Analysis of the Incidence Rates of Dengue Hemorrhagic Fever Based on Land Cover, NDVI, and NDBI in Bengkulu City in 2018-2021

Lala Foresta Valentine Gunasari[1], *Jonathan* Farrel Pricaro[2], *Yulian* Fauzi[3], and *Dessy* Triana[1*]

[1]Department of Parasitology, Faculty of Medicine and Health Science, University of Bengkulu, Bengkulu, Indonesia
[2]Medical Program, Faculty of Medicine and Health Science, University of Bengkulu, Bengkulu, Indonesia
[3]Faculty of Mathematics and Natural Science, University of Bengkulu, Bengkulu, Indonesia

Abstract. In 2022, the incidence rate (IR) of dengue in Indonesia was 34.33%, with environmental factors playing a role in its distribution. Changes in land cover can alter microclimatic conditions, such as rainfall and temperature, which indirectly affect the habitat, breeding, and activity of mosquito vectors This study employed a quantitative method with an ecological approach and a time series model to analyze land cover, the normalized difference vegetation index **(**NDVI), and the normalized difference built-up index **(**NDBI) in Bengkulu City between 2018 and 2021. Accuracy tests for each map involved 42 sample points, totaling 504 points overall. The samples were calculated using the overall accuracy and Kappa coefficient formulas assisted by a confusion matrix. Statistical tests, including multiple linear regression and classical assumption tests, were also carried out. The results indicated that the IR of dengue in Bengkulu City decreased from 2018 to 2021. The low-density category of NDVI had a non-directional influence on the IR of dengue (-0,733), while the moderate-density category of NDVI had a unidirectional influence on the IR of dengue (0,487). NDVI simultaneously influenced the IR of dengue (R^2 = 38%). Meanwhile, NDBI and land cover simultaneously and partially did not influence the IR of dengue. An increase in low-density NDVI areas reduced the IR of dengue, while a decrease in moderate-density NDVI areas reduced the IR of dengue (β = -0.487).

1 Introduction

Dengue is a mosquito-borne disease with the highest prevalence compared to other viral infections transmitted by mosquitoes [1]. Dengue is caused by the dengue virus, which has four different serotypes, namely DEN-1, DEN-2, DEN-3, and DEN-4 [2, 3]. Secondary infections with different serotypes can increase the risk of dengue [4, 5]. The spread of the dengue virus is caused by intermediary vectors, namely *Aedes aegypti* as the primary virus carrier and *Aedes albopictus* as the secondary virus carrier [6].

The human immune system defends against pathogens through two mechanisms: innate immunity and adaptive immunity [7, 8]. Dengue hemorrhagic fever (DHF) is triggered when an infected mosquito bites the skin, initiating the immune response. The innate immune response begins as the virus infects macrophages in the skin, and pathogen-associated molecular patterns (PAMPs) are recognized by pattern recognition receptors (PRRs) on

* Corresponding author: dessy.triana@unib.ac.id

macrophages [9]. This leads to the production of inflammatory agents such as type 1 IFN, cytokines, and chemokines [10]. The adaptive immune response follows, with Langerhans cells from the infected skin migrating to lymph nodes to activate CD4+ and TCD8+ [11, 12].

The global incidence of dengue has spiked in the last ten years. From 505,430 cases reported in 2000, the number surged to 2.4 million in 2010 and reached 5.2 million cases in 2019. However, these figures may underrepresent the actual situation, as many dengue cases go unreported due to non-reporting by patients, underdiagnosis, or asymptomatic manifestations. In Indonesia, the latest data recorded 95.893 cases of dengue with 661 deaths. In Bengkulu City, dengue incidence has been fluctuating, with the highest peak in 2016 reaching 850 cases. In response, the Indonesian Ministry of Health declared a dengue outbreak in 2016. By 2020, there were 162 reported cases with a case fatality rate (CFR) of 1% [13].

The spread of vector-borne diseases, including dengue, is influenced by many factors, such as demographics, environmental conditions, and social factors [14]. Dengue is endemic to tropical regions between 35° North to 35° South latitudes, with transmission peaking during the rainy season when the *Aedes aegypti* mosquito population increases due to environmental humidity [15, 16]. The optimal temperature range during the rainy season between 15℃ and 30℃ can increase the extrinsic incubation period of mosquitoes [17].

Land cover plays a vital role in the growth of dengue vectors. There are different types of land cover, such as vegetated areas (plantations, agriculture, forests), open land, settlements, and water bodies [18, 19]. Changes in land cover can lead to alterations in microclimatic conditions, such as rainfall [20]. These changes can indirectly affect the habitats of vectors. For instance, vegetation such as community forests can reduce the incidence of dengue and influence the local microclimate. Building and vegetation density are components of land cover that influence the incidence of dengue. An increase in building density causes an increase in the incidence of dengue, while a decrease in vegetation density causes an increase in the incidence of dengue [21].

Research on land cover and the incidence rate of dengue has been widely carried out in Indonesia, consistently showing a positive correlation between land cover and the incidence rate of dengue. Dengue cases have been rising since 2018, but there remains a lack of baseline data necessary for determining dengue control strategies. This study aims to analyze the incidence rate of dengue through environmental aspects, namely land cover, to raise public awareness of the importance of proper environmental management in preventing dengue incidents in Bengkulu City.

2 Methods

Bengkulu City was selected as the test site for data verification using Google Earth Pro and field surveys. The study area covered 15,170 hectares, encompassing the city's nine administrative subdistricts, namely Gading Cempaka, Kampung Melayu, Muara Bangkahulu, Ratu Agung, Ratu Samban, Selebar, Singaran Pati, Sungai Serut, and Teluk Segara.

This study employed a quantitative method with an ecological approach and a time series model to analyze land cover, the normalized difference vegetation index **(**NDVI), and the normalized difference built-up index **(**NDBI) of Bengkulu City between 2018 and 2021. Accuracy tests for each map involved 42 sample points, totaling 504 points overall. Land cover changes were visualized geospatially using the Geographic Information Systems (GIS) software, namely QGIS, with an overlay method to facilitate public understanding of the influence of land cover on the incidence rate of dengue in Bengkulu City. Land cover areas

were calculated as percentages through unsupervised classification techniques and converted into ratio data (hectares).

The land cover classifications analyzed included urban, vegetation, agricultural, and water areas. NDBI and NDVI as aspects of land cover were processed separately from the land cover classification data. NDBI and NDVI values were derived through specific formulas and processed using a raster calculator. Furthermore, changes in land cover and regional characteristics for each year were compared with the incidence rates of dengue.

The samples were calculated using the overall accuracy and Kappa coefficient formulas assisted by a confusion matrix. Statistical tests, including multiple linear regression and classical assumption tests, were also carried out. Land cover classification, NDBI, and NDVI were analyzed using a time series ecological approach to determine the relationship between the dependent variable and the independent variables. The processed ratio data for land cover, NDVI, and NDBI were subjected to multiple linear regression and classical assumption tests (normality, multicollinearity, heteroscedasticity, and autocorrelation) using SPSS 25. This study was approved by the Health Research Ethics Committee of the Faculty of Medicine and Health Sciences, University of Bengkulu with an approval number of 69/UN30.14.9/LT/2022.

3 Results

3.1 Incidence Rate (IR) of Dengue Hemorrhagic Fever in Bengkulu City

In 2018, Kampung Melayu was the only subdistrict in Bengkulu City with a low dengue incidence rate (under 49 per 100,000 population). In 2019, Teluk Segara was the only subdistrict in Bengkulu City with a low dengue incidence rate. In 2020, there was an overall improvement in the city's dengue incidence rate. In contrast to 2018 and 2019, high incidence rates were only found in two subdistricts in Bengkulu City, namely Gading Cempaka and Selebar. In 2021, Sungai Serut was the only subdistrict in Bengkulu City with a high dengue incidence rate.

3.2 Normalized Difference Vegetation Index (NDVI) in Bengkulu City

Between 2018 to 2021, Bengkulu City did not exhibit any areas classified as having dense vegetation. Vegetation in the moderately dense category continued to decline, while vegetation in the not-dense category continued to increase. The non-vegetated area experienced a decrease in 2019, but in 2020, there was a significant increase, from 2,833 hectares to 4,836 hectares.

Overall, vegetation density in Bengkulu City exhibited a declining trend from 2018 to 2021, with green areas shrinking and non-vegetated areas expanding. In 2020, Gading Cempaka, Kampung Melayu, Ratu Agung, and Singaran Pati began experiencing noticeable reductions in vegetated land. By 2021, significant changes were evident compared to the NDVI map from 2018. The area categorized as moderately dense vegetation decreased from 5,467.5 hectares to 1,804.18 hectares in 2021.

3.3 Normalized Difference Built-Up Index (NDBI) in Bengkulu City

Bengkulu City experienced significant development from 2018 to 2021. The area of undeveloped land decreased from 13,482.2 hectares to 12,748.6 hectares, indicating a shift in land cover to built-up areas. These areas are categorized into three classes based on NDBI values. In 2018, undeveloped land dominated the city's landscape, with densely built-up areas found primarily in Kampung Melayu.

3.4 Land Cover Classification in Bengkulu City

According to the NDBI map, the area of vacant land in Bengkulu City decreased over time. In 2018, vacant land covered 1,191.87 hectares but decreased to 1,039.41 hectares in 2021. Similarly, according to the NDVI map, the vegetated areas decreased from 9,921.27 hectares in 2018 to 9,124.23 hectares in 2021.

Water bodies in Bengkulu City also experienced a gradual decline every year. In 2018, water bodies covered 744.75 hectares but decreased to 657.83 hectares in 2021. In contrast, residential areas increased from 3,311.11 hectares in 2018 to 4,347.54 hectares in 2021.

3.5 Map Accuracy Test

Accuracy tests were carried out to evaluate the accuracy of the digital classification process and to compare the results with real-world situations observed in the field [22]. Accuracy tests were carried out using QGIS and Google Earth Pro software. The processed images were compared to filed conditions each year using Google Earth Pro. The results of the map accuracy test are presented in Table 1.

Table 1. Overall Accuracy and Kappa Coefficient

Map	Year	Accuracy Test	
		Overall Accuracy (%)	Kappa Coefficient (%)
NDVI	2018	79.1	68.6
	2019	90.7	85.5
	2020	81.4	69.6
	2021	88.3	78.1
NDBI	2018	81.4	72
	2019	83.7	81
	2020	79.1	68.2
	2021	83.7	75.5
Land Cover	2018	83.7	73.6
	2019	76.7	63.1
	2020	75.3	56.2
	2021	86	78.04
Mean		**82.43**	**72.45**

After conducting accuracy tests by comparing the map analysis results with field conditions, the overall accuracy and Kappa coefficient were calculated. The average overall accuracy across the 12 maps was 82.43%, while the average Kappa coefficient was 72.45%. Map accuracy based on Kappa coefficient are divided into six categories [23]. Based on Cohen's classification, the average Kappa coefficient of 72.45% indicated a reliable accuracy.

3.6 Quantitative Analysis Methods

3.6.1 Classic Assumption Tests

The normality test was conducted to ensure that residuals of the regression model followed a normal distribution [24]. The Shapiro-Wilk test was used, with a significance value greater than 0.05 indicating that the sample data were normally distributed, thereby passing the normality test. The results of the normality test are presented in Table 2.

Table 2. Normality Test Results

Variable	Sig.	Result
NDVI and IR	0,167	Passed the normality test
NDBI and IR	0,147	Passed the normality test
Land Cover and IR	0,065	Passed the normality test

The multicollinearity test was carried out to assess the correlation between the independent variables. High multicollinearity results in large standard errors [25]. The multicollinearity test results are presented in Table 3.

Table 3. Multicollinearity Test Results

Variable	Model	Collinearity Statistics	
		Tolerance	VIF
NDVI and IR	X1 (non-vegetation)	0.599	1.670
	X2 (slight density)	0.374	2.674
	X3 (moderate density)	0.54	1.852
NDBI and IR	X1 (non-building)	0.539	1.854
	X2 (spare built-up)	0.549	1.823
	X3 (dense built-up)	0.329	3.042
	X4 (very dense building)	0.453	2.205
Land Cover and IR	X1 (water body)	0.86	1.163
	X2 (open space)	0.221	4.529
	X3 (urban built-up)	0.925	1.081
	X4 (vegetation)	0.226	4.421

The results indicated that the data exhibited no multicollinearity, as evidenced by tolerance values above 0.1 and VIF values below 10 [26]. Therefore, no symptoms of multicollinearity were detected in this study.

The heteroscedasticity test assesses whether there is inequality in the variance of the residuals. The Glejser test was used to carry out the heteroscedasticity test in this study. A significance value greater than 0.05 indicates no symptoms of heteroscedasticity [27]. In this study, the test results revealed no symptoms of heteroscedasticity. The results of the heteroscedasticity test are presented in Table 4.

Table 4. Heteroscedasticity Test Results

Variable		Sig,	Result
NDVI and IR	Non-vegetation	0.282	Non-heteroscedasticity
	Slight density	0.091	Non-heteroscedasticity
	Moderate density	0.277	Non-heteroscedasticity
NDBI and IR	Non-building	0.488	Non-heteroscedasticity
	Spare built-up	0.460	Non-heteroscedasticity
	Dense built-up	0.164	Non-heteroscedasticity
	Very dense building	0.436	Non-heteroscedasticity

Land Cover and IR	Water body	0.149	Non-heteroscedasticity
	Open space	0.751	Non-heteroscedasticity
	Urban built-up	0.948	Non-heteroscedasticity
	Vegetation	0.977	Non-heteroscedasticity

The autocorrelation test aims to examine the correlation between residuals across different time periods. In this study, the Durbin-Watson test was used to carry out the autocorrelation test [25].

For the statistical tests between NDVI and IR, with a sample size of 36 and three independent variables, the Durbin-Watson table at a 5% significance level yielded a d_u value of 1.653. The Durbin-Watson value obtained from the analysis was 1.784. Since the results satisfied the condition 1.653 < 1.784 < 2.347, it can be concluded that no autocorrelation was present.

Table 5. Autocorrelation Test Results between NDVI and Incidence Rate

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate	Durbin-Watson
1	.616[a]	.380	.322	.72344	1.784

For the statistical tests between NDBI and IR, with a sample size of 36 and four independent variables, the Durbin-Watson table at a 5% significance level yielded a d_u value of 1.724. The Durbin-Watson value obtained from the analysis was 0.985. Since the results did not satisfy the condition 1.726 > 0.985 < 2.274, it can be concluded that there was a correlation. Autocorrelation symptoms can be addressed by applying the Cochrane-Orcutt method [28].

Table 6. Autocorrelation Test Results between NDBI and Incidence Rate

Autocorrelation Test	Durbin-Watson
Before Cochrane-Orcutt	0.985
After Cochrane-Orcutt	2.037

After applying the Cochrane-Orcutt method, the Durbin-Watson value improved to 2.037. When input into the Durbin-Watson test formula, with 1.726 < 2.037 < 2.274, it can be concluded that there was no autocorrelation.

For the statistical tests between land cover and IR with a sample size of 36 and four independent variables, the Durbin-Watson table at a 5% significance level yielded a d_u value of 1.724. The Durbin-Watson value obtain from the analysis was 0.772, indicating a correlation and satisfying the condition 1.724 > 0.772 < 2.274. The autocorrelation symptoms were addressed by applying the Cochrane-Orcutt method.

Table 7. Autocorrelation Test Results between Land Cover and IR

Autocorrelation Test	Durbin-Watson
Before Cochrane-Orcutt	0.772
After Cochrane-Orcutt	2.103

After applying the Cochrane-Orcutt method, the Durbin-Watson value improved to 2.103. When input into the Durbin-Watson test formula, with 1.724 < 2.103 < 2.274. So, it can be concluded that land cover and incidence rate had no correlation, passing the autocorrelation test.

3.7 Multiple Linear Regression Hypothesis Testing

Hypothesis testing was carried out using the F-test to determine whether the NDVI, NDBI, and land cover variables influenced the incidence rate. The null hypothesis was accepted if the significance value was greater than 0.05 and rejected if the significance value was less than 0.05 [29].

3.7.1 T-Test and F-Test between NDVI and Incidence Rate

Table 8. Results of T-Test between NDVI and Incidence Rate

Variable	Regression Coefficient	Sig.	Result
Non-Vegetation	0.275	0.093	No effect
Slight Density	-0.733	0.015	Effect
Moderate Density	0.487	<0.001	Effect

Based on Table 8, the results of the T-test analysis are as follows:

1. The significance value for X1 (non-vegetation) in relation to Y (incidence rate) is 0.093, which is greater than 0.05. This indicated no significant influence of NDVI in the non-vegetation category on the incidence rate.
2. The significance value for X2 (slight density) in relation to Y (incidence rate) is 0.015, which is less than 0.05. This indicated a significant influence of the slightly dense NDVI category on the incidence rate.
3. The significance value for X3 (moderate density) to Y (incidence rate) is 0.015, which is less than 0.05. This indicated a significant influence of the moderately dense NDVI category on the incidence rate.

Table 9. Results of F-Test between NDVI and Incidence Rate

Model	R^2	F	Sig.
Regression	0.380	6.530	0.001[b]

According to Table 9, a significance value of 0.001 was found. Therefore, it can be concluded that all NDVI map categories (non-vegetation, slight density, and moderate density) had a joint influence on the incidence rate. Consequently, the null hypothesis a ($H0_a$) was rejected, and the alternative hypothesis a (HA_a) was accepted. After determining that NDVI simultaneously influenced the incidence rate, the magnitude of the influence was assessed through the coefficient of determination. The R-squared value obtained was 0.380 (38%), indicating that NDVI influenced the incidence rate at 38%, while other variables influenced the others at 62%.

3.7.2 T-Test and F-Test between NDBI and Incidence Rate

Table 10. Results of T-Test between NDBI and Incidence Rate

Variable	Regression Coefficient	Sig.	Result
Non-Building	0.403	0.185	No effect
Spare Built-Up	-0.328	0.621	No effect
Dense Built-Up	0.488	0.337	No effect

Variable	Regression Coefficient	Sig.	Result
Very Dense Building	-0.343	0.135	No effect

Source: SPSS, 2023

Based on Table 10, the results of the T-test analysis are as follows:

1. The significance value for X1 (non-building) in relation to Y (incidence rate) is 0.185, which is greater than 0.05. This indicated no significant influence of the NDBI category on the incidence rate.
2. The significance value for X2 (spare built-up) in relation to Y (incidence rate) is 0.621, which is greater than 0.05. This indicated no significant influence of the non-meeting NDBI category on the incidence rate.
3. The significance value for X3 (dense built-up) in relation to Y (incidence rate) is 0.337, which is greater than 0.05. This indicated no significant influence of the fairly dense NDBI category on the incidence rate.
4. The significance value for X4 (very dense building) in relation to Y (incidence rate) is 0.135, which is greater than 0.05. This indicated no significant influence of the meeting NDBI category on the incidence rate.

Table 11. Result of F-Test Between NDBI and Incidence Rate

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.123	4	.531	1.102	.394[b]
	Residual	6.741	14	.481		
	Total	8.863	18			

According to Table 11, a significance value of 0.394 was found. Therefore, it can be concluded that all NDBI map categories (not built, not-dense, quite dense, and dense) did not have a joint influence on the incidence rate. Consequently, the null hypothesis b ($H0_b$) was accepted, and the alternative hypothesis b (HA_b) was rejected.

3.7.3 T-Test and F-Test between Land Cover and Incidence Rate

Table 12. Results of T-Test between Land Cover and Incidence Rate

Variable	Regression Coefficient	Sig.	Result
Water Body	-0.083	0.137	No Effect
Open Space	0.70	0.624	No Effect
Urban Built-Up	0.001	0.983	No Effect
Vegetation	-0.004	0.818	No Effect

Based on Table 12, the results of the T-test analysis are as follows:

1. The significance value for X1 (water body) in relation to Y (incidence rate) is 0.137, which is greater than 0.05. This indicated no significant influence of water bodies on the incidence rate.
2. The significance value for X2 (open space) in relation to Y (incidence rate) is 0.624, which is greater than 0.05. This indicated no significant influence of empty land on the incidence rate.
3. The significance value for X3 (urban built-up) in relation to Y (incidence rate) is 0.983, which is greater than 0.05. This indicated no significant influence of settlements on the incidence rate.
4. The significance value for X4 (vegetation) in relation to Y (incidence rate) is 0.818, which is greater than 0.05. This indicated no significant influence of vegetated areas on the incidence rate.

Table 13. Results of F-Test between Land Cover and Incidence Rate

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6259.491	4	1564.873	.639	.639[b]
	Residual	75920.128	31	2449.036		
	Total	82179.619	35			

According to Table 13, a significance value of 0.639 was found. Therefore, it can be concluded that land cover map categories (water bodies, empty land, settlements, and vegetated areas) had no significant influence the incidence rate. Consequently, the null hypothesis c ($H0_c$) was accepted, and the alternative hypothesis c (HA_c) was rejected.

4 Discussion

4.1 The Incidence Rate of Dengue in Bengkulu City between 2018 and 2021

The incidence rate of dengue in Bengkulu City decreased gradually from 2018 to 2021. This reduction suggested the success of efforts made by the Health Office of Bengkulu City to reduce the incidence of dengue by improving house conditions, maintaining clear stairways, and increasing efforts to prevent and control infectious diseases [13].

A significant decrease was found in Muara Bangkahulu, where the incidence rate dropped from 164.88 per 100,000 population to 10.71 per 100,000 population, a reduction of 154.18 per 100,000 population over four years. Despite this overall decrease in the incidence rate, the World Health Organization (WHO) stated that the reported figures may be lower than the actual number of cases. This under-reporting could be due to factors such as ureported dengue cases, underdiagnosis, and asymptomatic manifestations of the disease.

4.2 The Effect of Normalized Difference Vegetation Index (NDVI) on the Incidence Rate

The NDVI map used to assess vegetation density showed that Bengkulu City did not have any areas classified as dense vegetation from 2018 to 2021. There was a decrease in non-vegetation areas in 2019, which indicated an increase in green areas in Bengkulu City. However, in 2020, the non-vegetation area increased significantly from 2,833.4 hectares to 4,836.3 hectares, followed by a decrease in the area of moderately dense vegetation from 4.487.7 hectares to 2.222 hectares. These findings suggested that a significant reduction in vegetation occurred between 2019 and 2020.

The area classified as non-dense vegetation continued to increase from 2018 to 2021. The reduction in vegetation areas is supported by data from the Central Bureau of

Statistics (*Badan Pusat Statistik*/BPS), indicating that deforestation in Bengkulu Province amounted for 2,160.6 hectares during the 2018-2019 period, 3,359.8 hectares during the 2019-2020 period, and 2,033 hectares during the 2020-2021 period [30]

This study shows that areas with NDVI categories of non-dense and moderate dense partially influenced the incidence rate of dengue. In contrast, partially non-vegetated areas did not affect the incidence rate. The NDVI map showed that non-vegetation areas included settlements, water bodies, and other built-up areas lacked vegetation. Simultaneously, NDVI influenced the incidence rate of dengue, aligning with previous research suggesting that NDVI can serve as a predictor for spikes in the incidence rate of dengue [31]. The NDVI value can also influence environmental temperature, followed by an increasing incidence rate of dengue.

4.3 The Effect of Normalized Difference Built-up Index (NDBI) on the Incidence Rate

The NDBI map was used to assesses the density of buildings in Bengkulu City. As residential settlements continue to develop, the NDBI value in the built-up category increases. Bengkulu City has experienced consistent development, which results in a gradual reduction in the area of undeveloped land every year. In 2018, the undeveloped area of 13,482.2 hectares decreased to 12,748.4 hectares in 2021. This reduction in undeveloped land was oddest by an increase in built-up areas, categorized into levels: not dense, moderately dense, and slightly dense. All three categories from 2018 to 2021 showed an increase in built-up area from 2018 to 2020.

The study found no partial or simultaneous influence of NDBI on the incidence rate of dengue. In contrast, previous research in Jakarta Province in 2018 showed that an increase in NDBI values was associated with environmental temperatures [32]. In contrast to the spatial conditions in Bogor Regency, Bengkulu City had little land cover in the dense category from 2018 to 2021. The largest dense NDBI area was in 2021, covering only 14.04 hectares.

Bengkulu City's low NDBI values compared to those of larger cities may explain why the NDBI value doid not affect its incidence rate of dengue. A high NDBI value is typically associated with an increase in environmental temperature, which can affect the growth of dengue vectors. Therefore, environmental temperature must be considered to better understand the influence between NDBI and the incidence rate of dengue.

4.4 The Effect of Land Cover on the Incidence Rate

Changes in land cover typically occur due to human activities on the environment, altering the function of the land. Several factors can influence land cover changes, such as deforestation. For example, massive deforestation occurred on Bengkalis Island, Riau, from 1990 to 2019 due to plantations opened by transmigrants [33]. Forest deforestation on Bengkalis Island also occured due to social problems, namely land ownership disputes.

The findings of this study indicated that land cover in Bengkulu City did not significantly influence the incidence rate of dengue. Partially, vegetated areas did not influence the incidence rate in Bengkulu City. However, vegetated areas had a significant influence on the land surface temperature of an area, which plays a vital role in the spread of dengue. An increase of 1°C in land surface temperature can increase the incidence rate of dengue by 70.1 per 100,000 population [34].

Bengkulu City has various types of vegetation, such as mangrove forests and oil palm plantations, which contribute differently to land surface temperature. In 2018, Kampung Melayu contained 247.61 hectares of mangrove forest [35]. The incidence rate of

dengue in Kampung Melayu was consistently in the low category from 2018 to 2021. In 2018, the incidence rate of dengue in Kampung Melayu District was 25.23 per 100,000 population. In 2019, it increased to 51.09 per 100,000 population but decreased to 22.73 per 100,000 population in 2020 and 3.22 per 100,000 population in 2021. Mangrove forests can reduce dengue incidence by 259.1 per 100,000 population for every 1% increase in mangrove forest area [34]. However, deforestation of mangrove forests for settlements can cause land surface temperatures to increase by 1.8°C [36].

Apart from mangrove forests, Bengkulu City also contains oil palm plantations covering 270.302 hectares [37]. In contrast to mangrove forests, oil palm plantations can increase the dengue incidence by raising mosquito density [38]. The environmental temperature in oil palm plantations is 4°C warmer than in logged forest areas.

This study also found no relationship between settlements and the incidence rate of dengue. This finding contrasts with previous studies, which suggested that a 1% increase in built-up land could reduce the incidence rate of dengue by 6.94 per 100,000 population [39]. Increasing built-up land does not always negatively affect the environment, especially in terms of dengue transmission. Public knowledge of environmental sanitation can help reduce mosquito habitats. Additionally, the significant increase in residential areas was not accompanied by increased population density in Bengkulu City. From 2018 to 2021, the population density remained at approximately 2.500 inhabitants/km^2. Higher population densities can increase the incidence rate of dengue, as the flight range of dengue vector mosquitoes is about 100 meters, making virus spread easier in densely populated areas [40, 41].

In terms of water bodies in Bengkulu City, this study found that rivers and estuaries did not directly connect to seawater. It is important to differentiate between water bodies that are ideal for mosquitoes to breed and those that are not. Water salinity and pH levels can influence whether *Aedes aegypti* and *Aedes albopictus* mosquitoes can breed in these areas [42]. The results of this study showed no correlation between water bodies and the dengue incidence rate. However, an increase in surface water areas can provide breeding sites for dengue vector mosquitoes such as *Aedes albopictus*. Phylogenetic studies suggested a larger the mosquito population in a water surface area increases the likelihood of genetic mutations in the virus they carry, resulting in outbreaks [42].

5 Conclusion

The NDVI simultaneously influenced the IR of dengue, but the NDBI and land cover had no influence on the IR of dengue. These baseline data are necessary for determining more effective and efficient dengue control strategies.

References

1. S. Y. Irda Sari, Y. Adelwin, & F. R. Rinawan, Land use changes and cluster identification of dengue hemorrhagic fever cases in Bandung, Indonesia. Trop. Med. Infect. Dis. **5**(2) (2020).
2. P. Pongsumpun, I. M. Tang, & N. Wongvanich, Optimal control of the dengue dynamical transmission with vertical transmission. Adv. Differ. Equations. 2019(1) (2019).
3. J. Phadungsombat, H. T. T. Vu, Q. T. Nguyen, H. T. V. Nguyen, H. T. N. Nguyen, B. T. Dang, et al., Molecular characterization of dengue virus strains from the 2019–2020 epidemic in Hanoi, Vietnam. Microorganisms. **11**(5) (2023).

4. G. C. D. Podung, S. N. N. Tatura, & M. F. J. Mantik, Faktor risiko terjadinya sindroma syok dengue pada demam berdarah dengue. J. Biomedik. **13**(2):161 (2021).
5. Khanam, H. Gutiérrez-Barbosa, K. E. Lyke, & J. V. Chua, Immune-mediated pathogenesis in dengue virus infection. Viruses. **14**(11):1–19 (2022).
6. J. Guarner & G. L. Hale, Four human diseases with significant public health impact caused by mosquito-borne flaviviruses: West Nile, Zika, dengue and yellow fever. Semin. Diagn. Pathol. **36**(3):170–6 (2019).
7. S. Sinha, K. Singh, Y. S. Ravi Kumar, R. Roy, S. Phadnis, V. Meena, et al., Dengue virus pathogenesis and host molecular machineries. J. Biomed. Sci. **31**(1):1–24 (2024).
8. L. B. Nicholson, The immune system. Essays Biochem. **60**(3):275–301 (2016).
9. L. Zhou, X. Cao, J. Fang, Y. Li, & M. Fan, Macrophages polarization is mediated by the combination of PRR ligands and distinct inflammatory cytokines. Int. J. Clin. Exp. Pathol. **8**(9):10964–74 (2015).
10. Fernandes-Santos & E. L. de Azeredo, Innate immune response to dengue virus: Toll-like receptors and antiviral response. Viruses. **14**(5) (2022).
11. Cerny, M. Haniffa, A. Shin, P. Bigliardi, B. K. Tan, B. Lee, et al., Selective susceptibility of human skin antigen presenting cells to productive dengue virus infection. PLoS Pathog. **10**(12) (2014).
12. L. Zhou, A. Jiang, J. Veenstra, D. M. Ozog, & Q. S. Mi, The roles of skin Langerhans cells in immune tolerance and cancer immunity. Vaccines. **10**(9):1–18 (2022).
13. Dinas Kesehatan Kota Bengkulu, Rencana Strategis Dinas Kesehatan Kota Bengkulu 2019-2023 (2019).
14. WHO, Vector-Borne Diseases (2020).
15. R. Dolin, M. J. B. Martin, & J. E. Bennett, Principles and Practices of Infectious Disease, 8th ed. (Elsevier, 2015).
16. T. W. Kesetyaningsih, S. Andarini, & H. Pramoedyo, Determination of environmental factors affecting dengue incidence in Sleman District, Yogyakarta, Indonesia. J. Infect. Dis. **12**(S):13–25 (2018).
17. R. P. Sunarno, N. E. Wahyuningsih, & A. Budiharjo, Studi faktor suhu di dalam rumah dan kejadian demam berdarah dengue di Semarang tahun 2017. J. Kesehat. Masy. **5**(5):807–14 (2017).
18. P. Gao, E. Pilot, C. Rehbock, M. Gontariuk, S. Doreleijers, L. Wang, et al., Land use and land cover change and its impacts on dengue dynamics in China: A systematic review. PLoS Negl. Trop. Dis. **15**(10):1–21 (2021).
19. M. Sheela, A. Ghermandi, P. Vineetha, R. V. Sheeja, J. Justus, & K. Ajayakrishna, Assessment of relation of land use characteristics with vector-borne diseases in tropical areas. Land Use Policy. **63**:369–80 (2017).
20. A. Mustika, S. Bakri, & D. W. S. R. Wardan, Perubahan penggunaan lahan di Provinsi Lampung dan pengaruhnya terhadap insidensi demam berdarah dengue (DBD). **4**(3):35–46 (2016).
21. R. Lailarahma & I. W. S. Adnyana, Study of land use changes and its relationship with temperature and dengue fever in 2003 and 2016 over Jakarta Province using Landsat 7+ETM and Landsat 8 OLI. ECOTROPHIC J. Ilmu Lingkung (J. Environ. Sci.) **12**(1):18 (2018).
22. Wulansari, A. Darumurti, A. P. E. Hartomi, & D. Eldo, Pengembangan sumber daya manusia dalam manajemen bencana. J. Gov. Public Policy. **4**(3) (2017).
23. J. Cohen, Multiple regression as a general data-analytic system. Psychol. Bull. **70**(6 PART 1):426–43 (1968).
24. Soegiyono, Metode Penelitian Kuantitatif, Kualitatif dan R&D (2013).
25. N. A. Janie, Statistik Deskriptif dan Regresi Linear Berganda Dengan SPSS. Ardiani

Ika S., Ed. (Semarang University Press, 2012).
26. N. Soleh, C. Harini, & D. Djamaludin, The effect of service quality, price, and trust to customer satisfaction users of transportation services online ojek (2018).
27. Y. R. Utari & M. A. Aris, The effect of financial distress, capital intensity, leverage and operating complexity on accounting conservatism: Empirical study on food and beverage companies listed on the Indonesia Stock Exchange in 2020-2022. **4**(6):7051–63 (2023).
28. Ghozali, Aplikasi Analisis Multivariate Dengan Program IBM SPSS 25, 9th ed. (Badan Penerbit Undip, 2018).
29. S. H. Sahir, Metodologi Penelitian (2022), p. 16.
30. BPS Kota Bengkulu, Angka Deforestasi (Netto) Indonesia di Dalam dan di Luar Kawasan Hutan Tahun 2013-2021 (2023).
31. Ziemann, G. Fairchild, J. Conrad, C. Manore, N. Parikh, S. Del Valle, et al., Predicting dengue incidence in Brazil using broad-scale spectral remote sensing imagery. Int. Geosci. Remote Sens. Symp. 2018-July:**2076**–8 (2018).
32. M. Adeanti & M. C. Harist, Analisis spasial kerapatan bangunan dan pengaruhnya terhadap suhu (2018), p. 529–36.
33. L. Juniyanti, L. B. Prasetyo, D. P. Aprianto, H. Purnomo, & H. Kartodihardjo, Perubahan penggunaan dan tutupan lahan, serta faktor penyebabnya di Pulau Bengkalis, Provinsi Riau (periode 1990-2019). J. Pengelolaan Sumberd Alam dan Lingkung (J. Nat. Resour. Environ. Manag.) **10**(3):419–35 (2020).
34. Hastuty, D. W. S. Wardani, C. Wulandari, & S. Bakri, Peran hutan mangrove dalam ekosistem perairan terestris sebagai pengendali penyakit demam berdarah dengue (DBD) di bawah skenario pemanasan global. Pros. Semin. Nas. Hari Air Dunia (2019), p. 66–74.
35. Febriansyah, D. Hartono, B. F. Negara, P. P. Renta, & Y. P. Sari, Struktur komunitas hutan mangrove di Pulau Baai Kota Bengkulu. J. Enggano. **3**(1):112–28 (2018).
36. Genova, O. Dix, A. Saefan, M. Thakur, & A. Hassan, Carpal tunnel syndrome: a review of the literature. **62**(7):316
37. Pemerintah Provinsi Bengkulu. Laporan Status Lingkungan Hidup Daerah Provinsi Bengkulu Tahun 2014. P.1–23 (2014).
38. Gregory N, Ewers RM, Chung AYC, Cator LJ. Oil palm expansion increases the vectorial capacity of dengue vectors in Malaysian Borneo. PLoS Negl Trop Dis. **16**(3):1–17 (2022).
39. Astuti SD, Sarwani D, Rejeki S, Nurhayati S. Analisis Autokorelasi Spasial Kejadian Demam Berdarah Dengue (DBD) di Kabupaten Klaten Tahun 2020 Spatial Autocorrelation Analysis of Dengue Hemorrhagic Fever (DHF) in Klaten Regency 2020. J Vektor Penyakit. **16**(1):23–32 (2022).
40. Shrestha R, Pant ND, Gc G, Thapa S, Neupane B. Serological and Entomological Study of Dengue in Dang and Chitwan Districts of. p.1–10 (2016).
41. Triana D, Martini M, Suwondo A, Sofro MAU, Hadisaputro S, Suhartono S. Dengue Hemorrhagic Fever (DHF): Vulnerability Model Based on Population and Climate Factors in Bengkulu City. J Heal Sci Med Res. 1–11 (2023).
42. Tian H, Huang S, Zhou S, Bi P, Yang Z, Li X, et al. Surface water areas significantly impacted 2014 dengue outbreaks in Guangzhou, China. Environ Res. **150**:299–305 (2016).

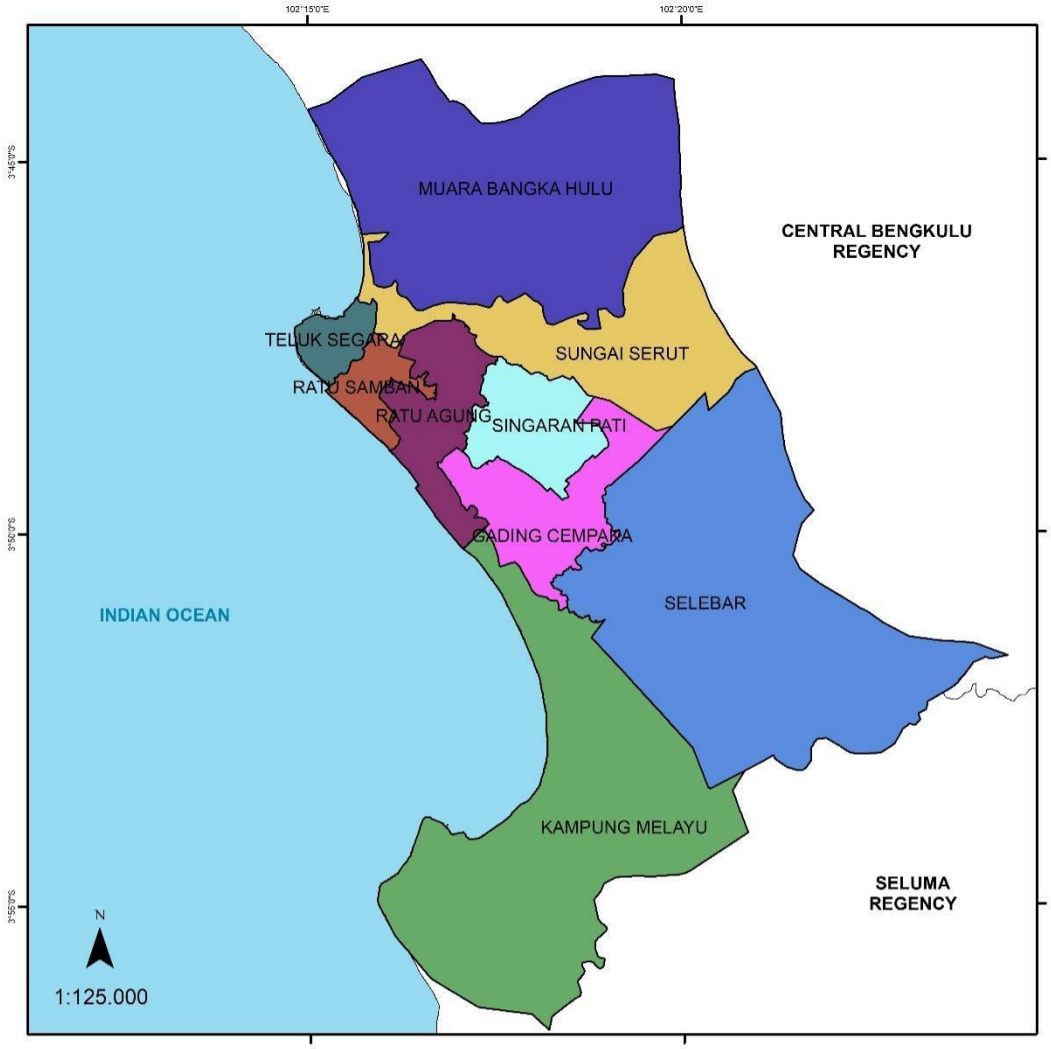

Figure 1. Map of Subdistricts in Bengkulu City

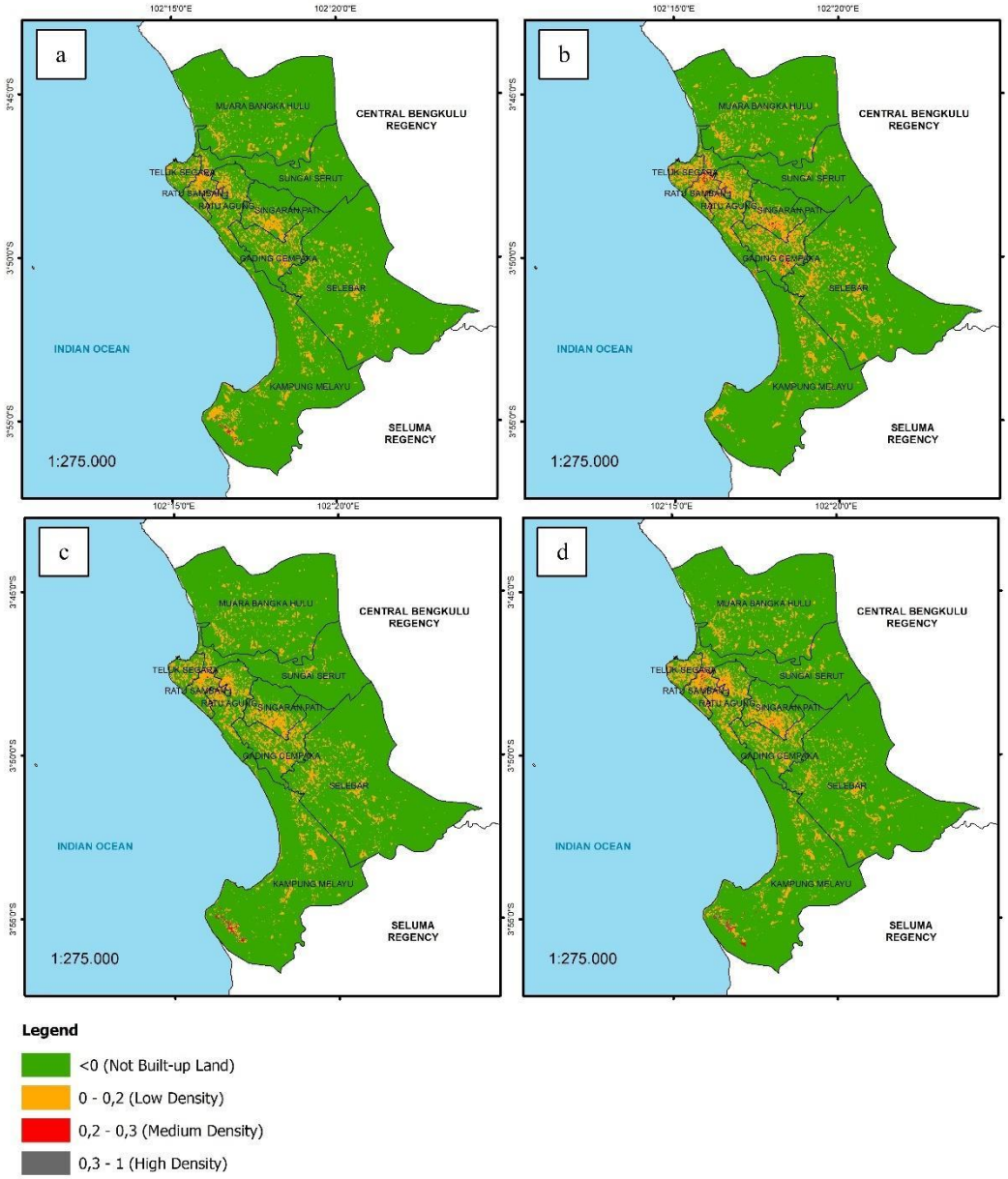

Figure 2. Map of NDBI in Bengkulu City

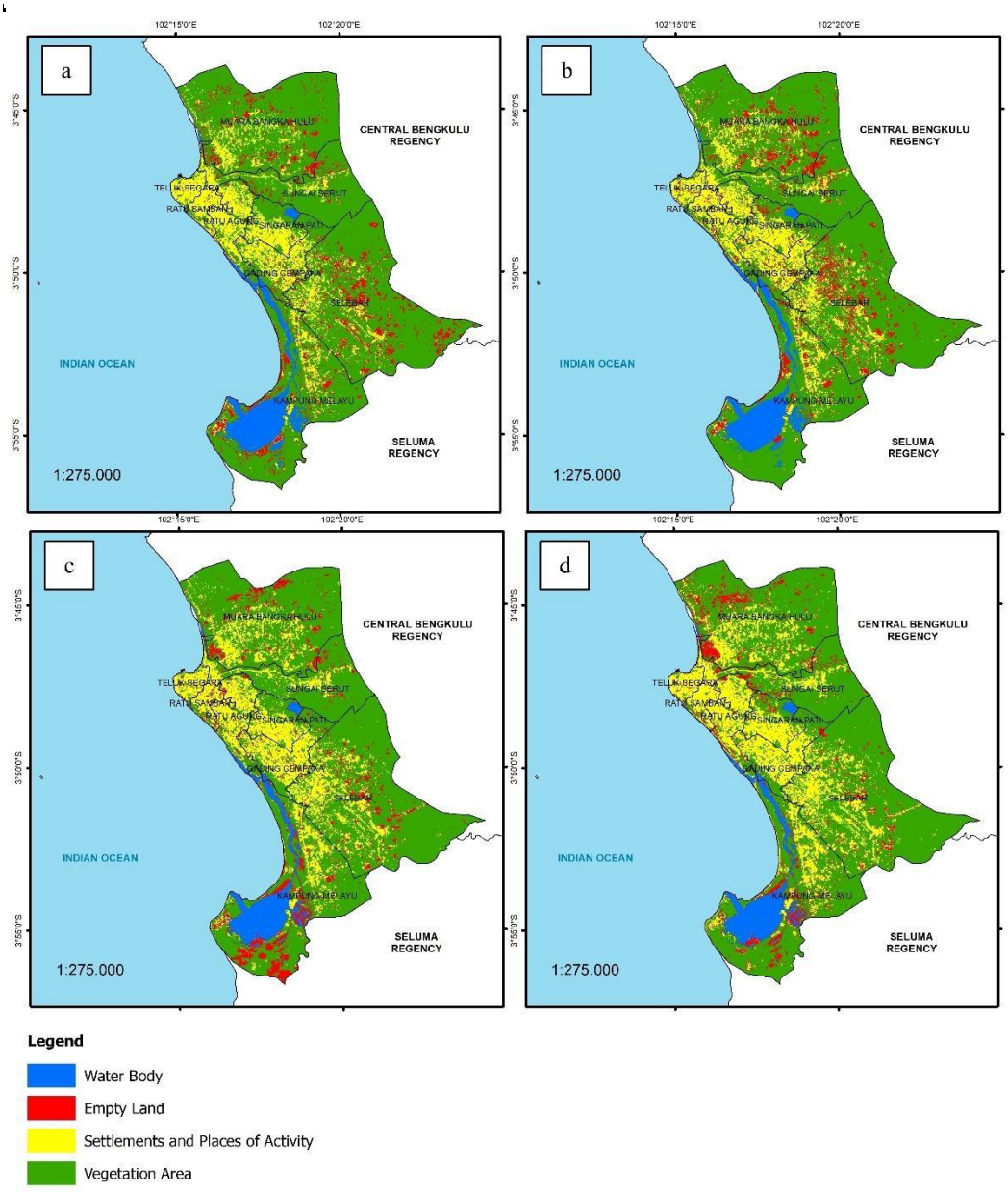

Figure 3. Map of Classification of Land Cover in Bengkulu City

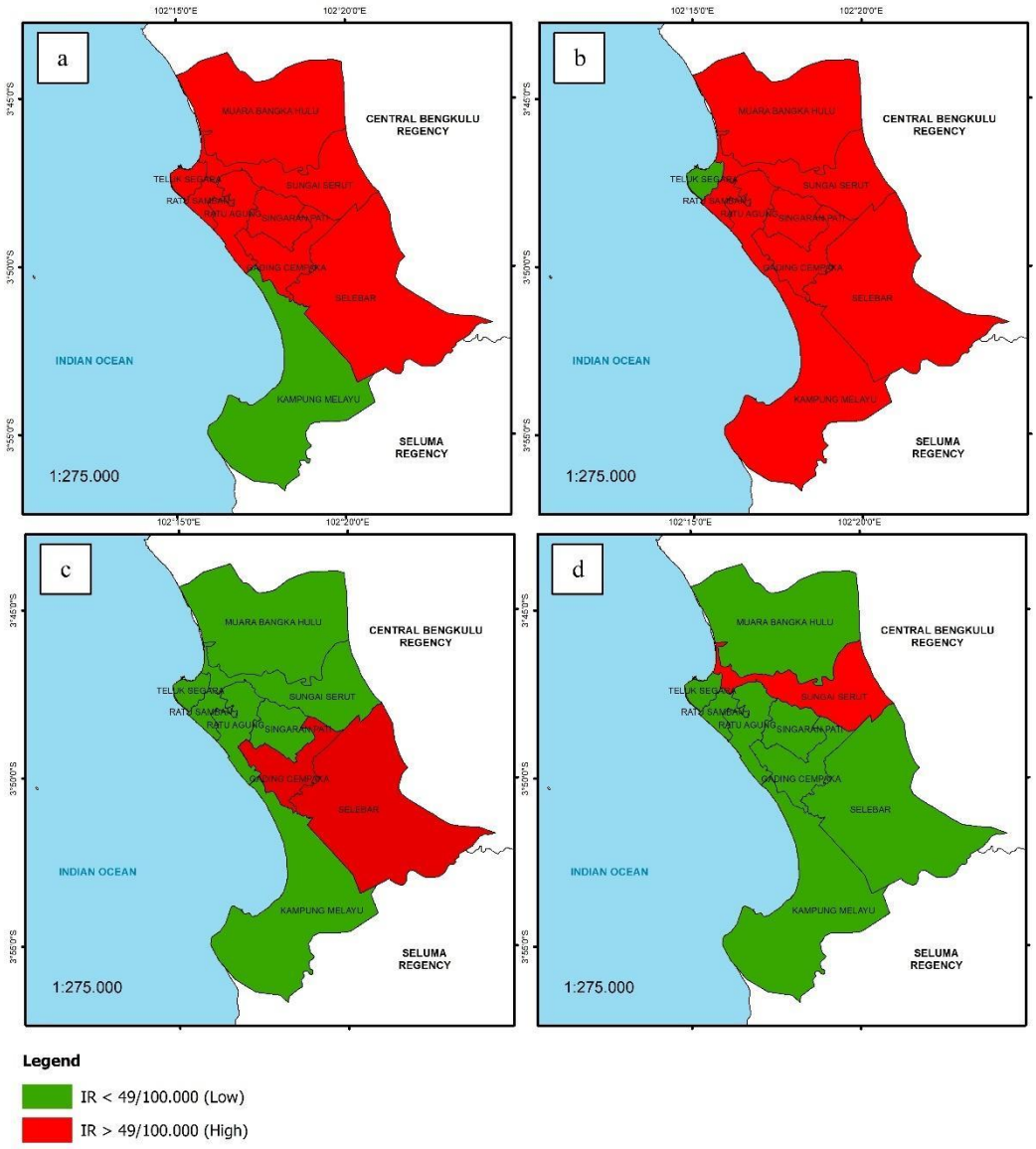

Figure 4. Map of Incidence Rate Distribution in Bengkulu City

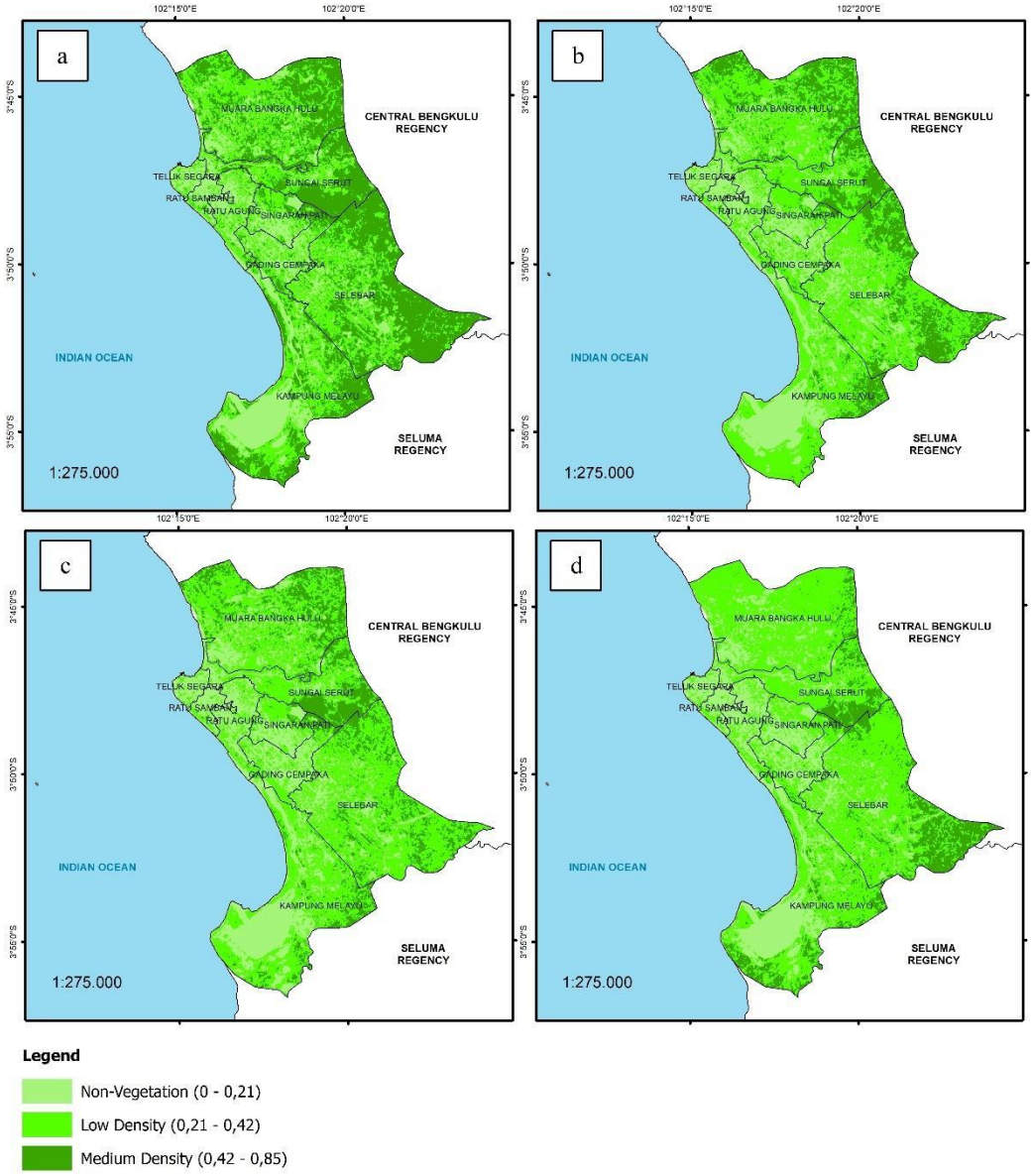

Figure 5. Map of NDVI in Bengkulu City