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Linking Land Cover to Flood Vulnerability: A Study on Vegetation Indices and Urban Build-Up in Hazard Mapping

Ikhlas Nur Muhammad[1,*], Sarpono Sarpono[2], Agus Wibowo[3], Rachmat Setiawibawa[1], Anwar Kurniadi[1]

[1]*Department of Disaster Management Program, Indonesia Defense University, Bogor, Indonesia*
[2]*Directorate of Census and Survey Methodology Development, Central Bureau of Statistics, Indonesia*
[3]*Directorate of Disaster Management System, Indonesia Disaster Management Agency, Indonesia*
[*]*Correspondance: ikhlasnurmuhammad@gmail.com*

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Abstract

Flooding is the most dominant disaster in Indonesia, with a major case in Greater Jakarta in March 2025, which is the issue of deforestation is highlighted as the main cause of this phenomenon. This study examines the relationship between vegetation canopy and built-up land on flood vulnerability. The analysis was conducted by correlating vegetation and built-up land indices against flood vulnerability maps from the National Disaster Management Agency using the Weighted Overlay method. Results show vegetation has a moderate correlation to flood vulnerability, while built-up land shows a lower correlation. The findings indicate that both contribute to flood risk, but are not a single factor. The study recommends further research with a spatio-temporal approach in smaller areas to be more specific.

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Abstrak

Banjir menjadi bencana paling dominan di Indonesia, dengan kasus besar di Jabodetabek pada Maret 2025, dimana isu deforestasi menjadi sorotan sebagai penyebab utama fenomena ini. Penelitian ini mengkaji hubungan antara kanopi vegetasi dan lahan terbangun terhadap kerentanan banjir. Analisis dilakukan dengan mengorelasikan indeks vegetasi dan lahan terbangun terhadap peta kerawanan banjir dari Badan Nasional Penanggulangan Bencana menggunakan metode Weighted Overlay. Hasil menunjukkan vegetasi memiliki korelasi moderat terhadap kerentanan banjir, sementara lahan terbangun menunjukkan korelasi yang lebih rendah. Temuan ini mengindikasikan bahwa keduanya berkontribusi terhadap risiko banjir, namun bukan faktor tunggal. Studi ini merekomendasikan penelitian lebih lanjut dengan pendekatan spasio-temporal di wilayah yang lebih kecil untuk lebih spesifik.

INTRODUCTION

Flooding is a very dominant hydro-meteorological disaster compared to other disasters in Indonesia. Indonesia's Disaster Management Agency recorded 1,478 disaster occurrence points in Indonesia in 2024, and 814 of them were floods, or 55% of the total disasters (BNPB, 2024). These floods are often attributed to factors such as climate change (Kundzewicz et al., 2019), poor risk management in land planning (Ianoș et al., 2019), and deforestation (Yan et al., 2022).

The cause of flooding cannot be ascertained through one causal factor alone, but each factor also contributes to its significance. Two general factors that can be seen from the occurrence of this disaster are anthropogenic and natural factors (Malik, 2022). Anthropogenic factors refer to human activities such as poor waste management, overpopulation, and unplanned urban development that increase flood risks (Abass, 2022). Natural factors include heavy rainfall, tidal surges, and land subsidence that naturally contribute to flooding events (Takagi et al., 2021). Understanding spatial patterns and perspectives needs to be used as a tool in viewing this phenomenon for disaster control.

Floods can bring socioeconomic activities to a complete halt, which greatly impacts human activities (Manzoor et al., 2022). The Jakarta floods in March 2025 affected over 60,000 residents and resulted in the shutdown of numerous shops and factories, causing a temporary halt in various sectors of the economy (Bloomberg, 2025). Flood disasters require attention to good governance in regional planning, especially in drainage planning and land use commensurate with the carrying capacity of the environment (Manzoor et al., 2022).

Regional planning exists as an approach to development in the social, economic, and environmental spheres. The application of sustainable development can minimize the impact of disasters. The implementation of sustainable development can minimize the impact of disasters by integrating disaster risk reduction into long-term planning and ensuring that communities are resilient to environmental hazards (Greve, 2016). Sustainable development planning saved the Netherlands from drowning (de Bruin et al., 2014), Japan implemented earthquake and tsunami resilience in its infrastructure (Suppasri et al., 2021), and Greensburg built hurricane-resistant infra-structure (Hagelman et al., 2012).

This research uses mapping assistance in providing information on the state of the environment or disaster in spatial aspects. Where this has become an important part of effective land use planning in flood areas and mitigation strategies is flood hazard mapping (Hong & Abdelkareem, 2022).

Areas with a high risk of flooding hazards, such as in some regions in Indonesia, need to be further investigated regarding this phenomenon in terms of spatial information. Greater Jakarta, which consists of Jakarta, Bogor, Depok, Tangerang, and Bekasi, is one of the areas with this vulnerability. This is relevant to previous research that revealed the relationship between the condition of the number of buildings and flood risk (Clar et al., 2023)

We face a complex aspect of densely populated urban areas and environmental quality. Ashillah et al. (2025) revealed that demographic factors and flooding had a significant impact on well water quality in Jakarta, where 83% of wells did not meet standardized quality during that period. Flooding and population density are commonly associated with the deterioration of environmental quality, particularly affecting the groundwater resource (Akhtar et al., 2021; Miller & Hutchins, 2017).

Greater Jakarta has experienced these major flood events repeatedly since 2002, 2007, 2012, 2017, 2020, and 2025. These events continue to recur and result in socioeconomic losses to the community (Kiparisov et al., 2023). Flood disaster risk mapping has been carried out quite a lot in assessing this condition. Mapping enables time-efficient use of decision-making in disaster response and management (Hussain et al., 2023).

This research produces flood hazard modeling using the Weighted Overlay method. This method has been widely used in hazard mapping for floods (Alharbi, 2024), landslides (Arumugam et al., 2023), and droughts (Gaurav & Singh, 2022). This method has been widely used because it can perform multivariable or multifactor weighting with adjustable scoring in each variable (Sun et al., 2023).

The Weighted Overlay method has proven to be effective in producing disaster risk maps, especially floods, with a very good level of accuracy. This is shown through several previous studies that use Area Under the Curve (AUC) as an indicator of model performance. An AUC value close to 1.0 indicates that the model has an almost perfect predictive ability in distinguishing between risky and non-risky areas (Avand et al., 2021).

Previous research by Bui et al. (2023) in Quang Binh, Vietnam, achieved an AUC of 0.98, while Lukose & Sunilkumar (2024) study in Kuttanad, India, obtained an AUC of 0.89. Similar results were also found in the study of Wardana et al. (2023) in South Jakarta with an AUC of 0.94. These AUC values are generated from Receiver Operating Characteristic (ROC) analysis, which compares True Positive Rate (accuracy of risk prediction) and False Positive Rate (prediction error) (Huang et al., 2021). The higher the AUC, the better the model can accurately predict flood risk.

This research is not concerned with mapping techniques or spatial distribution analyses, but rather aims to evaluate the correlative relationships between vegetation, built-up land canopy, with flood hazard vulnerability. Contrary to conventional mapping studies, our analysis specifically examines the interdependence of these three factors. There is limited previous research that directly correlates these relationships.

Previous research in the study area by Azaria (2024) correlated Normalized Difference Vegetation Index (NDVI) with Normalized Difference Build Index (NDBI) using Landsat 8 with 2023 data, resulting in a correlation level of -0.904, or categorized as a strong negative correlation. The results of the study indicate that when the NDVI value is high, it correlates with the decrease in NDBI value or vice versa. This study also has similarities with several previous studies that show a negative correlation between NDVI and NDBI. The study by Jaswal & Thakur (2023) had a correlation result of -0.73 and -0.98 by Roy & Bari (2022). However, there are conditions where other studies also show a relationship that is not too strong or moderately negative, with four trials resulting in several values, namely -0.56, -0.58, -0.53, and -0.24 (Chen et al., 2023). Another study also found lower results related to the second relationship, which was correlated at -0.38 (Guha & Govil, 2022).

This research examines how the level of correlation between vegetation pixels and built-up land is related to flood vulnerability itself. There have been many studies on the correlation between these two indices, but not enough have been conducted on the correlation between these indices and flood disaster mapping, especially in the study area.

METHOD

This research uses a quantitative descriptive approach. This research will reveal how the correlation (r) relationship between vegetation canopy and built structures is one of the factors in increasing flood hazards and risks. Flood mapping will use the Weighted Overlay method and one secondary data source in the form of flood hazard risk map data by the National Disaster Management Agency, which is one of the data sources that is used in revealing this statistical correlation.

Study Area

The focus of the study looks deeper into what happened to the Greater Jakarta (Jakarta, Bogor, Depok, Tangerang, and Bekasi) region (Figure 1), which experienced a major flood in early March 2025. This disaster is linked to the deforestation that is happening in the upstream area. This study examines the correlation between areas with vegetation canopy and built-up areas on flood risk.

Correlation Method

This research correlates raster pixel data using two correlation calculation methods: the Spearman Correlation and the Pearson Correlation. The data processing is supported by the Orange Data Mining application. Pearson's correlation coefficient is used to measure the strength and direction of the linear relationship between two variables. The formula for calculating Person Correlation was developed by Karl Pearson and is commonly known as the Pearson Correlation Coefficient (Pearson, 1896).This correlation calculation utilizes a scale of -1 to +1. A correlation value close to -1 is a perfect negative correlation, and +1 is a perfect positive correlation (Ratner, 2009). The data used for this correlation analysis consists of raster values that are extracted into point data, which are then processed to calculate the correlation using equation 1 below.

$$r = \frac{\sum(Xi - \overline{X})(Yi - \overline{Y})}{\sqrt{\sum(Xi - \overline{X})^2(Yi - \overline{Y})^2}} \quad (1)$$

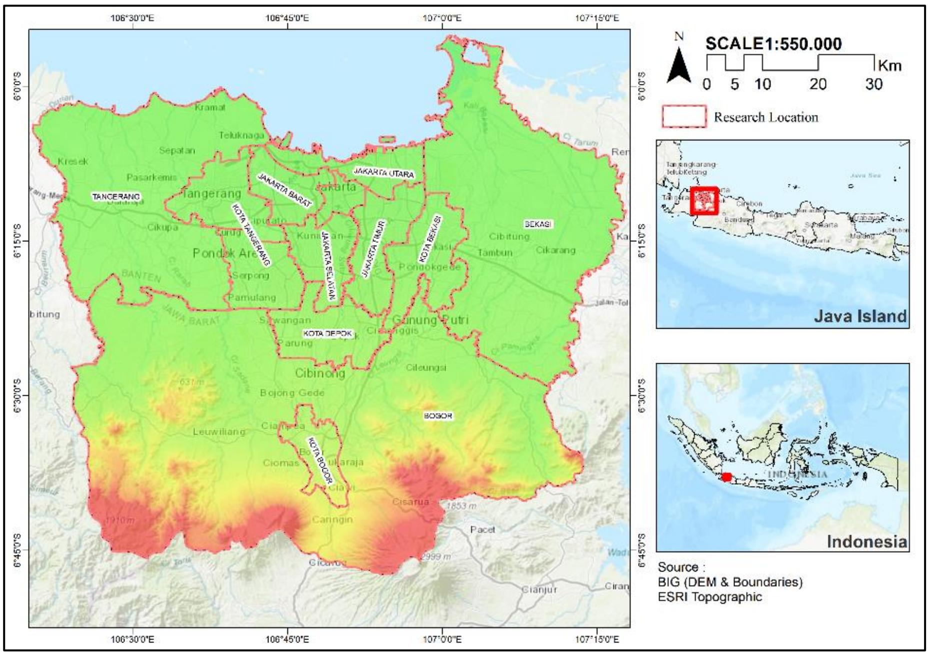

Figure 1. Research Location of Great Jakarta

where r denotes the correlation coefficient, X, Y represent individual data points of the two variables being compared, $\bar{X}i$, $\bar{Y}i$ refer to the mean (average) values of X and Y, respectively, and Σ is the summation of the calculation values.

The Spearman Correlation calculation formula was developed by Charles Spearman (Spearman, 1961). The given equation 2 represents Spearman's rank correlation coefficient, which quantifies the strength and direction of a monotonic relationship between two ranked variables.

$$\rho = 1 - \frac{6\sum d_1^2}{n(n^2 - 1)} \qquad (2)$$

where ρ represents Spearman's rank correlation, d_1^2 denotes the difference between the ranks of corresponding observations in the two variables, is the sum of these squared differences, and $\sum d_1^2$ is the number of observations. The constants 6 and $n^2 - 1$. Normalize the coefficient to ensure it ranges from −1 (perfect negative correlation) to +1 (perfect positive correlation).

Unlike Pearson's correlation, which assesses linear relationships using raw data, Spearman's method relies on ranks, making it robust to outliers and non-linear trends (Ali & Al-Hameed, 2022). Contrary to the Pearson Correlation, the Spearman Correlation measures a monotonic or not necessarily linear relationship based on the ranking of the data.

This study employed two correlation methods, Pearson and Spearman, to compare the relationships between different types of data. The continuous variables, such as NDVI and NDBI, and classified categorical data were derived from the BNPB disaster vulnerability map. Pearson correlation was used to assess linear relationships among continuous datasets, while Spearman correlation was applied to evaluate the strength and direction of monotonic relationships, especially involving the ranked or classified disaster data.

Land Cover Index

The index models used in this research are Normalized Difference Vegetation Index (NDVI) and Normalized Difference Building Index (NDBI). These two indices are the assessment of land cover canopy types that will be used in this study. NDVI was developed and introduced by Rouse et al. (1973). This index uses a calculation formula with the ratio between near-infrared and reflectance divided and then summed together. The NDVI formula is shown in equation 3 below.

$$NDVI = \frac{NIR - Red}{NIR + Red} \qquad (3)$$

where NIR is near infrared light, while Red is visible red light.

The other comparative index in this study is the built-up land index. The NDBI calculation model was developed by Zha et al. (2003). The NDBI calculation uses short-wave infrared and near-infrared bands. The formula for calculating NDBI is shown in equation 4 below.

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \tag{4}$$

where $SWIR$ is short-wave infrared band, while NIR is near infrared light.

Both indices have pixel values that range between -1 and 1. In the NDVI index, pixels with values close to 1 are identified as vegetation and close to -1 as non-vegetation. The same applies to NDBI, where close to 1 is identified as built-up land cover, and close to -1 is non-built-up land area.

Flood Hazard Modelling

The correlation value between the selected land cover indices will be correlated with the disaster hazard. This research reveals how the correlation between vegetation canopy and built-up land relates to the increased risk of flood hazards. Testing the correlation on flood hazards, this research uses Weighted Overlay-based flood hazard modeling and also uses secondary data on flood hazard mapping by the National Disaster Management Agency (BNPB). Weighted overlay is used because it effectively combines multiple factors, such as elevation, land use, water distance, and assigns different weights (Sun et al., 2023).

This study employed five key variables in the hazard weighting process by Bello et al. (2024): distance from water, Topographic Position Index, elevation, vegetation, and wetness score. All variables are presented in Table 1. Data were sourced from authorized institutions via the Google Earth Engine (GEE) cloud platform. Permanent and seasonal water mapping used the JRC Global Surface Water dataset, elevation data came from NASA's SRTM DEM 30 m, and Sentinel-2 10 m imagery from the ESA was used to calculate NDWI and NDVI for flood detection and vegetation monitoring. All data are freely available through the GEE catalogue. The series of methodologies is illustrated in Figure 2 below.

Table 1. Selected Indicators for Weighted Overlay in Flood Hazard Mapping

Variable	Value	Condition	Data Source
Distance from Water (m)	1	> 4000	European Commission's Joint Research Centre-Global Surface Water
	2	3000 - 4000	
	3	2000 - 3000	
	4	1000 - 2000	
	5	≤ 1000	
Topographic Position Index	1	> 0	SRTM DEM 30 m
	2	-0.2 to 0	
	3	-0.4 to -2	
	4	-0.6 to -0.4	
	5	≤ -0.8	
Elevation (m.a.s.l)	1	> 20	SRTM DEM 30 m
	2	15 - 20	
	3	10 - 15	
	4	5 - 10	
	5	≤ 5	
Vegetation	1	NDVI > 0.8	Sentinel 2 10 m
	2	0.6 < NDVI ≤ 0.8	
	3	0.4 < NDVI ≤ 0.6	
	4	0.2 < NDVI ≤ 0.4	
	5	NDVI ≤ 0.2	
Wetness	1	NDWI > 0.6	Sentinel 2 10 m
	2	0.2 < NDWI ≤ 0.6	
	3	-0.2 < NDWI ≤ 0.2	
	4	-0.6 < NDWI ≤ -0.2	
	5	NDWI ≤ -0.6	

Source: Bello et al., 2024.

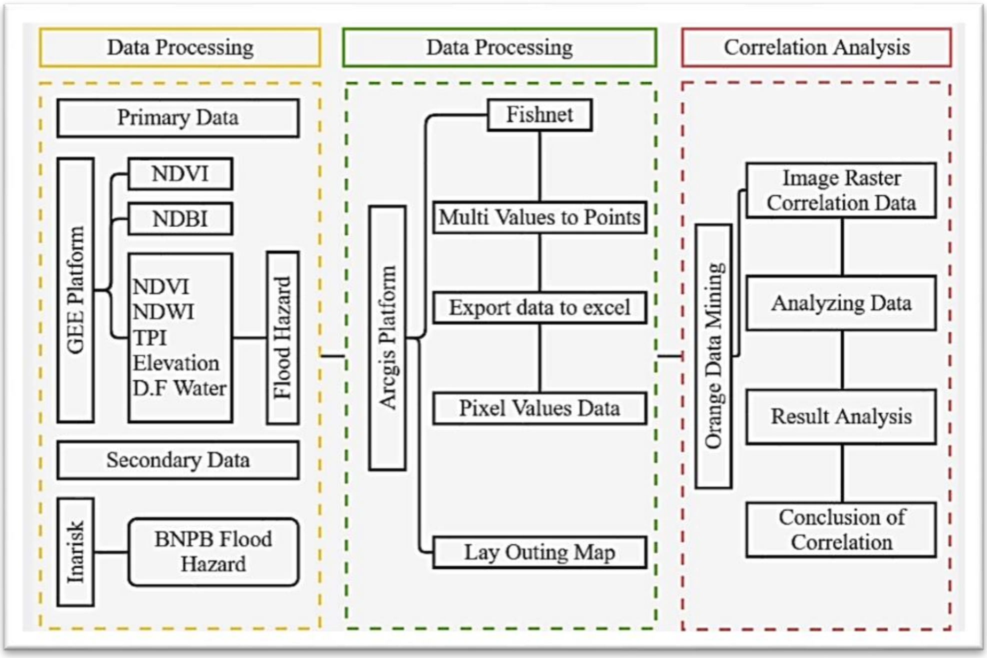

Figure 1. Research Workflow

RESULT AND DISCUSSION

Relationship of NDVI, NDBI, and Flood Hazard

The use of geospatial technology provides fast and accurate information in producing data that can be easily used and modified according to the needs required. The use of geospatial technology in this research was developed to see how a variable, namely vegetation and built-up land, can affect the results in disaster risk. The workflow in this research involves extracting raster pixel values into points, which are then used to analyze and correlate spatial relationships between flood-related variables.

The resulting map in Figure 3 is used to assess any existing correlations. Visually, areas with high vulnerability can be seen in areas with lower vegetation and areas with denser built-up land. Visual information has less in-depth analysis, where we need to provide a quantitative analysis of the relationship and correlation on the maps. The results of this research analysis are in the form of correlation (r) values extracted from raster point values and processed with the Orange Data Mining application. This information provides how the relationship of the value of each raster on the map with each other (Table 2).

Table 2. Calculation Result of Variables Statistical Correlation

Variable	Correlation Value (r)	
	Spearman Correlation	Pearson Correlation
NDVI - NDBI	-0.709	-0.622
NDVI -BNPB Flood Hazard	-0.411	-0.401
NDVI - Modelled Flood Hazard	-0.588	-0.506
NDBI – BNPB Flood Hazard	+0.275	+0.250
NDBI- Modelled Flood Hazard	+0.365	+0.350

Based on Table 2 correlation analysis, there are several relationships between vegetation index (NDVI), development index (NDBI), and flood hazard levels sourced from two types of maps: flood hazard maps from BNPB and modeling maps. The correlation between NDVI and NDBI shows a strong negative value of -0.709 for the Spearman correlation and -0.622 for the Pearson correlation. This indicates that areas with high vegetation cover tend to have lower urban or built-up land values, and vice versa (Chen et al., 2023). This relationship is natural to find, as vegetation usually decreases as physical development increases (Zhang et al., 2023), especially in urban areas like Greater Jakarta.

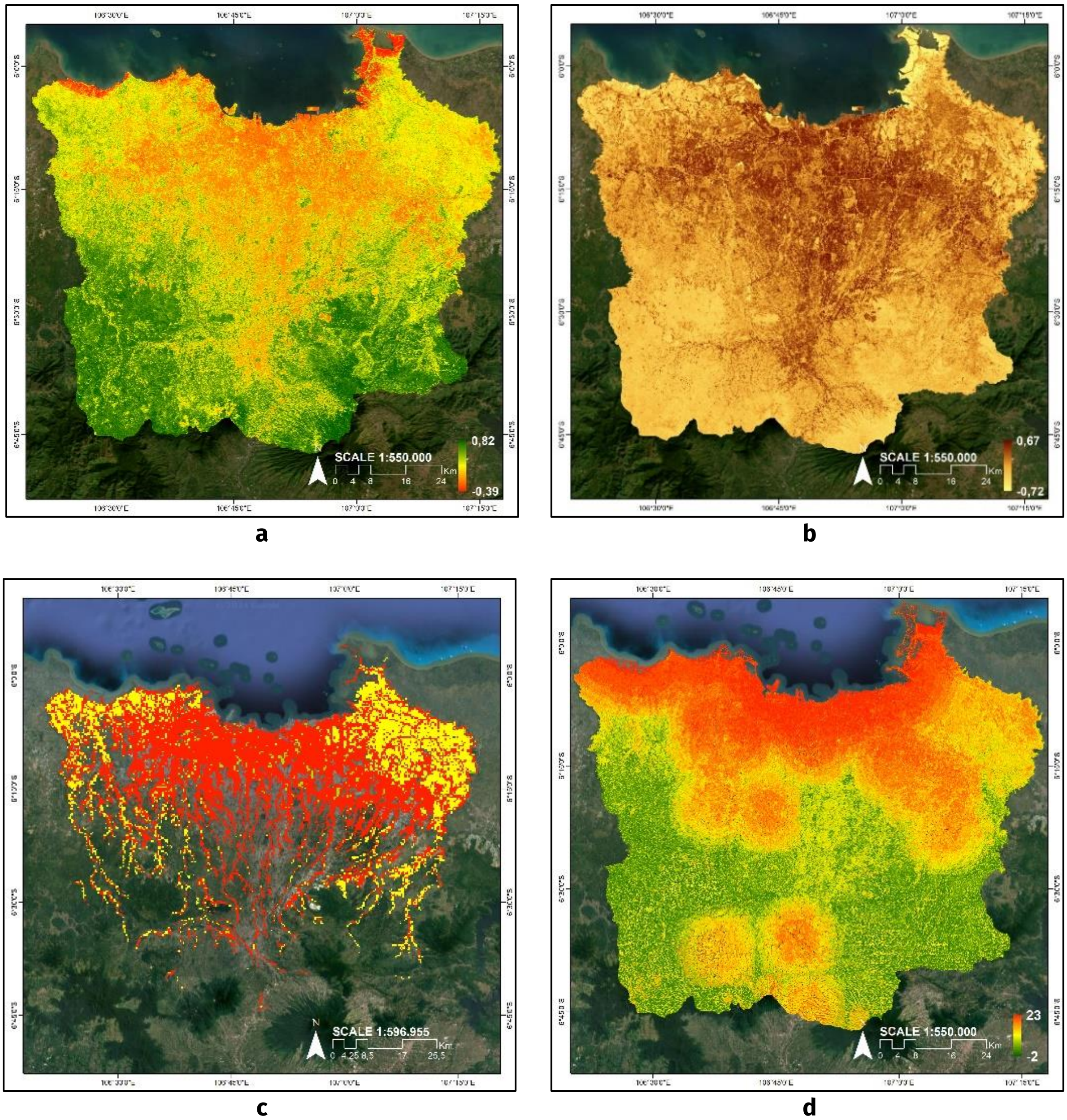

Figure 3. a) Vegetation Indices; b) Build-up Indices; c) BNPB Flood Hazard; d) Modelled Flood Hazard

The relationship between NDVI and flood hazard maps from BNPB shows a negative correlation (-0.411 Spearman; -0.401 Pearson). Similarly, the modeled maps show a slightly higher negative correlation (-0.588 Spearman; -0.506 Pearson). These negative correlation values indicate that areas with higher vegetation cover tend to have lower flood hazard levels, both according to BNPB and the modeling results. These results show that both are in the medium correlation category, so this relationship cannot be concluded as a direct cause, but still shows a consistent trend.

Meanwhile, the correlation between NDBI and flood hazard is positive in both the BNPB data (+0.275 Spearman; +0.250 Pearson) and the modeled maps (+0.365 Spearman; +0.350 Pearson). This indicates that more developed areas tend to be in a higher flood hazard category. However, these correlation values are weak to moderate, so the relationship only indicates a link, not certainty. The NDBI values indicate built-up areas (Kaur & Pandey, 2022), built-up areas have implications for low infiltration capability and runoff water that exceeds the absorption capacity (Mohamed & Worku, 2021).

Generally, the correlation results show that the land cover variables, both vegetation and development, have a fairly consistent relationship with the flood hazard maps, both from official sources (BNPB) and modeling results. The Spearman correlation value, which is slightly higher than that of Pearson, indicates that the relationship between the variables is not entirely linear. As such, this analysis provides an initial insight into spatial patterns that can be further considered in the evaluation of flood risk based on land cover data.

Canopy's Role in Disasters

The land formation and existing natural conditions of the land reflect the risks that can occur. Coastal communities will understand the dangers of tidal floods and tsunamis, as well as mountain communities who are aware of the risks of landslides and mountain eruptions. Disasters have a cycle, humans have choices and plans for their responsibility to prevent these risks.

Urban areas are also at risk of flooding. Urban environments are different from more natural environments. Disasters in urban environments are more influenced by the presence of human influence itself. Disaster is a process that is built by humans themselves and their choices to deal with these risks (Kelman, 2020).

This research informs a correlation and relationship between vegetation and built-up land affects the condition of disaster vulnerability. There are many factors that influence a disaster, whether it comes from anthropogenic or natural factors. These factors form the basis for finding a cause, but it is important to understand that factors alone cannot create disasters. Finding answers to the root causes of disasters requires understanding complex systems and diverse disciplines to determine the causes of disasters (Ray-Bennett, 2025).

Previous studies generally only mapped flood hazards using the Weighted Overlay method without further examining the quantitative relationship between vegetation index (NDVI) or built-up land (NDBI) and flood hazard levels. For example, Mukhtar et al. (2024) in Nagar, Pakistan mentioned that vegetated areas have lower vulnerability and are negatively correlated with flood hazard, but did not explicitly include Pearson or Spearman correlation values, and only gave 3% weight to the vegetation element. Meanwhile, Rahman et al. (2023) showed the highest frequency ratio of flood risk in water areas (8.86%), built-up areas (5.55%) and agricultural land (2.77%), but focused on frequency without a statistical correlation approach. Rehman et al. (2022) used objective weighting and showed that non-vegetated areas accounted for 70.1% of high-risk areas, while dense vegetation was only 8.5%, but without analysing the numerical correlation between the NDVI index and flood hazard maps. Thus, there is a research gap in revealing the statistical relationship between this spatial index and flood hazard levels.

This study still needs to be further tested with more data on the correlation of vegetation, built-up land, and flood hazard more broadly. The application of this method to this study area may result in differences with other study areas, where indeed disaster conditions cannot use one factor as the main reason. Temporal data testing would be useful in this study to further research with a more complete variety of temporal data to prevent bias in this study. However, the results of this study are sufficient to provide a basic understanding of how to mitigate flood disasters, especially in urban areas that tend to develop rapidly.

CONCLUSION

Flooding, as the most dominant disaster, is closely associated with regional development. Regional development has a definite impact on the increase in land use. This research produces a correlation of how vegetation and built-up land in spatial aspects correlate with flood hazard vulnerability. The results of this study show how vegetation has a fairly high correlation with built-up land. Vegetation itself also has a moderate but not certain correlation with flood hazard risk, and built-up land has a lower correlation with flood hazard. This research requires more data and experiments in other areas, as this research focuses on urbanized areas and a wide range of coverage. Experiments in narrower areas would be beneficial in future studies.

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