results of each other?

v. What are the most important and the least important indicator in each model?

vi. Does the developed model good enough to predict burglary susceptibility?

1.5 Study Area

The study area, Damansara-Penchala is an area located at the side of Kuala Lumpur City with the size of 45.18 km^2. There are 226 residential areas comprises of various typology from traditional Malay settlement, to land-based and high-rise planned residential development bounded inside this region. Damansara-Penchala is an official strategic zoning demarcated by Kuala Lumpur City Hall (Dewan Bandaraya Kuala Lumpur) for strategic planning and urban development under the Kuala Lumpur Structure Plan 2020 (DBKL, 2015). Figure 1.3 depicts the location of the study area at the edge of Kuala Lumpur and Selangor boundary.

This area was chosen as the study area due to the highest association of burglary incidences and detriment value. Figure 1.4 shows the top ten list of residential areas with the highest detriment value caused by burglary crime in Kuala Lumpur. Two highest committed incidence and loss values are from the residential area in the region of Damansara-Penchala. Based on the data obtained from PDRM, the total detriment value from the burglary crime offences in this area were summed up to RM 54,418,062 (RM 54 million), meanwhile for the area of Damansara Heights alone accounted to RM 15,796,027.00 (RM 15 million) with 270 burglary incidence accumulated from 2011 – 2016, with the mean of RM 58,503.80 for each offend (PDRM, 2016). Apart from monetary loss, burglary also affected the social values of the society and in terms of the perception of safe living.

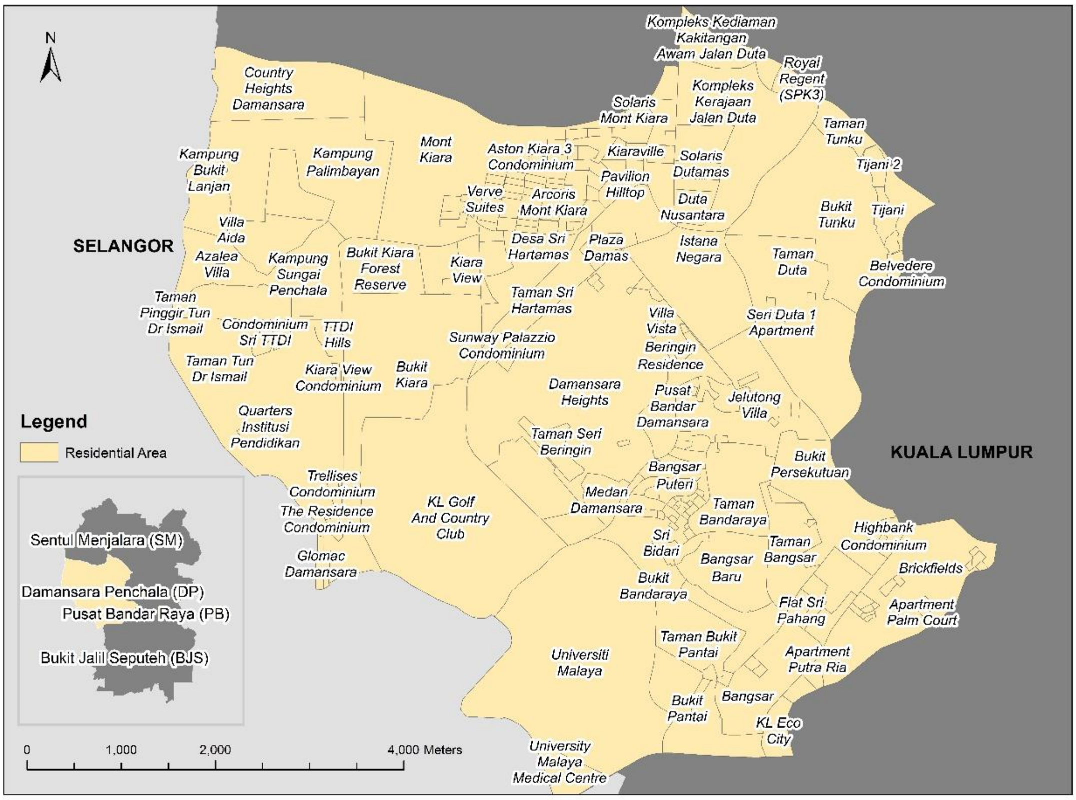

Figure 1.3: The study area of Damansara-Penchala

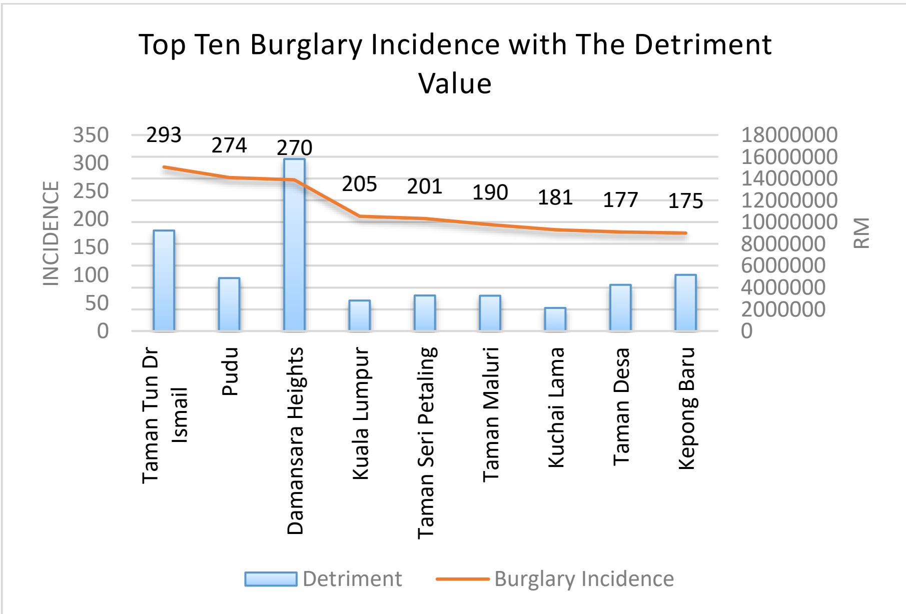

Figure 1.4: The top ten burglary incidence and corresponding detriment value according to the residential area in Kuala Lumpur (PDRM, 2016)

The variety of social and demography make up of Damansara-Penchala zone is also another factor for the site selection. This area is inhabited by 41% of Malay, 23% Chinese, 13% Indian and 18% of immigrant (non-Malaysian). With regard to housing typography, this area comprises of various house types which reflect the socioeconomic gaps (Seo and Omar, 2011). Affluence and inequality are some of the reasons that attract the offending of burglary (Bernasco and Nieuwbeerta, 2005; Chiu and Madden, 1998). In this study context, the affluence level is represented by the type of house which portrayed in the form of house design, size and residential area types. Figure 1.5 shows the distribution of building types in the study area as well as the distribution of burglary incidence.

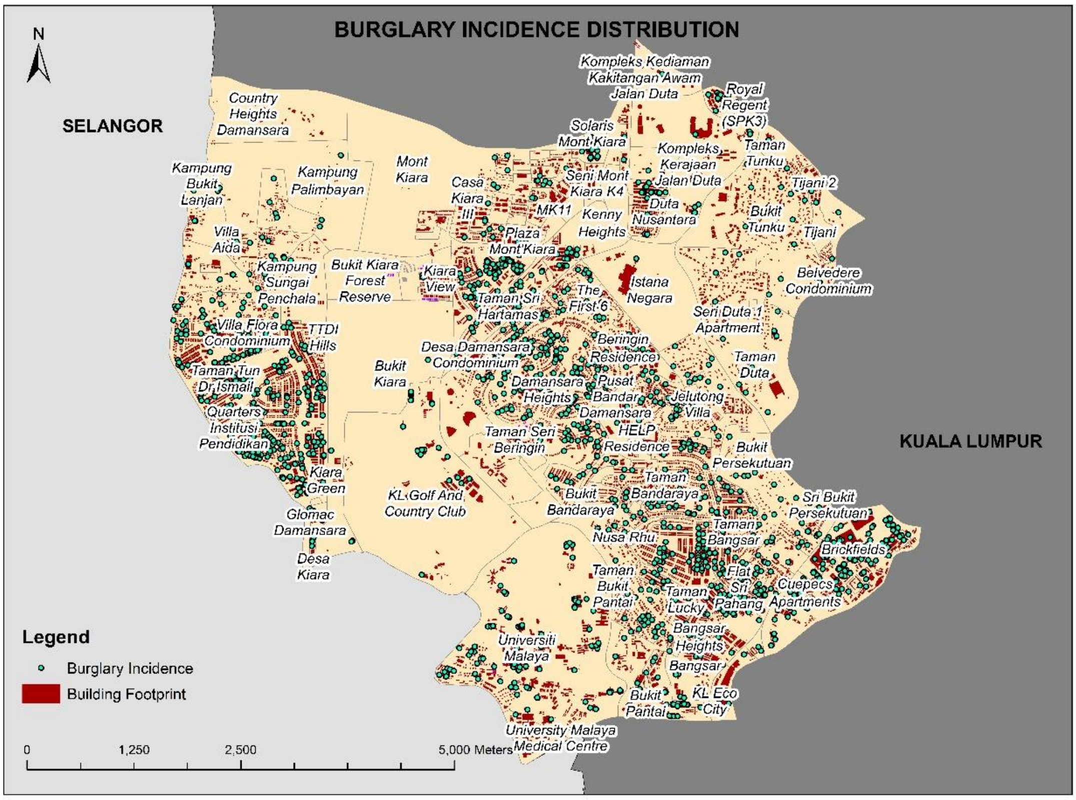

Figure 1.5: The distribution of burglary incidence in the area of Damansara-Penchala (PDRM, 2016)

1.6 Significance of Study

The contribution of this research to the existing body of knowledge will be in terms of the framework of spatial indicators in defining the burglary crime susceptibility for the urban region in Malaysia. Besides the development of the burglary susceptibility mapping and the sets of burglary indicators establishment, this research also contributes to the methodological procedures of translating the social factor of crime into spatial implementation. This study also incorporates the element of human behavioural in modelling the burglary susceptibility which believed to elevate the representation of real-world interaction in geospatial research. In terms of local scale contribution, the outcome of this study has identified the spatially projected indicator to determine the susceptibility of burglary in urban areas and the burglar preferences on selecting the burglar target specifically from the local perspective.

The deliverables of this research focusing on becoming an aid to authority in preventing the burglary occurrences are as stated below:

i. The list of indicators contributing to burglary susceptibility in urban areas.

ii. The characteristics of location with high susceptibility towards burglary crime.

iii. The location of high burglary susceptibility buildings produced based on data-driven approach.

iv. The location of high burglary susceptibility buildings produced based on knowledge-driven approach.

v. The burglar preference in target selection.

vi. The bi-variate model of burglary susceptibility.

vii. The machine learning model of burglary susceptibility.

viii. The expert judgment model of burglary susceptibility.

These deliverables will benefit Polis Diraja Malaysia (PDRM) and PlanMalaysia in becoming the aid of burglary crime prediction and prevention. The results and methodological adapted in this research have the potential to be applied as an add-on tool to *Sistem Pemantauan Bandar Selamat* (SPBS) in mitigating the susceptibility of crime occurrences. On the bigger view, these deliverables are believed to contribute in aiding the local authority to designing a comprehensive crime prevention plan by taking into consideration of the highlighted burglary indicators of social-spatial placement apart from crime prevention through environmental design as a reference.

1.7 Scope of Study

This study is conducted on burglary incidences occurred in Damansara-Penchala region focusing on finding the contribution of each indicator's attribute in determining the level of burglary susceptibility for each building in the study area. The data of burglary occurrences used in this study are dated from January 2011 to December 2016 obtained from the JPJKK of PDRM through the data extraction from SPBS system which will be used as the spatial distribution of active sites of burglary crime, meanwhile the other eighteen (18) indicators to burglary susceptibility are extracted from census 2010 data from Jabatan Statistik Malaysia (Department of Statistics Malaysia, DOSM), Building footprint data of 2013 from Dewan Bandaraya Kuala Lumpur (Kuala Lumpur City Hall, DBKL), Demarcation data from Malaysia Centre of Geospatial Data Infrastructure (MaCGDI) and Google Street Image as the source for physical building parameters. These 18 indicators were verified to be significant as they are the consideration factors during the target selection from the burglar and expert point of view.

In regard to burglar behaviour, this research incorporated the knowledge-driven modelling approach which involves the expert opinion in the scoring of target preferences of the burglary through distribution of questionnaires. The indicators and sub-indicators mainly consist of house characteristics generally in terms of location, physical appearance and social make ups of the house owner. From the interview, the burglars are grouped into four (4) categories based on similarity of the answer and the key factor of decision making and traits of target. This interview output was used in the questionnaire design and further verified by 60 respondents of policemen in ranking placement of each characteristics describing vulnerability based on the burglar selection trend.

The limitation of the data could be in terms of location and attributive accuracy which entails by:

i. The location of burglary incidences is assumed to have been verified by the data manager for SPBS system.

ii. The data for burglary only concerns the location, but do not include the details of offenders such as their age, race, education background and etc. Separated surveys are required in order to develop the profiling and behaviour modelling of the burglar.

iii. Number and sample size obtained during a burglar behaviour survey is very limited. The offender is not properly distributed in terms of race, whereby all the respondents are Malay.

iv. The different year on supporting spatial data are considered relevant to be used with burglary data. The socio-demography data extracted from 2010 census data, meanwhile the building data was collected in 2013.

v. The aggregation of census data from *Blok Perhitungan*, the unofficial boundary of census into the *Taman* (Residential Area) are assumed to be correct.

vi. The aggregation of burglary points on the nearest building footprint are assumed to be correct.

vii. The burglary crime susceptibility in this study excludes the dependent on temporal factor such as seasonal holiday celebration due to data constraint. Burglary susceptibility is assumed to be uniform at all times. The burglary data were treated uniformly, without slicing based on temporal properties.

viii. The model was developed in micro-scale, in which event each classes of susceptibility represented by each building as spatial unit in the study area.

1.8 Thesis Outline

This thesis comprised of five (5) chapters. Chapter 1 shed on the research problems and the background of the research which form the research structure. Meanwhile, chapter 2 reviewed previous studies which aided in the designing of the methodology of this study, especially in forming the indicators and the component of burglary crime itself. Chapter 3 embarks on the methodology concept and workflow which covers the study area, the data collection, data pre-processing and processing which has been enforced in this research to achieve the aim of the study. Subsequently, Chapter 4 will report and discuss the findings of the research results where the burglary susceptibility model was developed based on knowledge-driven approach, bivariate statistics of IVM and machine learning. Finally, Chapter 5 will conclude the findings of the research and recommending the future works on how this research can be extended.

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