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Research Paper

Green Spaces and Crime: Spatial Modeling of Socio-Economic Influences in Jakarta's Urban Areas, 2022

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Abstract

Urban crime is a multidimensional issue influenced by environmental, economic, and social interactions. This study investigates factors affecting crime rates in DKI Jakarta, including green open space (RTH), night light intensity (NTL), security services and worship facilities, extreme poverty, relative wealth index (RWI), and population density. Using remote sensing and spectral indices, green open spaces were identified and classified with a random forest model, achieving 95.53% overall accuracy and a kappa coefficient of 94.19%. Spatial regression analysis with Queen Contiguity weights was employed to examine the influence of these factors on crime rates. Results from the Spatial Autoregressive Moving Average (SARMA) model show that green space area, NTL, and extreme poverty significantly impact crime rates. Districts with more green spaces, such as South Jakarta, experienced lower crime rates, while densely populated and impoverished areas, such as North Jakarta, exhibited higher crime rates. The study highlights the importance of ecological factors in crime prevention, emphasizing the integration of green space planning and big data analytics. These findings provide actionable insights for policymakers to develop safer urban environments and support Indonesia's efforts toward achieving SDG 16 on peace and justice.

Keywords: Crime; Green Space; Random Forest; Spatial Socioeconomic Ecology.

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1. Introduction

Urban development is a major factor influencing the global community (Al'Alim et al., 2023). Metropolitan areas, such as DKI Jakarta, with populations exceeding 1,000,000, often experience complex social dynamics, leading to impersonal relationships and social indifference (Kusmana, 2015). These dynamics usually manifest as social problems, including crime, which is a violation of societal norms and laws, causing harm to individuals and communities. Therefore, crime will be a problem that must be resolved immediately to achieve sustainable development goals in crime prevention by SDGs Goal 16 (Whaites, 2016). In urban areas, crime tends to occur more frequently than in non-urban areas (Pringle, 1984). Therefore DKI Jakarta, as one of the largest urban provinces in Indonesia, is faced with complex challenges related to crime. DKI Jakarta has a fairly high crime total. According to BPS publication in the 2023 criminal statistics, the third highest number of crimes in 2022 came from the Metro Jaya Police report (covering DKI Jakarta, Depok, Tangerang, and Bekasi) with 32,534 incidents (BPS, 2023).

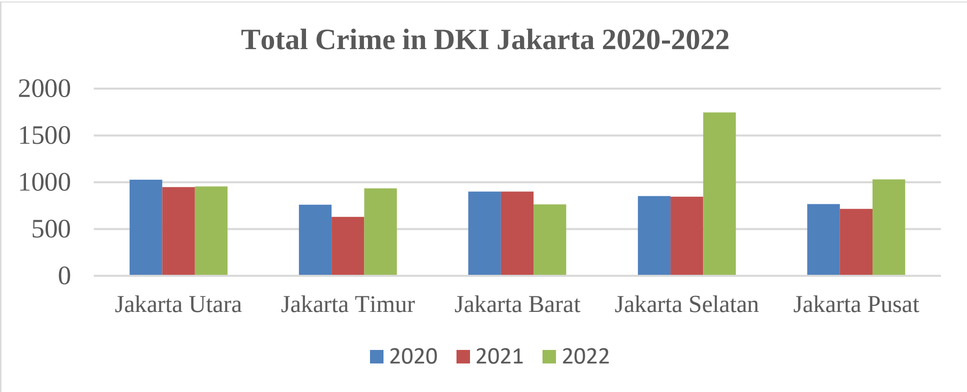

Figure 1. Total Crime in DKI Jakarta 2020-2022
Source: BPS, 2023

It is difficult to expect that crime can be completely eliminated in an area (Jamaludin, 2017), but it is not impossible if crime can be prevented. Crime prevention is an effort to intervene by inhibiting, weakening, or diverting the factors that cause crime reduce its risk and seriousness. Research on crime prevention has primarily focused on social and economic factors, such as poverty, unemployment, and inequality (Farrington, 2000). In contrast, the role of ecological and environmental variables, such as urban design and green spaces, has been less explored, particularly in developing countries like Indonesia.

Environmental factors play a critical role in shaping urban crime patterns. The Crime Prevention Through Environmental Design (CPTED) framework emphasizes optimizing the built environment to reduce crime opportunities and enhance residents' perceptions of safety (Pringle, 1984). The preparation of Green Open Space (RTH) plans in urban areas is one of the common practices in an effort to maintain the quality of the urban environment (Wizaka, 2012; Haider & Lamtrakul, 2018).

Public and private green spaces not only provide places for recreation, exercise, and healthy social interaction but also act as an antidote to the negative psychological impacts of urban life (Kuo & Sullivan, 2001). Activities in green spaces can increase positive emotions, such as life satisfaction, happiness, and self-esteem, and decrease negative emotions, such as depression, anxiety, and stress (Gascon et al., 2018), which can cause "outbursts" of anger and lead to violence. Previous research has shown that well-managed green spaces can reduce crime rates by creating a safer and more well-maintained environment (Sukartini et al., 2021).

In Law No. 26 of 2007 on Spatial Planning and Government Regulation No. 15 of 2010, the ideal need for green spaces is at least 30% of the city area (20% public green open space and 10% private green open space) (No, 2007). The availability of data from the Ministry of Environment and Forestry (MoEF) is not able to estimate up to the sub-district level and cover the entire area of public and private green spaces. Innovation is needed to obtain more detailed data. Therefore, in estimating the area of green spaces, satellite imagery and machine learning can be utilized with the advantage of being more efficient and real-time.

Adequate night lighting can create a sense of security for residents who do activities at night (Uttley et al., 2024). Dark Places and Crime Theory and Natural Surveillance Theory reveal that a lack of lighting at night can increase opportunities for criminals to commit criminal acts. Well-lit areas allow for more natural surveillance by the community. From a social perspective, densely populated areas coupled with a highly poor population can create opportunities for crime due to more intense interactions in accordance with Social Disorganization Theory. This is a challenge for law enforcement to provide effective supervision of criminal activity, so a better supervision system is needed through community empowerment.

The phenomenon of criminality is interesting to study in its spatial aspects from the point of view of social ecology and criminal economics, such as the availability of green spaces, nighttime time lighting, population density, relative wealth index, extreme poverty, and point of interest security services and worship facilities. Tobler's Law (1970) states that phenomena in a point or area have a close relationship with phenomena in adjacent points or areas (Anselin & Li, 2020). In the context of crime, this implies that crime in an area tends to be influenced by conditions in neighboring areas. To understand the influence of ecological, social, and economic aspects on urban crime in a geographical context, spatial regression analysis was conducted.

While previous studies (Mardinsyah & Sukartini, 2020; Riyardi & Guritno, 2022; Wicaksono, 2023) have examined crime in urban areas, most focus on social and economic dimensions (using conventional data and often overlook ecological aspects, particularly green open space as in studies (Deng, 2015; Bogar & Beyer, 2016; Shepley et al., 2019), in the context of developing countries. Additionally, existing studies rarely integrate high-resolution spatial data or advanced analytics such as machine learning and spatial econometrics at the sub-district level. This study addresses these gaps by combining remote sensing, Random Forest classification, and spatial regression (SARMA) to explore the relationship between green open space, socioeconomic indicators, and crime in Jakarta. The novelty lies in the integration of big data (satellite imagery), machine learning, and spatial statistical modeling to assess crime risk at a fine spatial scale, supported by the creation of an interactive dashboard for policy use.

Based on the description and background that have been conveyed, the objectives of this study are as follows: (1) To estimate the measurement of green space area based on the results of regional classification using Random Forest; (2) to know the general description of crime-prone areas, and ecological, social, and economic factors for each sub-district in DKI Jakarta; (3) to measure the influence between ecological, social, economic factors on urban crime rates in DKI Jakarta with a spatial analysis approach; and (4) create an interactive dashboard presenting the results of the estimation of green space area and spatial analysis of the crime rate.

Moreover, conventional data sources, such as police reports and surveys, remain the dominant approach in analyzing crime in Indonesia. These methods often lack spatial granularity and real-time capabilities. By contrast, big data technologies, including satellite imagery and machine learning, offer innovative solutions to assess environmental factors and their relationship to crime with greater precision and efficiency. As Indonesia transitions into the era of big data utilization, incorporating advanced analytics into crime prevention strategies represents a novel and timely approach (Wang et al., 2012).

2. Methods

This research uses data from various sources, both big data and conventional data, covering the reference year 2022. The reference year 2022 was chosen due to its relevance and the availability of comprehensive data, offering the latest insights into urban crime patterns in DKI Jakarta. This year also marks a transitional period from the COVID-19 pandemic and is considered relatively stable. Additionally, it signals Indonesia's shift towards broader use of satellite imagery and machine learning technologies, allowing for more detailed and real-time analysis of green open spaces and their impact on urban crime. Focusing on this year aims to provide actionable recommendations for policymakers. The unit of analysis in this study is the sub-districts in DKI Jakarta in order to get more specific results and in-depth analysis for the smallest level of a region. The study does not include the Thousand Islands Regency, as it will cause regional anomalies because the scope of the study only discusses cities, not regencies.

The study includes both public and private green open spaces, such as parks, urban forests, cemeteries, green areas in settlements, offices, home yards, green lanes along roads, rivers, industrial areas, railroad tracks, agricultural land, plantations, and others. The use of both public and private green open spaces is important because, from the perspective of satellite imagery using various indices to show land cover, the resulting green open space areas are integrated as a whole, making it difficult to distinguish whether they fall under public or private categories. Additionally, data from the Ministry of Environment and Forestry (KLHK) does not yet include or facilitate green open space data in SHP format, meaning official data is not yet available. Crime typically occurs not only in public spaces but also in private areas, such as in victims' homes. Therefore, understanding both public and private green open spaces remains essential (Brown, 2018).

The identification and estimation of green open space areas in the study utilize a combined satellite image approach using Landsat 8 OLI-TIRS and Landsat 9 OLI-TIRS, with random forest techniques applied to improve classification accuracy up to the sub-district level. Data on crimes up to the sub-district level is not available from the Central Bureau of Statistics, so data recorded in E-MP (Electronic Investigation Management) from PUSIKNAS (National Criminality Information Center) is used. The crimes recorded, based on investigator reports, include serious maltreatment, light maltreatment, domestic violence, rape, sexual abuse, theft with violence, theft with firearms, theft with sharp weapons, narcotics offenses, and public order crimes.

2.1 Study Area

This research utilizes data at the sub-district level in the urban area of DKI Jakarta without including the Thousand Islands district wih period of 2022 to spatially analyze the impact of green open space and other social and economic ecological factors on crime rates per 100,000 population. The study area covers five administrative cities, namely North Jakarta, East Jakarta, South Jakarta, West Jakarta, and Central Jakarta with a total of 42 sub-districts.

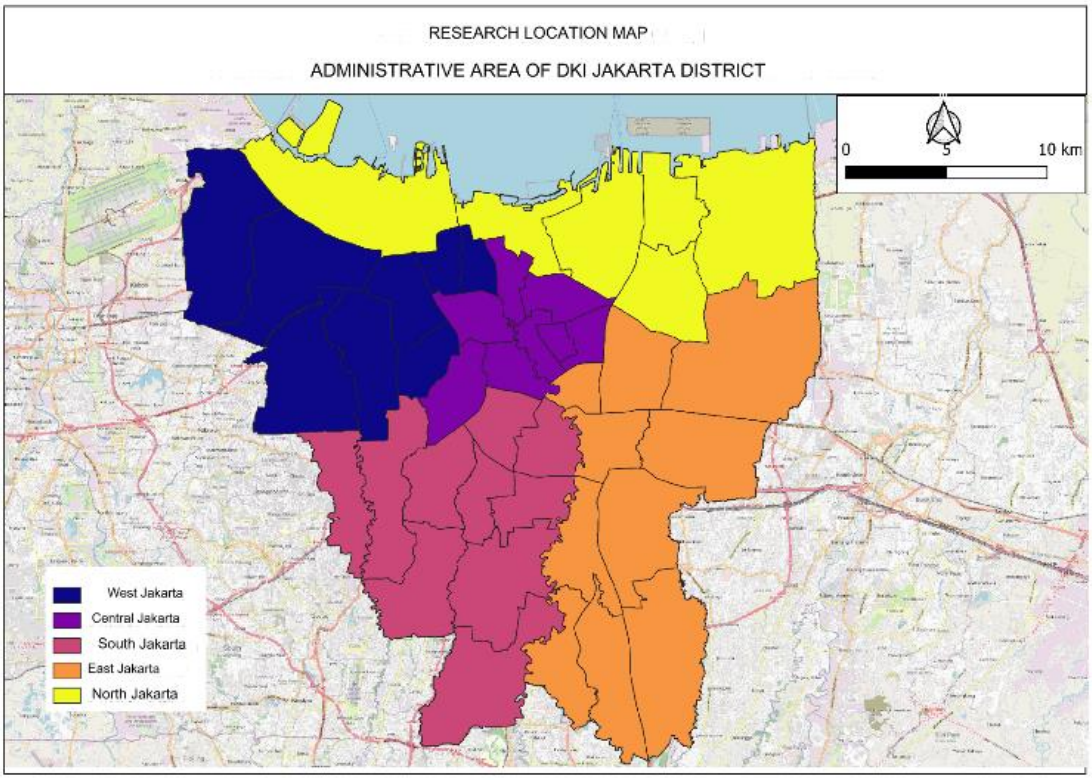

Figure 2. Study Area
Source: PPBW BIG processed with Qgis

2.2 Data Collection

Information about the data used in the study is described in the following table.

Table 1. Data used in the study

Variable	Unit	Source	Explanation
CR (Crime Rate)	Per 100,000 population	PUSIKNAS	Measures the security level of an area based on the number of reported criminal incidents. A common standard for comparing crime rates.
x_{LRTH} (Green Open Space Area)	Hectares (Ha)	Sentinel-2	Green open spaces function as natural surveillance and improve social interactions, helping to reduce crime. (Sukartini et al.,2021; Burley,2018)
x_{RWI} (*Relative Wealth Index*)		Facebook	Measures wealth distribution, indicating socioeconomic inequality, which is often associated with crime rates (Meta, 2022).
x_{NTL} (*Nighttime Time Light*)	*nanowatt* per hectare per steradian (nW/ha/sr)	NOAA/NASA VIIRS Satellite Image	Light intensity at night can affect environmental safety by increasing visibility and reducing criminal opportunities.
x_{POI} (Security Services & Worship Facilities POI)	Building units	Indonesian Earth Map (RBI)	Measures the availability of infrastructure supporting social security and crime control. (Sukartini et al., 2021; Pyle et al.,1974)
x_{KEI} (Number of Extreme Poor Individuals)	Individuals	PPKE Data, Coordinating Ministry for Human Development and Culture	Extreme poverty can create economic pressures that lead to criminal behavior.
x_{KP} (Population Density)	Individuals/km^2	BPS	High population density is often linked to social tension, which can increase the risk of crime.
Sub-district SHP Map of Indonesia		PPBW BIG	

The following presents the data collection process used in this study.

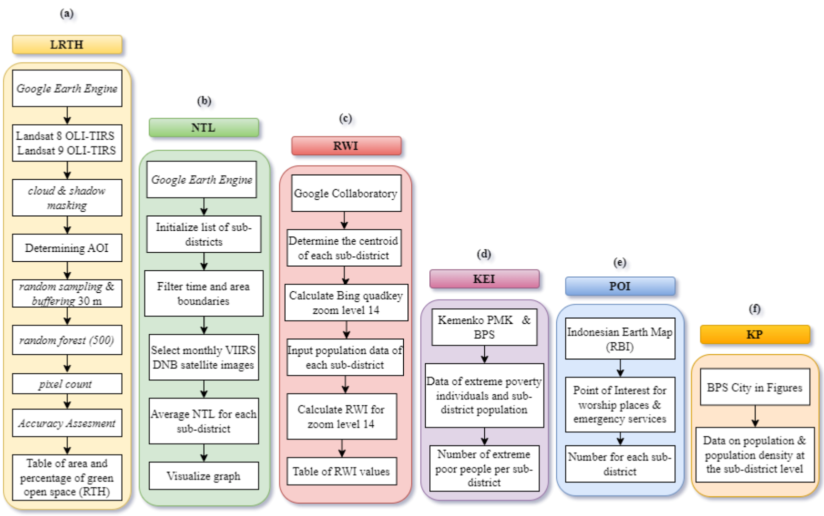

Figure 3. Data Collection Process

Source: Rahmawati & Apriyanti (2023), Sanjaya & Fianty (2023), *Meta (2022), Keputusan Menteri Koordinator Bidang Pembangunan Manusia Dan Kebudayaan Republik Indonesia No.32 Tahun 2022 (2022)* , *Nukita & Subiyanto (2017)*

2.3 Data Analysis

2.3.1 Analysis of Green Space Processing

The analysis conducted to obtain the classification of Green Open Space (RTH) in the study area involves several important steps using remote sensing data from Landsat satellites and image processing techniques, as shown in Figure 3.

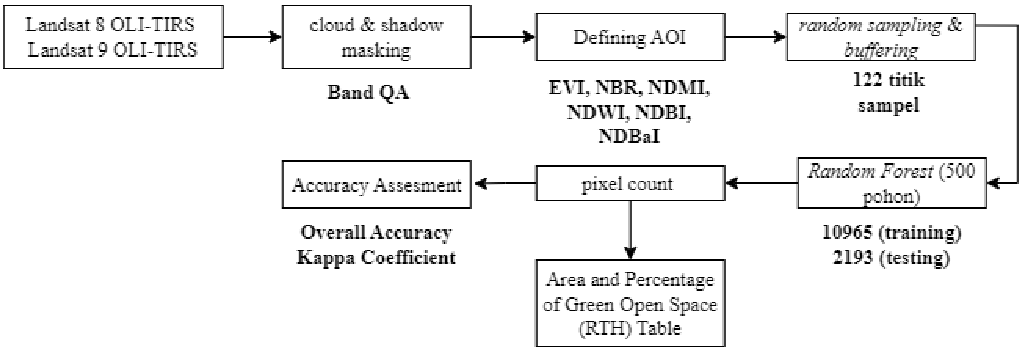

Figure 4. Green Open Space Analysis Method
Source: Rivki et al. (2020)

First, the study area was defined and displayed on a map as the Region of Interest (ROI). Next, satellite images from Landsat 8 and 9 were filtered for a specific period and processed to remove cloud interference using cloud masking techniques. The cloud process involved the band QA (Quality Assessment) technique and the median reducer function available in GEE. This results in an image that avoids pixel values that are too bright (e.g., clouds) or too dark (e.g., shadows) (Rivki et al. 2020). The clean images were then merged, and spectral indices such as EVI, NBR, NDMI, NDWI, NDBI, and NDBaI were calculated to identify specific characteristics of vegetation, soil, and water. These spectral indices were visualized on maps for visual analysis. A total of 122 samples from different land classes were taken by random sampling.

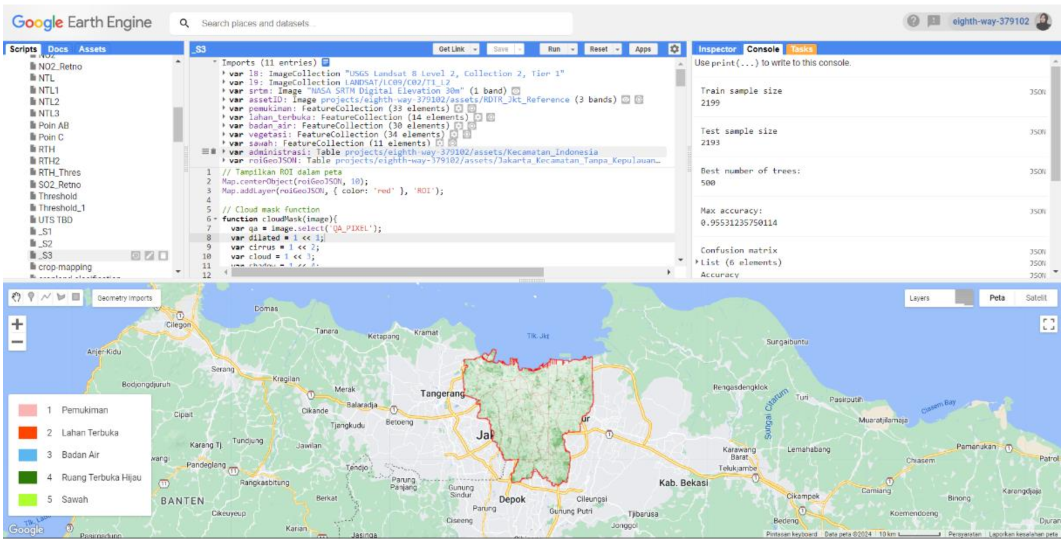

Figure 5. Green space classification process
Source: processed with Google Earth Engine

Each of these samples was then expanded with a 30-meter buffer to improve representativeness. The samples were divided into training and testing sets with a proportion of 80%:20%. There were 2199 training data points and 10965 testing data points. These were then used to train the Random Forest model. The model was validated using a confusion matrix to assess overall accuracy and the kappa coefficient. The trained model was then applied to image classification of the entire ROI. The area of each land class was calculated, and its percentage of the total area was determined to obtain a proportional distribution of green space.

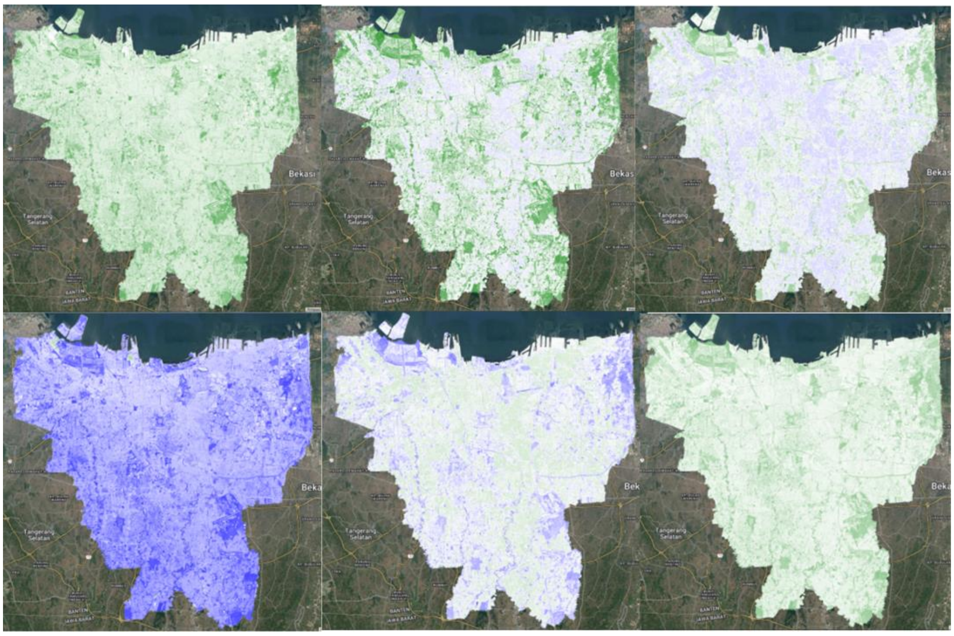

Figure 6. Spectral Index (EVI, NBR, NDMI, NDWI, NDBI, NDBaI)
Source: processed with Google Earth Engine

2.3.2 Descriptive analysis

Descriptive analysis describes the spatial distribution pattern of crime-prone areas, green space areas and other independent factors in sub-districts in DKI Jakarta. Descriptive analysis was conducted using GEE and QGIS 3.30.1 software to create thematic maps by classifying the dependent variable into five categories, namely very high, high, medium, low, and very low using the natural breaks method. Natural breaks are a method that divides observed data into classes to reduce variation within each class and maximize variance between classes.

2.3.3 Inferential Analysis

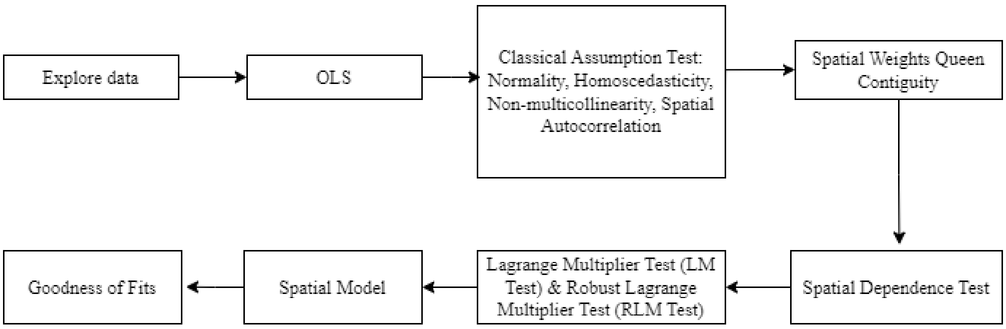

Figure 7. Spatial Analysis Method
Source: Anselin, L. (1988)

a. OLS Formation and Assumption Testing

OLS (Ordinary Least Square) is a regression method that estimates the regression coefficient (β) by reducing the sum of squared errors to be as small as possible. At this stage, an OLS model of crime risk with six independent variables will be formed. The assumption tests that must be met in the model are as follows.

(1) Normality Assumption: Checking the normality assumption is done with the Kolmogorov-Smirnov test. The hypothesis is as follows.
$H0$: The error of the regression model is normally distributed.
$H1$: The error of the regression model is not normally distributed. The test criterion is to fail to reject $H0$ if p-value ≥ α.

(2) Homoscedasticity Assumption: Checking the homoscedasticity assumption is measured using the Breusch-Pagan test. The hypothesis is as follows.
$H0$: There is homoscedasticity of the regression model.
$H1$: There is no homoscedasticity of the regression model. The test criterion is to fail to reject $H0$ if p-value ≥ α.

(3) Non-Multicollinearity Assumption: Checking the non-multicollinearity assumption can be measured by looking at the VIF value. The test criterion is to fail to reject $H0$ if the VIF value < 10. The VIF value < 10 means that there is no multicollinearity between the independent variables in the regression model.

b. Spatial Weight Matrix

The spatial weight matrix is very important in providing an overview of the relationship between one location and another in spatial regression. The basic structure of this adjacency is denoted in the spatial weighting matrix, where adjacent or intersecting regions are assigned a value of 1, while other regions are assigned a value of 0 (Anselin & Li, 2020). In this study, the Queen Contiguity weighting matrix is used, which considers the intersection of the edges with other regions.

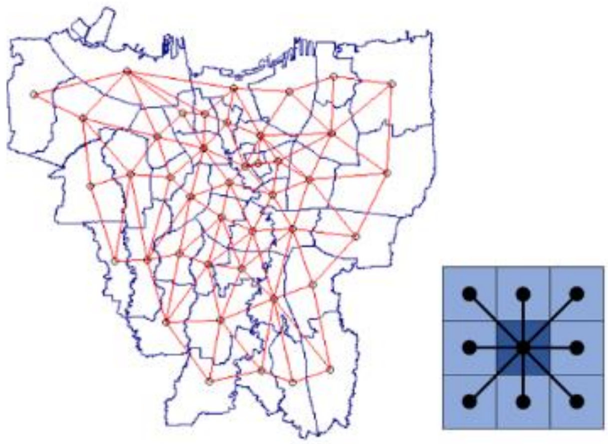

Figure 8. Queen Contiguity DKI Jakarta
Source: processed with R Studio

c. Spatial Autocorrelation Testing

Spatial autocorrelation can be measured using the Global Moran's I test. The hypothesis is as follows.
$H0$: There is no spatial autocorrelation in the crime rate.
$H1$: There is spatial autocorrelation in the crime rate.

The test criterion is to reject $H0$ if p-value < α d. Testing for Spatial Effects. Select a spatial model using the Lagrange Multiplier (LM) test because it is able to identify the existence of spatial dependence on the dependent variable, error, or both. The Lagrange Multiplier lag and Robust Lagrange Multiplier lag hypotheses are as follows.

$H0$: There is no spatial dependence of the regression model lag.
$H1$: There is spatial dependence of the regression model lag.

The Lagrange Multiplier error and Robust Lagrange Multiplier error hypotheses are as follows.

$H0$: There is no spatial dependence of the regression model error.
$H1$: There is spatial dependence of the regression model error.

The test criterion is to reject $H0$ if p-value < α. After testing, the model is selected based on the Lagrange Multiplier test results. The selected model is the model that is significant and has the largest statistical value.

d. Spatial Model Formation

Anselin explained that the SAR model arises because spatial effects occur in the lag and dependent variables, while the SEM model occurs because spatial effects are present in the error. When the data shows lag dependence and error dependence on the dependent variable, the SARMA model can be used.

3. Results and Discussions

3.1 Calculation of Green Open Space Area

Land cover data was processed using Google Earth Engine, utilizing the random forest algorithm in the classification process over a period of 1 year, January 1, 2022-December 31, 2022. The numTrees parameter is used to determine the maximum number of trees that produce the highest overall accuracy and kappa coefficient values in random forest. The maximum number of trees is 500 trees. The following confusion matrix (Table 10) is generated in the land cover classification process (settlement: label 1, open land: label 2, water body: label 3, green open space: label 4, and rice field: label 5).

Table 2. Confusion matrix of random forest classification results

		Prediction					Totally
		1	**2**	**3**	**4**	**5**	
Actual	1	665	6	0	26	1	698
	2	9	178	0	30	1	218
	3	5	0	462	2	5	474
	4	4	2	1	490	1	498
	5	0	0	0	5	300	305
Totally		683	186	463	553	308	2193

Source: processed with Google Earth Engine

The overall accuracy value for land cover in DKI Jakarta is 95.53% and the Kappa accuracy is 94.19%. These results show that the assessment of both accuracies has exceeded 85%. If the kappa value is 0.81 - 0.99, it indicates that the resulting land cover map can be fully used. The following is the area and percentage of land cover from the classification results.

Table 3. Estimation and percentage of land cover

Land Cover	Area (Km^2)	Percentage (%)
Pemukiman	417,2358	64,4668
Lahan Terbuka	19,61413	3,0306
Badan Air	27,35074	4,2259
Ruang Terbuka Hijau/Vegetasi	18,03184	2,7861
Sawah	74,31269	11,4820

Source: processed with Google Earth Engine

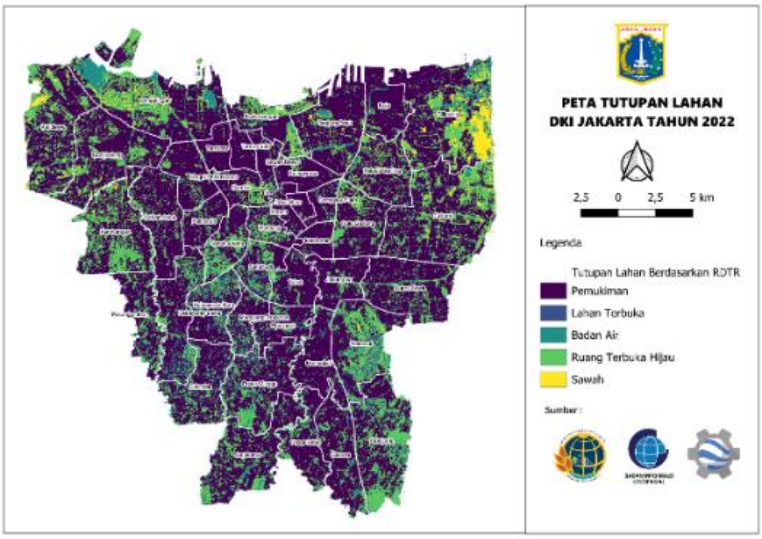

Figure 9. Estimation of Classification Results Using Random Forest
Source: processed with Google Earth Engine

Based on Figure 4, the image shows a varied distribution among the five main land cover classes. The classification is done into two main categories, namely Green Open Space (RTH) and Non-RTH (settlements, open land, water bodies, and rice fields) with the following distribution pattern.

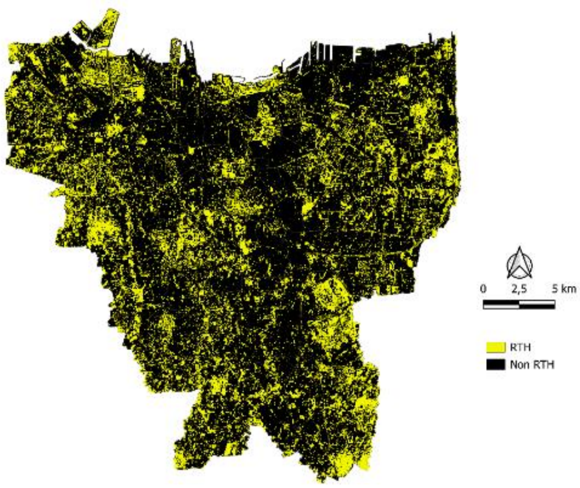

Figure 10. RTH and Non-RTH
Source: processed with Google Earth Engine

Table 4. Area and percentage of green open space in Jakarta

City	Area of green open space / RTH (Km^2)	Percentage (%)
Jakarta Utara	0.8311	0.5762
Jakarta Timur	0.0091	0.0049
Jakarta Selatan	3.2086	2.2183
Jakarta Barat	0.0224	0.0180
Jakarta Pusat	0.8375	1.7473

Source: processed with Google Earth Engine

Thus it can be concluded that the available green space in DKI Jakarta has not met the target, while the available green space in DKI Jakarta has met the target with PP No.15 of 2010 which must reach 30% of the area.

3.2 Overview of Socioeconomic Ecological Factors

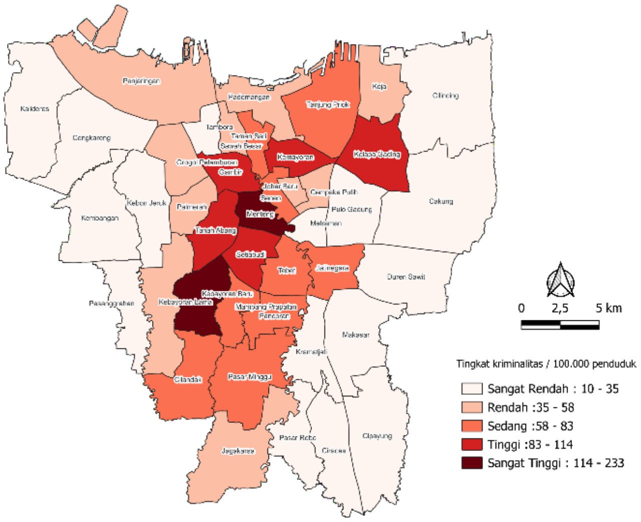

Figure 11. Crime prone areas
Source: processed with QGis

DKI Jakarta shows variations in crime rates in each region with a clustered distribution pattern, marked by colors that tend to be the same in adjacent areas. Sub-districts with moderate, high, and very high crime risk are concentrated in the urban center, influenced by central city development and high RWI values. Menteng sub-district has the highest crime rate (233/100,000 population), while Kalideres has the lowest (10/100,000 population).

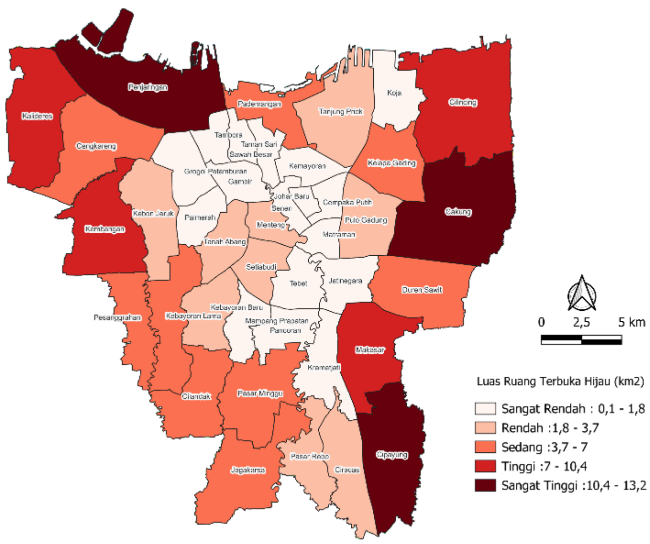

Figure 12. Thematic map of green space distribution
Source: processed with QGis

On the thematic map of the distribution of green spaces, a clustering pattern can be seen in areas that are close to each other. Sub-districts with medium, high, and very high levels of green space are scattered on the outskirts of DKI Jakarta, while sub-districts with low and very low levels of green space tend to be concentrated in the city center.

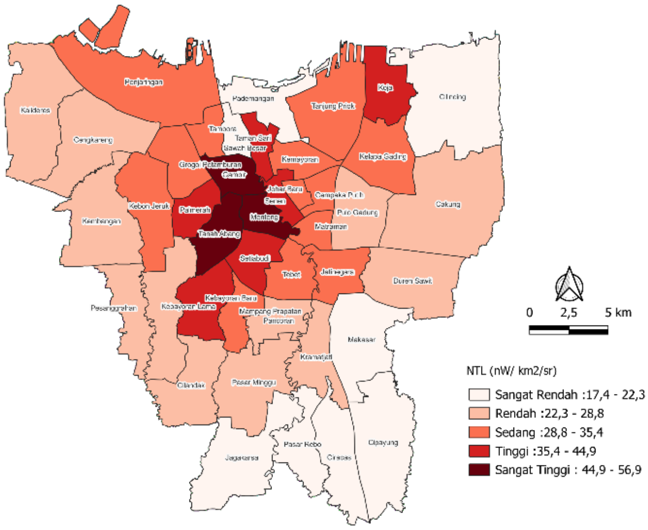

Figure 13. Thematic map of NTL distribution
Source: processed with QGis

Night light brightness level (NTL) is used as a proxy for human activity and urban development (Afrianto, 2022). Areas with high night light intensity tend to be concentrated in urban centers. The distribution of night lighting shows that city centers with high lighting have denser commercial and office activities. High lighting levels reflect the intensity of economic activity and create a safer environment for residents and visitors at night.

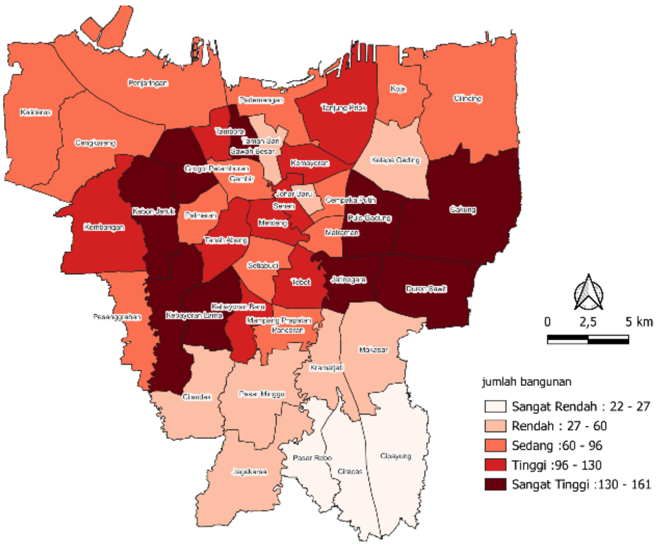

Figure 14. Thematic map of security services & worship facilities
Source: processed with QGis

The number of security services and worship facilities reflects the level of security and quality of life in an area. From the thematic map, it can be seen that security services and worship facilities are evenly distributed across regions, reflecting efforts to create an inclusive environment where every individual has equal access to these essential services, regardless of where they live. Areas with equitable access to security services and worship facilities tend to create a safer and more comfortable environment. The presence of adequate security services can reduce opportunities for crime, while the availability of worship facilities can strengthen social and moral values in the community.

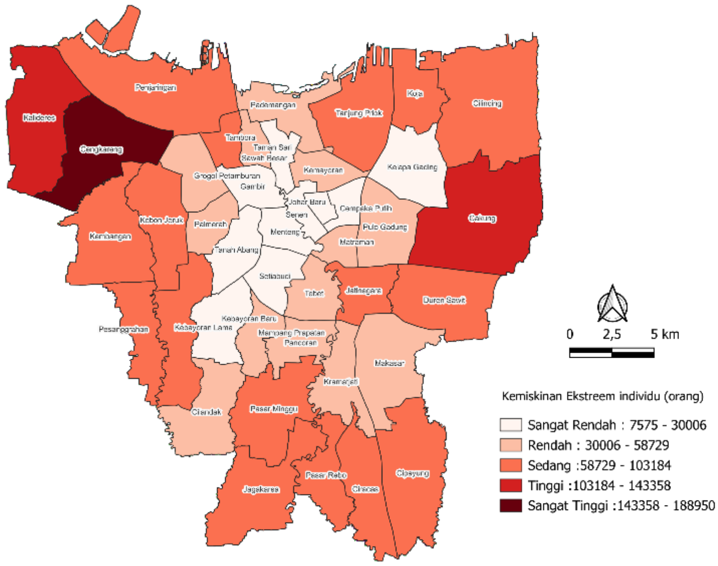

Figure 15. Thematic map of the extremely poor
Source: processed with QGis

The number of extremely poor represents the number of people who live below the minimum basic needs for proper survival, including access to food, shelter, health services, and basic education. The high number of extremely poor people tends to spread to the suburbs. The sub-district with the highest number of extremely poor people is Cengkareng, with 188,950 people, while the sub-district with the lowest number is Cempaka Putih with 7,575 people. This distribution shows that extreme poverty is not only concentrated in the city center but also extends to the periphery, reflecting the uneven pattern of urbanization and economic inequality in Jakarta. Suburbs often experience rapid population growth without adequate infrastructure development, exacerbating conditions of extreme poverty.

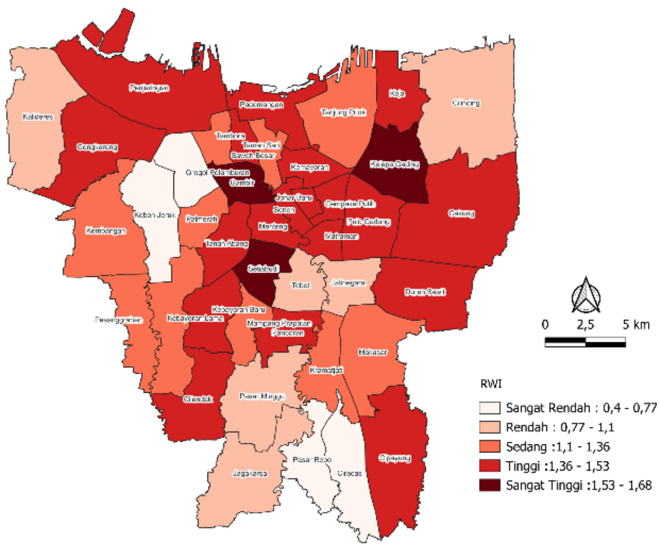

Figure 16. RWI thematic map
Source: processed with QGis

RWI can give an indication of the relative distribution of wealth or income in a region. Areas with high RWI in DKI Jakarta tend to be spread out. Some areas that have a darker color (high or very high), show a higher concentration of relative wealth due to access to jobs, education, and services, and can be an indicator of areas with a high concentration of wealth or economic investment. In this context, some sub-districts, such as Setiabudi, Kelapa Gading, and Gambir stand out with the highest RWI, which is indicated by the darker color on the map. Conversely, areas with lower RWI will be shown with lighter colors, indicating areas with greater economic challenges in terms of inequality.

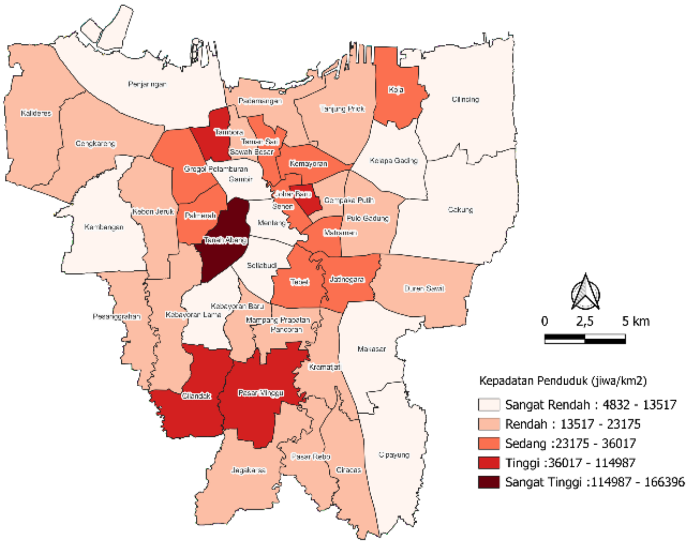

Figure 17. Population density thematic map
Source: processed with QGis

Population density is an important indicator for understanding population pressure on resources and infrastructure in an area. Areas with high population density tend to experience problems such as crime, congestion, pressure on public services, poverty, and higher levels of pollution. Thus, population density is expected to have a positive effect on the number of crimes in an area. From the figure, it can be seen that the DKI Jakarta area has a fairly even population density; it is just that some sub-districts, such as Tanah Abang Sub-district, have a very high population density of 166,396 people / km^2 compared to the surrounding sub-districts.

3.3 Analysis of Spatial Relationship with Criminality

Since the data in this study has different units, the data is first transformed or converted into LN (Natural Logarithm) form to reduce the scale of the data and to normalize the data distribution.

3.3.1 OLS formation and assumption testing

Table 5. Parameter estimation of the OLS model

Variable	Estimates	*p-value**
Intercept	4.7589	0.0617
$\text{Ln}(x_{LRTH})$	0.0818	0.3432
$\text{Ln}(x_{NTL})$	0.9996	0.0091
$\text{Ln}(x_{POI})$	0.0220	0.8960
$\text{Ln}(x_{KEI})$	-0.4424	0.0070
x_{RWI}	-0.1444	0.6456
$\text{Ln}(x_{KP})$	0.0513	0.6947

* 5% significance level
Source: processed with RStudio

Table 6. Summary of Classical Assumption Testing and Spatial Dependence

Classical Assumption	Test Statistics		p-value*
Normality	Kolmogorov-Smirnov		0.7940
Homoscedasticity	Breusch-Pagan		0.8296
Multicollinearity	VIF	$Ln\ (x_{LRTH})$	0.7940
		$Ln\ (x_{NTL})$	1.6172
		$Ln\ (x_{POI})$	1.8400
		x_{KEI}	1.3650
		$Ln\ (x_{RWI})$	2.0507
		$Ln\ (x_{KP})$	1.2586
Spatial Autocorrelation	Global Moran's I		0.1761

* 5% significance level
Source: processed with RStudio

Based on Table 5 above, the results of the OLS model parameter estimation are obtained. It can be seen that there are only two independent variables that are significant with p-value < 0.05, namely NTL and KEI variables. After the OLS model is formed, the OLS model assumptions are tested. Based on Table 6, all classical assumption tests are met, indicating that the data used in regression analysis meets several important assumptions that underlie the validity and reliability of the regression model results.

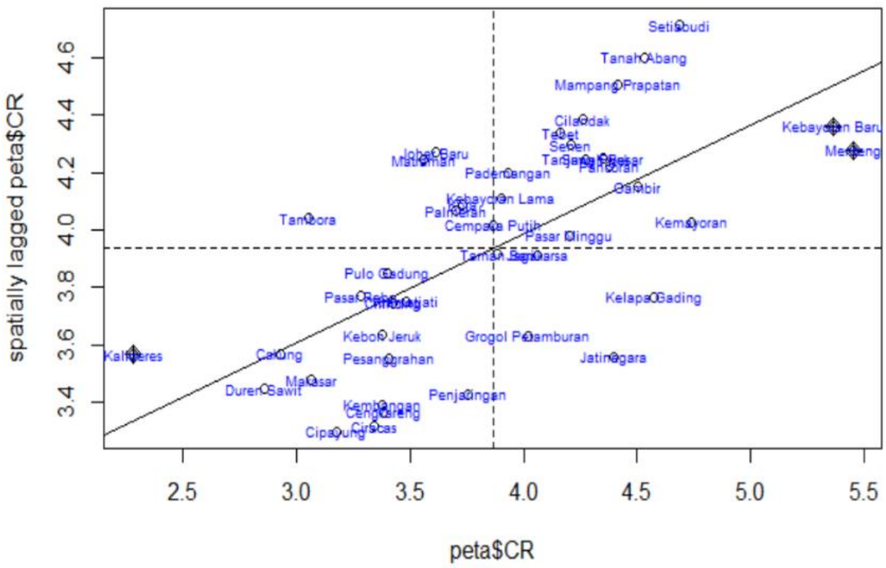

Figure 18. Moran's Scatterplot of crime-prone areas
Source: processed with R Studio

(1) Quadrant I, HH (High-High): Menteng, Kebayoran Baru, Setiabudi, Tanah Abang, Mampang Prapatan, Cilandak, Tebet, Kemayoran, Senen, Pancoran, Gambir, Pademangan, Kebayoran Lama, Pasar Minggu, and Tanjung Priok sub-districts.

(2) Quadrant II, LH (Low-High): Tambora, Pal Merah, Matraman, Cempaka Putih, Koja, and Johar Baru sub-districts.

(3) Quadrant III, LL (Low-Low): Kecamatan Pulo Gadung, Pasar Rebo, Keramat Jati, Kebon Jeruk, Pesanggrahan, Cakung, Penjaringan, Makasar, Duren Sawit, Kembangan, Cengkareng, Ciracas, Cipayung and Kalideres.

(4) Quadrant IV, HL (Hiigh-Low): Kecamatan Taman Sari, Jagakarsa, Kelapa Gading, Jatinegara, and Grogol Petamburan.

3.3.2 Lagrange Multiplier Test

Table 7. Summary of Model Determination

Test Statistics	Value	*p-value**	Decision
Lagrange Multiplier (error)	3.1385	0.0765	Failure reject $H0$
Lagrange Multiplier (lag)	5.7843	0.0162	Reject $H0$
Robust Lagrange Multiplier (error)	0.7163	0.3974	Failed reject $H0$
Robust Lagrange Multiplier (lag)	3.3621	0.0667	Failed reject $H0$
SARMA	6.5006	0.0388	Reject $H0$

Source: processed with R Studio

In testing the residuals of the multiple linear regression model with Moran's I test, the p-value is 0.0313, which means that there is spatial dependence in the residuals of the classical regression model. Thus, the multiple linear regression model is considered less capable of modeling the crime rate in DKI Jakarta. In further testing, namely LM and RLM testing on lags and errors. The LM-lag p-value is 0.0162, and the SARMA p-value is 0.0388, where both values are less than 0.05, so the decision rejects $H0$. The models that can be used are the spatial lag model (SAR) and spatial autoregressive moving average (SARMA).

Table 8. SAR and SARMA models

Variable	SAR		SARMA	
	Estimate	*p-value**	Estimate	*p-value**
Intercept	3.5662	0.0855	2.8860	0.1476
$\mathrm{Ln}\ (x_{\mathrm{LRTH}})$	0.1064	0.1360	0.1279	0.0418
$\mathrm{Ln}\ (x_{\mathrm{NTL}})$	0.8027	0.0089	0.6706	0.0150
$\mathrm{Ln}\ (x_{\mathrm{POI}})$	0.0225	0.8725	-0.0510	0.6664
$\mathrm{Ln}\ (x_{\mathrm{KEI}})$	-0.3781	-0.2551	-0.3654	0.0039
x_{RWI}	-0.0096	0.9291	-0.2635	0.2833
$\mathrm{Ln}\ (x_{\mathrm{KP}})$	0.4802	0.0032	0.0286	0.7773
Rho (ρ)	3.5662	0.0855	0.7186	4.3213×10^{-5}
Lambda (λ)			-0.5566	0.1558

Source: processed with R Studio

3.3.3 Goodness of Fit

Table 9. Goodness of Fit Summary

Parameters	OLS	SAR	SARMA
AIC	67.3960	63.4176	64.3535
R^2	0.4495	0.5924	0.6026
p-value Rho (ρ)	NA	0.0032	4.3213×10^{-5}
p-value Lamda (λ)	NA	NA	0.1558
Normality	0.7940	0.9306	0.8118
Homoscedasticity	0.8296	0.8783	0.8945

Source: processed with R Studio

Based on the output of each model, the AIC value of the SAR model is smaller than the AIC value of the OLS model and the SARMA model, but the R^2 value of SARMA is greater than the OLS model and the SAR model, which can explain the variables affecting the crime rate in DKI Jakarta by 60.26 percent, and more significant variables make the SARMA spatial regression model more appropriate and have considered the spatial effects of the data used.

$$Ln\left(\widehat{CR}_{ij}\right) = 2{,}8860 + 0{,}7186 \sum_{i=1,i=j}^{42} w_{ij}y_j + 0{,}1279\, ln(x_{LRTH}) + 0{,}6706\, ln(x_{NTL}) - 0{,}0510\, ln(x_{POI}) - 0{,}3654\, ln\,(x_{KEI}) - 0{,}2635\, x_{RWI} + 0{,}0286\, ln\,(x_{KP}) + u_i$$

$$u_i = -0{,}5566 \sum_{i=1,i=j}^{42} w_{ij}u_j$$

With a significance level of 5 percent, the results show that the area of green open space, Nighttime Time Light, and the number of extremely poor people have a significant effect on crime rates. Based on the model formed, the coefficient of determination is 0.60264, meaning that the independent variables can explain the variation in crime rates by 60.264 percent, and the rest can be explained by other variables not included in the model. The spatial lag coefficient value (ρ) is 0.7186, and the spatial error coefficient value (λ) is -0.5566, so it can be concluded that the crime rate in the DKI Jakarta sub-district area is influenced by the lag variable value of the surrounding sub-districts. The following bivariate choropleth variables are significant to the crime rate.

3.3.4 Ground Checks: Theory and Findings

Ground checks serve to verify the accuracy of data obtained from secondary sources such as satellite imagery and are important to ensure that the data analysis used truly reflects the actual conditions on the ground.

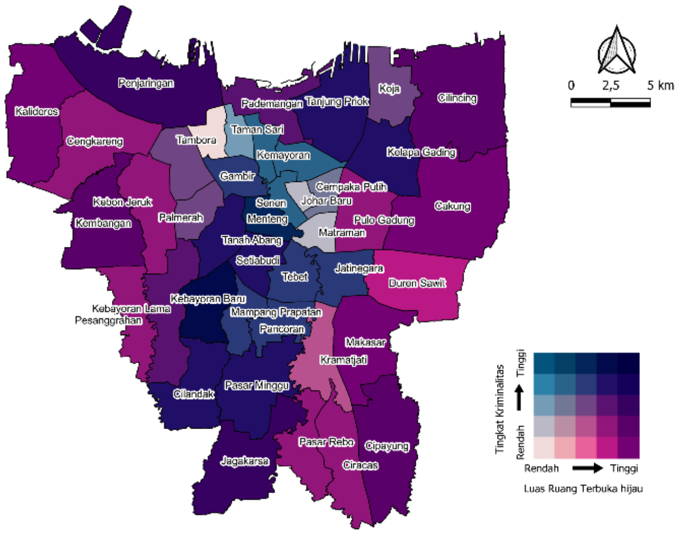

Figure 13. Bivariate Choropleth Map of RTH and Crime Rate
Source: processed with QGis

In CPTED theory, green open spaces are expected to reduce crime **(Branas et al., 2011),** but spatial analysis shows that green open spaces actually increase crime. Routine Activities Theory and Crime Opportunity Theory explain that green open spaces can become a gathering place for criminal elements due to lack of supervision. Ground checks in the Kebayoran Baru sub-district, which has many public and private green spaces, show that although Taman Langsat and Taman Ayodia are popular, their quality and management are often less than optimal. Spots with poor lighting and minimal supervision create crime-prone areas such as theft and property damage. In 2022, Kebayoran Baru reported 2,112 cases of aggravated theft. In addition, there are no security guard posts nearby, and the high nighttime economic activity with many street vendors creates opportunities for criminals.

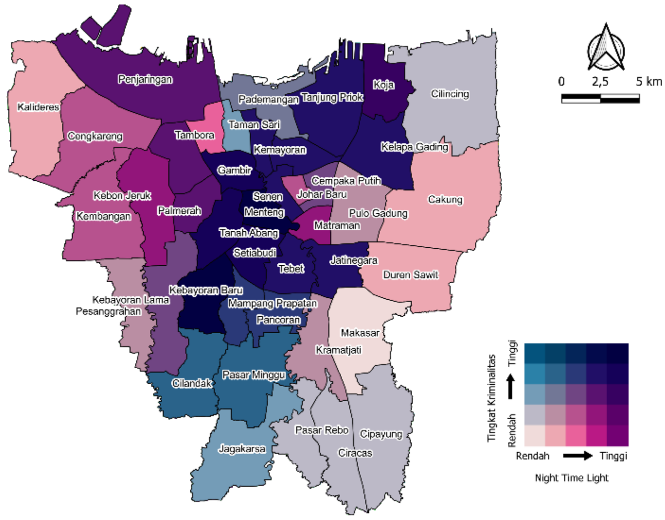

Figure 14. Bivariate Choropleth Map of NTL and Criminality
Source: processed with QGis

The theory of dark places and crime states that a lack of nighttime lighting increases opportunities for crime. The natural surveillance theory supports that well-lit areas allow for more community surveillance, thus reducing crime. However, spatial analysis found that the variable has a positive effect on increasing crime. Areas with brighter lighting have more intense night activity, increasing opportunities for criminals. Ground checks in Menteng Sub-district, which has high night light intensity but high crime rates, show that good lighting does not always reduce crime. This could be due to the high-profit potential in elite housing estates like Menteng, which attracts criminals despite good lighting. According to the E-MP report, theft cases in Menteng are the highest in Central Jakarta.

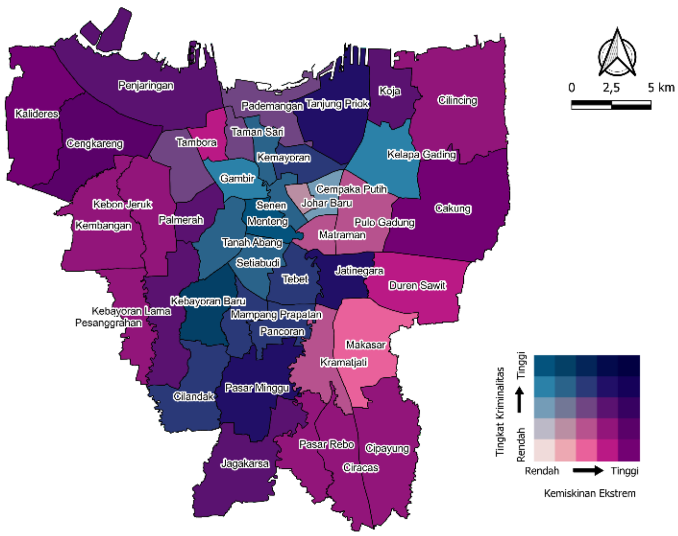

Figure 15. Bivariate Choropleth Map of Extreme Poverty and Criminality
Source: processed with QGis

According to strain theory, the social stress experienced due to the gap between cultural goals and legitimate means of achieving them can drive individuals to commit criminal acts. Extreme economic deprivation creates significant stress, which can encourage illegal actions to fulfill basic needs and societal goals. Ground checks were conducted in Tanjung Priok Sub-district, which has extreme poverty and high crime rates according to the bivariate choropleth map. The most common cases in Tanjung Priok are theft, violence, and drugs. Densely populated and slum areas often lack public facilities and services such as education, health, and recreation, leading to frustration and dissatisfaction and increasing vulnerability to negative influences.

The finding that green open spaces are significantly associated with higher crime rates aligns with Routine Activity Theory, which suggests that public spaces may increase the opportunity for crime when not properly managed or supervised. This contrasts with the CPTED theory, which posits that well-designed green spaces can deter crime. This discrepancy may be explained by poor lighting, lack of security personnel, and the presence of unmonitored areas in Jakarta's green spaces, as confirmed by ground checks in Kebayoran Baru. This is consistent with the findings of Gascon et al. (2018) and Kuo & Sullivan (2001), who emphasize that the quality and maintenance of green space are crucial in determining its effect on social behavior.

Furthermore, the significant positive effect of nighttime lighting on crime rates appears contradictory to the Natural Surveillance Theory, which suggests that lighting reduces criminal activity. However, in the context of urban Jakarta, brighter areas may also indicate more active commercial zones, attracting both economic activity and crime, which supports the findings of Uttley et al. (2024). Lastly, the influence of extreme poverty on higher crime rates supports strain theory, which links economic hardship with increased social stress and criminal behavior, also supported by Sukartini et al. (2021) in their urban crime study in Indonesia.

3.4 Interactive Dashboard

The interactive dashboard on the Tableau Public platform titled "More Green Open Space Lowers Urban Crime Risk?" presents research on the relationship between Green Open Space (RTH) and crime rates in DKI Jakarta in 2022.

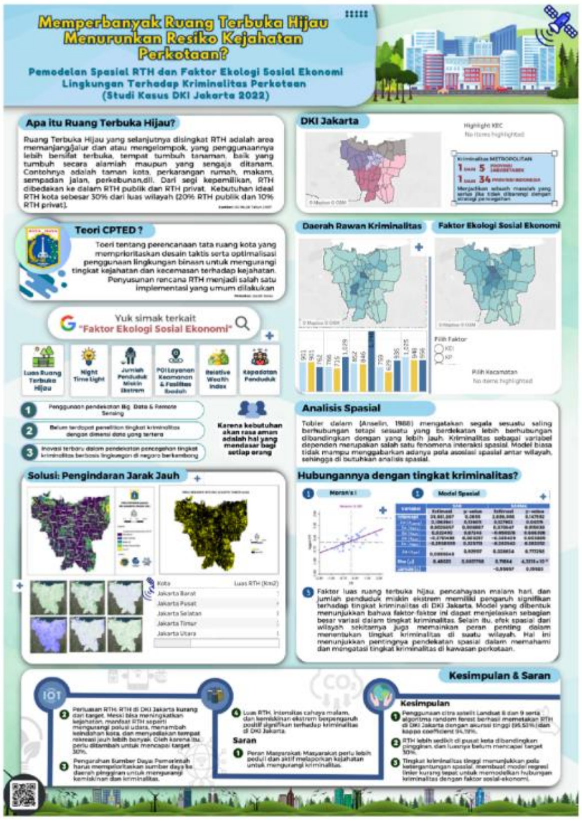

Figure 16. Tableau Interactive Dashboard

This dashboard is designed visually and interactively with several features such as filters, highlights, zoom in, zoom out, search map, hover, and legend that facilitate understanding of the data and spatial analysis presented. This dashboard was created using the Tableau Public platform with the link (https://s.stis.ac.id/Dashboard_Interaktif_RTH) and the following display.

Conclusion

The research demonstrates that the application of Landsat 8 and Landsat 9 satellite imagery, combined with the random forest algorithm (with a maximum tree depth of 500), effectively captured the distribution pattern of green spaces in DKI Jakarta. The model achieved impressive results, with an overall accuracy of 95.53% and a kappa coefficient of 94.19%. The analysis of land cover distribution revealed that settlements dominate the land use in the area.

Additionally, the research identified a tendency for spatial dependence in regions with high crime risk. The multiple linear regression model, however, was found to be less effective in capturing the complexities of crime rates in DKI Jakarta and their relationship with socio-economic and ecological factors. High-crime sub-districts tend to cluster around the urban center, where values for wealth (RWI) and nighttime lighting (NTL) are elevated. These sub-districts also exhibit a lower amount of green open space compared to peripheral areas. The overall green space in DKI Jakarta remains below the target of 30% of the total area, primarily due to the city's centralized development focused around the Central Business District (CBD).

The Spatial Autoregressive Moving Average (SARMA) model indicated that the area of green open space, night light intensity (NTL), and extreme poverty have a significant positive impact on crime rates in DKI Jakarta. A ground verification process was successfully carried out to confirm the accuracy of the spatial data, ensuring that the analysis accurately reflects the actual conditions on the ground.

Finally, to facilitate the presentation of the research findings, an interactive dashboard was developed, providing infographics and 2D interactive thematic maps. These tools enhance the accessibility and understanding of the data, allowing users to explore the relationships between green space distribution and crime rates in DKI Jakarta.

The research demonstrates the effective use of Landsat 8 and 9 imagery combined with the random forest algorithm to capture green space distribution in DKI Jakarta, achieving high accuracy. However, there are several weaknesses. First, while socio-economic factors like wealth and poverty are considered, the study doesn't deeply explore other factors such as education or employment, which could provide a more nuanced understanding of crime. The multiple linear regression model used was found to be less effective in capturing the complexities of crime rates, suggesting the need for more advanced modeling techniques. Additionally, the research focuses on green space quantity but doesn't assess its quality or accessibility, which could influence crime prevention. The study also centers on the Central Business District, neglecting peripheral areas, which might show different patterns. To improve, future research could incorporate a wider range of socioeconomic factors, use more sophisticated models like random forest regression or neural networks, and explore the quality and accessibility of green spaces. Expanding the scope to other regions or cities and examining longitudinal data would also enhance the generalizability of the findings.

The suggestions based on this research are as follows:

The absence of official data on the area of green spaces at the sub-district level in DKI Jakarta makes estimation and classification using machine learning a practical and real-time solution. The estimation results show that the area of green spaces is less than the target of 30% of the area, so additional public and private green spaces equipped with security and lighting facilities are needed. The government is expected to focus on peripheral areas in need to reduce inequality and improve welfare, given that poverty is often correlated with high crime.

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