ACRS 2022
MONGOLIA

ASSESSING AND ANALYZING THE CORRELATION BETWEEN CRIME AND BUILT-UP INDEX USING MULTI-TEMPORAL LANDSAT IMAGES IN PENINSULAR MALAYSIA

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KEY WORDS: remote sensing, crime pattern, regression, indices

ABSTRACT: Nowadays, the rate of criminal threats to countries across the world is increasing. According to the crime and safety index, Malaysia's crime index was ranked at number 53, which is 63.85 and 36.15 for the crime and safety index value, respectively. Physical development, which is sometimes closely linked to crime and security, plays a pivotal role in promoting a peaceful environment. Hence, this research evaluates and discusses the relationship between development areas and crime patterns as an initiative to improve the security aspect of the Malaysian people. In addition, it also looks at population and other crime-related causes to further reduce the criminal activities index. Landsat image was used to detect built-up areas change from 2009 to 2018, based on Built-up Index (BUI) algorithm. BUI gave their relative simplicity and ease of implementation, such methods have been widely adopted for monitoring built-up areas and besides will provide information on population and household income data. Historical data on property crime and violence were extracted from the analysis of crime patterns. The result indicated that BUI data and population had a positive relationship with criminal cases while household income had a negative relationship. This study demonstrates the advantages of using multi-temporal Landsat imagery in the extraction of the built-in environment together with population data and household income to predict criminal cases where R^2 is 80%.

1. INTRODUCTION

The violence and crime that exists in the most countries, experiencing a significant increase and it is affecting the economy to develop and grow. According to the crime and safety index, Malaysia's crime index was ranked at number 53, which is 63.85 and 36.15 for the crime and safety index value, respectively (Numbeo, 2022). As reporting by the Royal Malaysian Police (RMP), there are two types of crimes that often occur in Malaysia, namely property crimes and violence crimes. The first category includes motor vehicle theft, household theft, and burglary. Meanwhile, types of violent crime are murder, robbery, rape and causing hurt. As the reporting is based on the classification case, a total of violent crime cases are 16,902 while 71,760 of property crime cases (RMP, 2018). Selangor ranks the highest crime cases among the states, followed by Kuala Lumpur and Johor.

There are various indicators used to assess the level of the crime index, one of the ways is by assessing its association with the built-up area. Rapidly built-up areas is challenge in social change and social transformation and are associated with an increase in criminal activity. This was reviewed by Ludin et al., 2013, who studied the relationship between criminal activity and physical and social space. In addition, Mansor et al. (2019) studied about criminal activity, and was also found to have a positive relationship between urban development and criminal activity. These are particularly violent crimes, property crimes, and drug abuse cases. However, there is also other research that examines the relationship between population and crime. According to Chang et al. (2018), in their study they found that, if the population size increases by 100%, crime incidence may increase by 120%. Meanwhile , an investigation by Chan (2015), obtained different results. This is because the study was tried to track the link between crime and Normalized Difference Vegetation Index (NDVI). He has conclusively found that the correlation between crime and vegetation in Jefferson County, Kentucy was significantly negative. Researchers provide evidence in exploring the influence of plants on crime and how the condition of plants can be better incorporated in managing crime in built-up areas.

In Malaysia, small-scale research and case studies are beginning to emerge linking between built-up areas and crime guided by imagery. The limited use of remote sensing images for this task is due to most studies focusing on geographical distributions and temporal patterns using Geographic Information Systems (GIS), such as the study conducted by Anak et al., (2020). In this study, they found a high density of property crime in the Kota Kinabalu zone, while violent crime is found in two zones, namely Kota Kinabalu and Signal Hill. The study used the Kernal density analysis method. Meanwhile, another study, Ludin et al. (2013) used a hotspot analysis and found a strong relationship between crimes and land use patterns in Ampang Jaya Municipal Council. In additional, some of the past studies also focus on the statistical method such as by Zakaria & Rahman (2015). They found out that crime occurred nonrandomly in Penisular Malaysia, suggesting positive spatial autocorrelation. There are also another studies focused on expert opinion or discussing the causes and consequences of crime. The study conducted by Hamzah & Daud (2018), has found that, there is a measurable correlation in which foreign workers benefit the national development process in various sectors. However, their growing number has disrupted the local economy and communities

Therefore, this research was conducted to explores the feasibility and utility of remotely sensed satellite imagery to identify urban remote sensing indices that may be associated with criminal activity. A review of the remote sensing literature suggests that, imagery is compatible with the monitoring and mapping of changes in built-up within urban areas as the impacts of population growth and urbanization increase (As-syakur et al., 2012). Our interest in this research is to identify whether remote sensing images can provide information about the relative risk of this crime that may not be available to crime analysts. The objectives in this study are:

1. To study crime patterns in Peninsular Malaysia.
2. To extract the Built-up Index (BUI) using Landsat-8 images.
3. To identify the strength of the relationship between BUI and criminal cases, together with population data and household income.

2. METHODOLOGY

2.1 Study Area

The study was conducted in Peninsular Malaysia (Figure 1). Peninsular Malaysia, also known as West Malaysia, is the part of Malaysia which occupies the southern half of the Malay Peninsula in Southeast Asia and the nearby islands. Its area totals 132,091 km^2, which is nearly 39.97% of the total area of the country; the other 60.03% is East Malaysia. It shares a land border with Thailand to the north. Peninsular Malaysia, consists of 11 states, details are shown in Table 1. The population of Peninsular Malaysia in 2010 was 21,898,991 with a breakdown of 13,312,942 being Bumiputera, 5,348,730 Chinese, 1,837,919 Indians, 127,915 were other races and 1,271,484 were non-citizens. Meanwhile, as a result of rapid growth in the 2020, the population increase to 26,465,721 people of which 16,469,559 are Bumiputeras, 6,088,155 Chinese, 1,986,431 Indians, 169,050 other races and a total of 1,752,526 non-citizens (DOSM, 2020). The increase in population resulted in many new settlements and built-up areas being established. These new settlements and construction areas are typically located in major urban areas, with fast-growing economic sectors, such as Kuala Lumpur, Johor Bahru, and Georgetown. The sheer amount of built-up areas and the increasing multi-racial population in the place can invite various problems of social symptoms and criminal behaviour.

Table 1 : Shows the states in Peninsular Malaysia as well as the area and percentage of area (Department of Survey and Mapping Malaysia, 2017)

No	STATE	Area (km^2)	Percentage Area (%)
1	Johor	19,166	5.80
2	Kedah	9,425	2.85
3	Kelantan	15,105	4.57
4	Melaka	1,713	0.52
5	Negeri Sembilan	6,657	2.01
6	Pahang	35,965	10.88
7	Perak	21,038	6.36
8	Perlis	795	0.24
9	Pulau Pinang	1,031	0.31
10	Selangor	7,930	2.40
11	Terengganu	12,974	3.93
12	Federal Territories of Kuala Lumpur	243	0.07

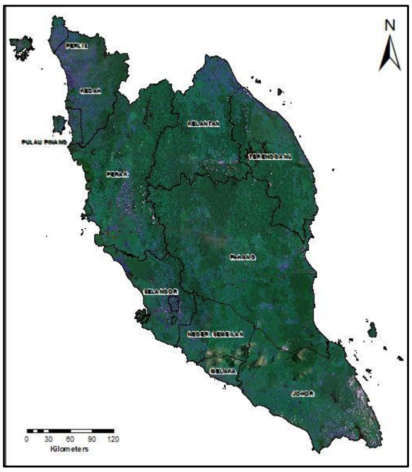

Figure 1: Map of Peninsular Malaysia

In this paper, the planning and preparation of information is an important stage to achieve the objectives of the research. The information and techniques that enable the interactive process to be performed are described in Figure 2. It consists of two steps before reaching to the analysis part and result. Data preparation is the basic step for implementation, after that projection of the raster dataset takes place. On the other hands, the spatial features from the historical criminal dataset was mapped. In the last step, a crime database was created, after which the BUI was applied to it and then results and analysis were implemented respectively.

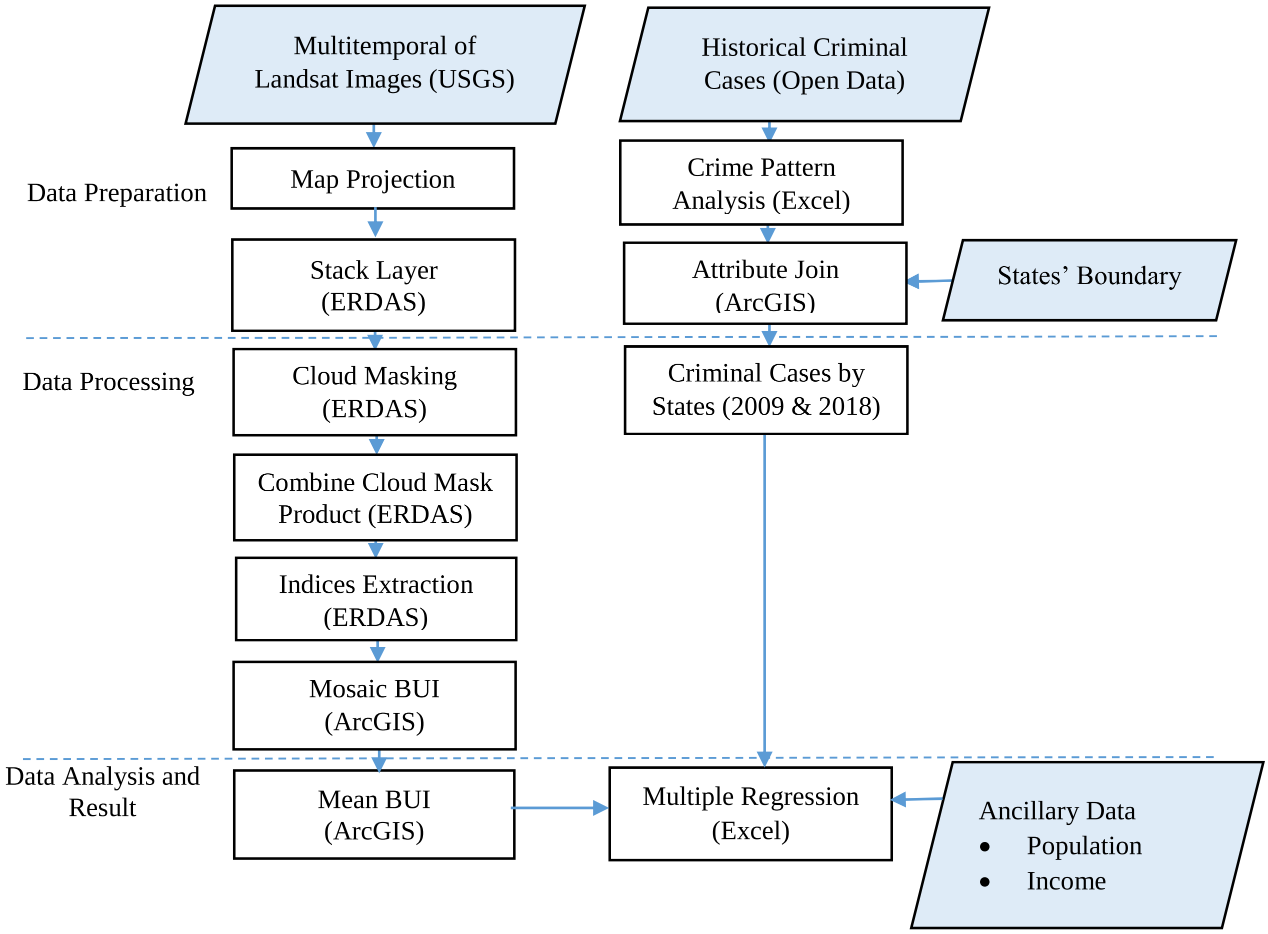

Figure 2 : Flow Chart of methodology research

2.2 Data Collection

2.2.1 Landsat-8 and Landsat-5

Multi-bands satellite image has proved potential and has been widely used to investigate the changes on the earth's surface. For large coverage and regional land use studies, satellite images are suitable and can derive useful information to fulfill the purposes. Land use planning and change are the other crucial missions derived from the investigation of Landsat data (Prasomsup et al., 2020). In order to achieve the aim of the study, there are two types of Landsat satellite images used. Landsat 8 OLI/TIRS Collection 1 Level-1 for the year 2018 and Landsat 5 TM Collection 1 Level-1 for the year 2009 were downloaded from the earthexplorer.usgs.gov website. Twelve (12) path/row of Landsat-8 and Landsat-5 data covered Peninsular Malaysia were processes. At least 94 scenes for corresponding years 2018 and 2009 are used to cover the whole study area. Nevertheless, Due to cloud covers presence on most of the images, hence, more than one dates over the same path/row for each year we utilized. Cloud mask processing with an objective to extract BUI from cloud-free images will be discussed in detail in the Image Processing part of this paper. Only band 4 (Red), band 5 (NIR), and band 6 (SWIR-1) from Landsat-8 image and band 3 (Red), band 4 (NIR), and band 5 (SWIR-1) from Landsat-5 image were used in this study. A total of 48 scenes from Landsat-8 in the year 2018 and 46 scenes from Landsat-5 in the year 2009 were downloaded.

2.2.2 Historical Criminal Cases

The Royal Malaysian Police (RMP) uses the terms crime index as a measure of the general crime situation in the country. Crimes index are defined as crimes that are reported with sufficient regularity and with sufficient significance to be meaningful as an index to the crime situation. For a crime to be classified as a crime index, it has to be reported to the police and those that are unreported are not included in the index. To achieve the objective of finding the correlation between criminal cases and built-up environment, historical crime data for the whole study area from the year 2004 to 2018 are downloaded from an online open-source data sharing website introduced by the Ministry in the Prime Minister's Office, Government of Malaysia. All data are available at www.data.gov.my. The data consist of two types of crime which are property and violence crime and organized in tabular form by State in Peninsular

Malaysia. All the data were analyzed statistically for better understanding and will be discussed further in the crime pattern analysis part of this paper.

2.2.3 Ancillary Data

Ancillary data from Department of Statistics Malaysia (DOSM) which is the source of Malaysia's official statistics via website https://www.dosm.gov.my were used. Population and Income statistical data for year 2009 and 2018 were analized to find if there is any correlation or significant factor that can be relate to the crime cases. Figure 3 and Figure 4 shows the population graduated colour map for the study area. According to DOSM description, the household mean income refer to total mean incomes received (accrued) by members of households, both in cash or in kinds which occur repeatedly within the reference period. Figure 5 and Figure 6 shows the mean income choropleth map for the study area.

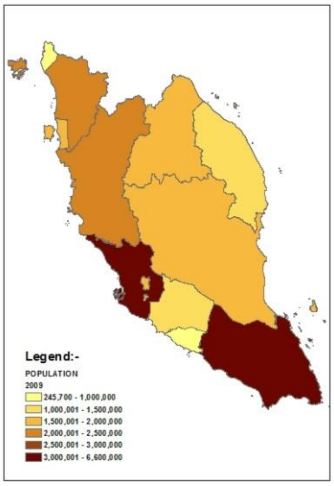

Figure 3: **Population graduated colour map for year 2009**

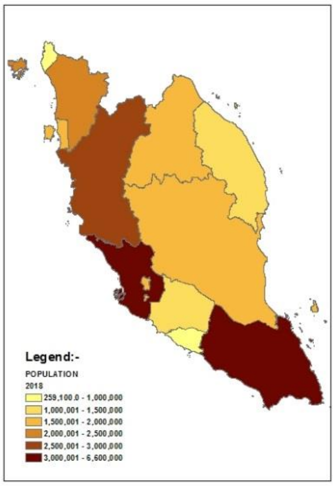

Figure 4: **Population graduated colour map for year 2018**

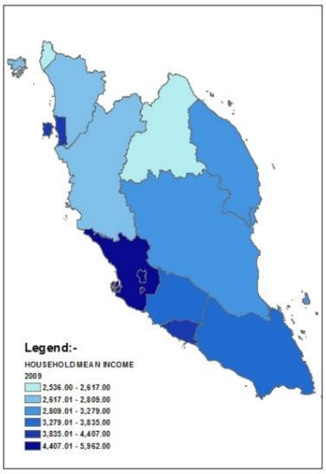

Figure 5: **Household mean income graduated colour map for year 2009**

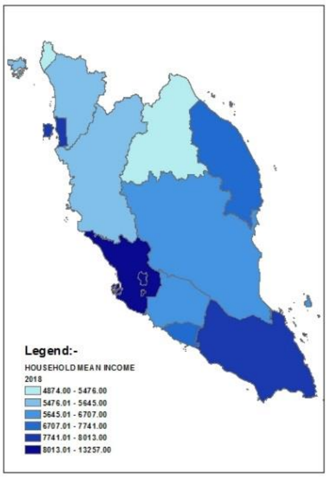

Figure 6: **Household mean income graduated colour map for year 2018**

2.3 Data Preparation

2.3.1 Define Map Projection

Map projections were used for presentation purposes and simplifying calculations of distances, areas, and volumes (Manchuk, 2009). All multi-temporal remote sensing imagery downloaded from The Landsat Collection 1 Level-1 via website https://earthexplorer.usgs.gov/ used in this study was original in Universal Transverse Mercator (UTM) Grid System and based on World Geodetic System 1984 (WGS84) datum. For our study area, Peninsular Malaysia (West Malaysia) projection was UTM Zone 47N and UTM Zone 48N. The raster projection conversion step was necessary to make those satellite images useful, accurately matched, and uniform with the crime ancillary data in the WGS84 coordinate system.

2.3.2 Stack Layers

Stack layers is a process of join a single. In this study, only band 4 (Red), band 5 (NIR), and band 6 (SWIR-1) from Landsat-8 image and band 3 (Red), band 4 (NIR), and band 5 (SWIR-1) from Landsat-5 image were used in stack layers processes.

2.3.3 Crime Pattern Analysis

The analysis of crime patterns provides general trends of crime occurring in the country to gain a better understanding of the most prevalent crimes. The analysis of crime patterns was done using crime data over a period of 15 years in 12 States of Peninsular Malaysia. Then we decided to use the data in 2009 and 2018 followed by joining attributes with state boundaries to issue criminal cases by state.

2.4 Image Processing

2.4.1 Cloud Masking

Cloud masking was a step to remove the cloud and their shadows before producing a cloud-free scene product. The cloud-free scene is the virtuous product to monitor the land area and related applications. Each pixel in the quality assessment (QA) band contains unsigned integers that represent bit-packed combinations of surface, atmospheric, and sensor conditions that can affect the overall usefulness of a given pixel. QA band holds information on the cloud and its shadow confidence in three levels, low (0%-33%), medium (34%-46%), and high 67%-100% (Duong, 2020). The pixel value for the QA band is also explained briefly in the USGS Landsat Collection 1 Level-1 Quality Assessment Band (USGS, 2018). For fast and standard work for all multi-temporal Landsat imagery, this study applied cloud masking using a 16-bit Landsat Collection 1 Level-1 quality assessment band (QA) to all data products used in the study. Table 2 below portrays the suggested QA band values for sensor Landsat 5 and Landsat 8 Operational Land Imager (OLI) used in this study.

Table 2: **QA band value for cloud masking**

No.	Sensor	Bit band	QA Band Value for Cloud Masking
1.	Landsat 5	16	>672
2.	Landsat 8 OLI	16	>=2800

Then we apply the formula using Equation 1 to produce a cloud mask product.

(EITHER Band QA *0 IF (Band QA >= 2800) OR Band QA * 1 OTHERWISE) * Stack Layers (1)

Then we combine the cloud mask image using Equation 2 to produce a cloud-free scene product for each path/row of Landsat images. We chose the least cloudy image for the first image.

EITHER Image 1_cloudmask + Image 2_cloudmask IF (Image 1_cloudmask == 0) OR Image 1_cloudmask * 1 OTHERWISE (2)

2.4.2 Indices Extraction

Urban sprawl can be easily investigated by using remote sensing multi-temporal data. The urban or built-up area expansion always shows significance to economic and population growth. According to Land Use and Land Cover Classification System for Use with Remote Sensor Data developed by the United States Geological Survey, there are six sub-level defined as urban or built-up areas which are Residential, Commercial and Services, Industrial, Transportation, Communication and Utilities, Industrial and Commercial Complexes, Mixed Urban or Built-up Land, and Other Urban or Built-up Land (James R. Anderson, Ernest E. Hardy, John T. Roach, 1976). The researcher has developed a combination of spectral indices as a tool to classify the urban spatial using remote sensing data. Built-Up Index (BUI) was significant to extract urban patterns and differentiate between built-up area, non-urban, and vegetation area (Badlani et al., 2017) (Prasomsup et al., 2020). BUI is the index for analysis of urban pattern using Normalize Difference Built-up Index (NDBI) and Normalized Difference Vegetation Index (NDVI). Built-up index is the binary image with only higher positive value indicates built-up and barren thus, allows BUI to map the built-up area automatically (Table 3).

Table 3: Indices

Indices	Equation	Range	Interpretation
BUI	NDBI – NDVI	-2 to +2	Higher positive value indicates built-up and barren.
NDBI	(SWIR – NIR) / (SWIR + NIR)	-1 to +1	Negative value represents water bodies where as higher value represents built-up areas. NDBI value for vegetation is low.
NDVI	(NIR – Red) / (NIR + Red)	-1 to +1	NDVI = -1 to 0 represent water bodies. NDVI = -0.1 to 0.1 represent barren rocks, sand, or snow. NDVI = 0.2 to 0.5 represent shrubs and grasslands or senescing crops. NDVI = 0.6 to 1.0 represent dense vegetation or tropical rainforest.

Then we mosaic all the individual scene of BUI extraction into a single scene of BUI's Peninsular Malaysia. Finally we calculate the average of all BUI cells in the value raster that belong to the same states as the output cell (Chan, 2015).

2.5 Multiple Regression

For statistical analysis, multiple regression analysis was used to estimate the relationship between criminal cases, BUI data, population and household income. Crimical cases was used as dependent variables while BUI, population and income as independent variables. The multiple R is the correlation coefficient, can be any value between -1 to 1, and indicates the relationship strength:

1	strong positive relationship
-1	strong negative relationship
0	no relationship

R square (R^2) is the coefficient of determination, which is used as an indicator of the goodness of fit. In other words, the percentage (%) of the dependent variable (y-value) are explained by the independent variables (x-values).

The regression result such as **Equation 3**.

$$Y= \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_2 X_2 \qquad (3)$$

Y= dependent variable
α = Intercept
β = Coefficient

3. RESULT AND DISCUSSION

3.1 Crime Pattern Analysis

The numerical crime counts for each states are shown in Figure 7. Criminal cases are declining in most states from 2004 to 2018. The general pattern shows the lowest number of criminal cases was in 2018 while 2009 represented the highest number of criminal cases for all states. Figure 8 shown the crime density in 2009 and 2018. Criminal cases decreased by 60% in 2018, not exceeded 30,000 cases compared to 2009. However, Selangor still has the highest number of cases. This proves that the crime rate in urban areas is higher than in rural areas is true.

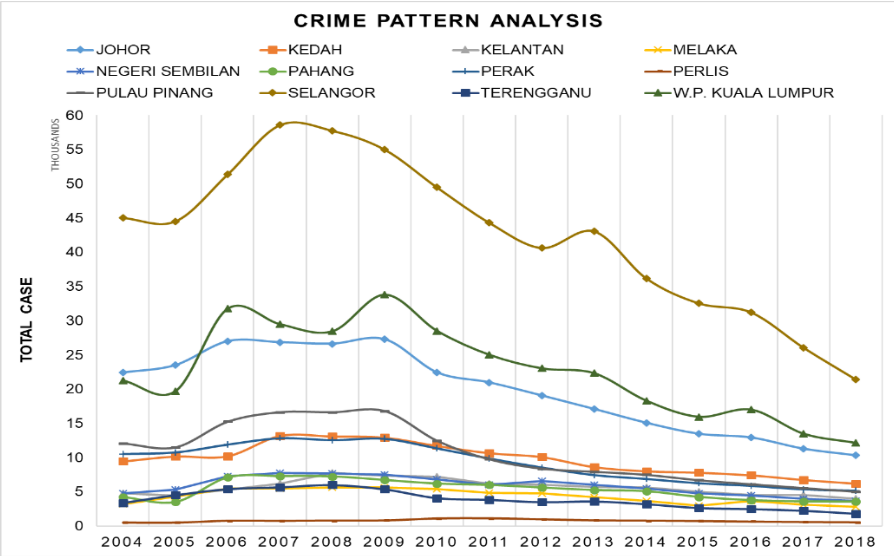

Figure 7: Crime pattern analysis (source**:** www.data.gov.my)

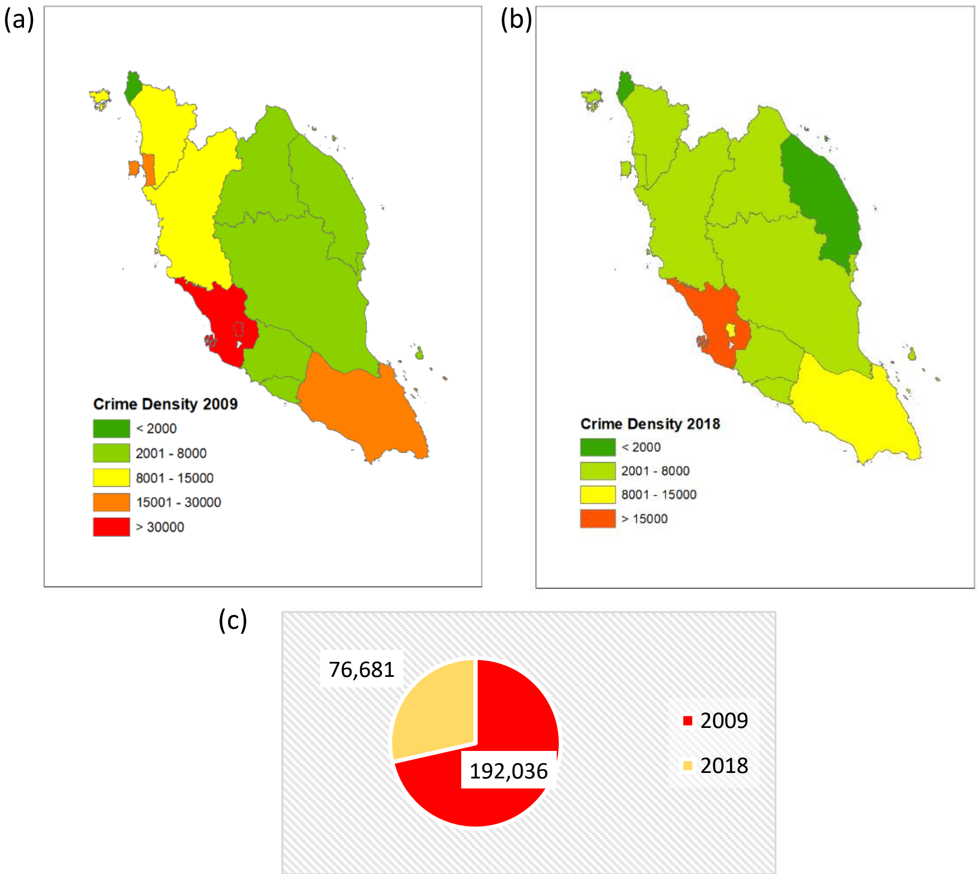

Figure 8: Crime density; (a) 2009; (b) 2018; (c) total crime cases in Peninsular Malaysia

3.2 BUI Extraction

Figure 9 shows the extraction of BUI results from a combination of Landsat TM 2009 and Landsat OLI 2018 time-series images using a total of 46 to 48 images (4 times more than the actual scene), for BUI extraction for both 2009 and 2018, respectively due to cloud coverage limit. For further analysis, mean BUI was examine (Chan, 2015). By examining the mean BUI map (Figure 10), the highest BUI value is in Kuala Lumpur which indicates built-up and barren areas are the dominant land use, and low vegetation. In Penang the mean value of BUI decreased, from 2009 to 2018. This was hypothesized that, it was due to the change of the paddy planting season, the condition being like barren during plowing and after harvest (Figure 11). However, the overall mean of BUI for each states did not show a significant change between 2009 and 2018, probably due to the large coverage for each state border and the green area still being the majority land cover.

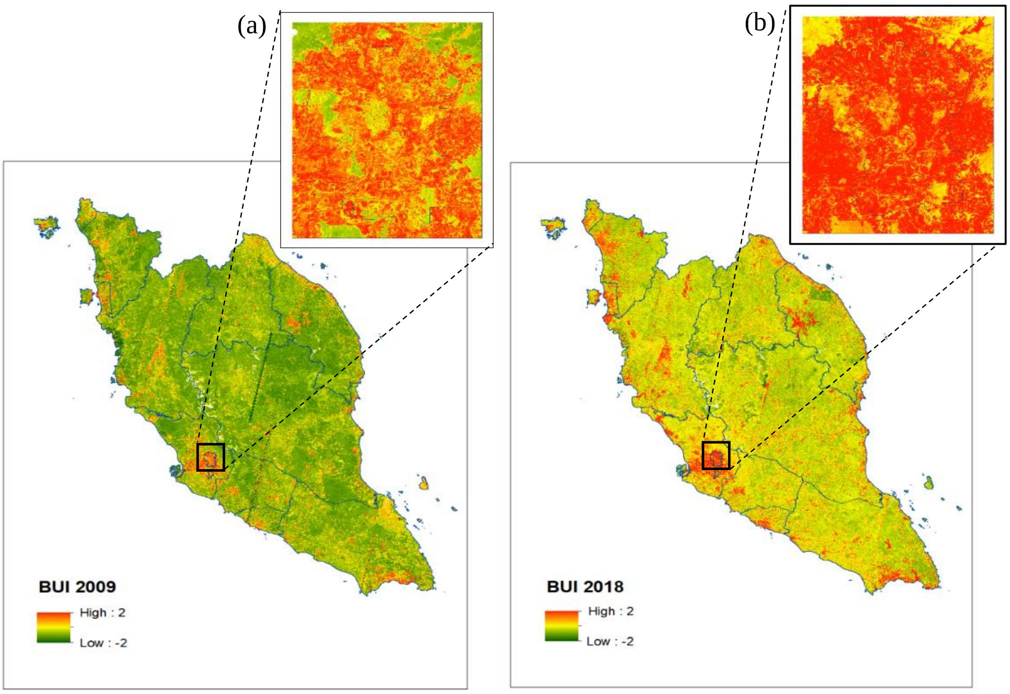

Figure 9: BUI extraction; (a) Kuala Lumpur 2009; (b) Kuala Lumpur 2018

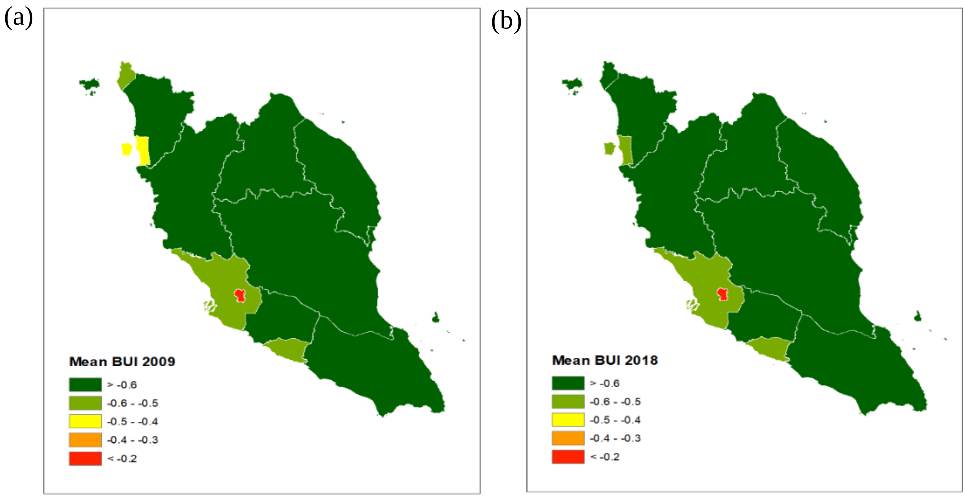

Figure 10: Mean BUI (a) 2009; (b) 2018

Figure 11: BUI value change due to paddy planting season

3.3 Regression Analysis

Table 4 shows the relationship between crime rate with BUI, population and income. Multiple R value of 89% indicate a strong relationship between crime rate with BUI, population and income. There was a positive relationship between crime rate with BUI and population while negative relationship between crime rate and income (Equation 4). This indicate that crime rate will high when the population increase, BUI value higher and lower income. R square value 0.8 indicate that 80% of criminal cases are contributed by urban development, population and household income and 20% may be contributed by other factors such as foreign workers, education and many more. The standard error value of 6005 is a relatively large number, probably due to the BUI value where it does not show a significant change between the two years but there is a large range difference between criminal cases in 2009 and 2018. We hypothesize that the results of the study will improved if running the analysis for the same year but would reduce the robustness of the model. ANOVA Significance F value below 0.05 means the model is statistically significant and the independent variable represent the dependent variable.

$$\text{Crime rate} = 42582 + 0.01*\text{population} + 54987*\text{BUI} - 2.37*\text{income} \quad (4)$$

Table 4: Regression Analysis

Regression Statistics	
Multiple R	0.89
R Square	0.80
Adjusted R Square	0.77
Standard Error	6005.25
Observations	24

ANOVA	*df*	*SS*	*MS*	*F*	*Significance F*
Regression	3	2866732563	955577521	26.49	3.60E-07
Residual	20	721261631.3	36063081.6		
Total	23	3587994194			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	42581.85	7545.85	5.64	0.00
Population	0.01	0.00	7.57	0.00
BUI	54987.00	9734.09	5.65	0.00
Household Income	-2.37	0.57	-4.15	0.00

4. CONCLUSION

Based on the analysis of crime patterns, criminal cases are declining in most states from 2004 to 2018 in Peninsular Malaysia. This is likely due to increased household income, tighter enforcement activities by the authorities, as well as public awareness in increasing protection from the threat of crime. The results of the study showed that the highest number of criminal cases was in 2009 while the lowest number of criminal cases was in 2018, a decrease of 60%. This study was also undertaken to analyze crime analysis and the number of criminals in BUI. This revealed that population and BUI had a positive relationship with criminal cases, while income had a negative relationship with criminal cases with an R^2 of 80%. We can conclude that 80% of criminal cases are contributed by urban development, population, and household income and 20% may be contributed by other factors such as foreign workers, education, and many more. As a recommendation for future works, we suggest using location-specific crime data and possibly focusing on specific types of crime for more detailed analysis. In addition, modification of the BUI index may be required to improve accuracy.

ACKNOWLEDGEMENT

The authors would like to thank Dr. Mohamed Kamal Azidy bin Musa for his useful comments, suggestions and revised the manuscript. Special thanks also to MYSA Research and Development Program Management Committee for allowing us to conduct this research study and revised the manuscript.

DISCLAIMER

Historical crime data for the study area from the year 2004 to 2018 are downloaded from an online open-source data sharing website introduced by the Ministry in the Prime Minister's Office, Government of Malaysia. All data are available at www.data.gov.my.

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