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Urban Heat Island Spatial Model for Climate Village Program Planning

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Abstract

Global warming and climate change are critical issues impacting ecosystems, human habitats, and the overall environment. Urban Heat Island (UHI) is a significant phenomenon resulting from increased urban temperatures due to dense urban development, the use of heat-absorbing materials, and reduced vegetation. This study focuses on analyzing the UHI effect in Banjarmasin, Indonesia, using spatial regression and descriptive spatial analysis methods. By employing Land Surface Temperature (LST) data from Landsat 9 and Sentinel-2 satellite imagery, combined with data from wireless sensor networks (WSN), this research aims to develop a comprehensive UHI spatial model to inform climate village program planning. The specific objectives of this study are to: (1) map high-temperature areas within Banjarmasin near from Climate Village Program Planning, (2) validate satellite-derived LST data with real-time WSN measurements, and (3) propose actionable strategies for urban planners to mitigate UHI effects through the enhancement of green spaces and sustainable spatial planning in Climate Village Program Planning. The results reveal substantial temperature variations within Banjarmasin, with urban areas showing significantly higher LST values compared to vegetated outskirts. The integration of satellite data with real-time WSN measurements provides a robust validation method, ensuring accurate environmental monitoring. Additionally, this study includes an analysis of the Vegetation Health Index (VHI), which integrates both the Temperature Condition Index (TCI) and the Vegetation Condition Index (VCI) to assess the health and stress levels of vegetation. The VHI analysis highlights the importance of maintaining healthy vegetation to reduce surface temperatures and mitigate UHI effects. This study underscores the importance of enhancing green spaces and implementing sustainable spatial planning to mitigate UHI effects. The proposed UHI spatial model offers a valuable tool for urban planners and policymakers in developing strategies to improve urban environmental quality and resilience to climate change.

Keywords: UHI, LST, NDVI, VHI, Climate Village Program, WSN

1. Introduction

Global warming and climate change are two of the serious issues currently faced by humanity, among other significant problems occurring over time worldwide [1], [2], [3]. These phenomena have substantial impacts on ecosystems, humans, and the habitats of all living beings on the planet. The increase in global temperatures over the past few decades has led to dramatic changes in weather patterns, sea levels, and the availability of natural resources [4], [5]. Global warming is characterized by the increase in Earth's average temperature due to the rising concentration of greenhouse gases in the atmosphere [6], [7], [8]. These gases, such as carbon dioxide (CO2), methane (CH4), and nitrous oxide (N2O), are released into the atmosphere through various human activities, including the burning of fossil fuels, deforestation, and intensive agriculture [4]. The levels of greenhouse gas emissions have increased significantly since the Industrial Revolution in the 18th century and continue to rise in the current era of the Fourth Industrial Revolution [9], [10]. The development of technology in the era of the Industrial Revolution has had both positive and negative impacts on environmental conditions worldwide. One negative impact of this development is the increase in

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urban temperature, known as the UHI effect [11]. UHI is a phenomenon observed in urban environments where higher air temperatures are recorded in urban areas compared to the surrounding rural areas [12]. The UHI phenomenon is caused by the interaction between human activities, such as dense urban development, the use of heat-absorbing building materials, deforestation, and industrial activities, with the physical and thermal characteristics of the urban environment [13].

Many researchers have been conducted to prevent the adverse effects of the UHI phenomenon in the future, one of which involves using spatial data mapping through remote sensing of thermal detection captured via satellite imagery [14]. Researchers have developed knowledge about UHI through remote sensing by utilizing satellite imagery data extracted using LST data from satellite images [15]. The Indonesian government, through the Ministry of Environment and Forestry, has initiated the Climate Village Program [16]. Climate village program is a national program based on community empowerment in the field of environmental protection. This program is one of the Ministry of Environment Indonesian initiatives to encourage the role of the community and all stakeholders in enhancing resilience to the impacts of climate change and reducing greenhouse gas emissions [17]. Climate village program aims to protect the environment and the Indonesian community from the impacts of climate change.

In addressing the current climate change, reducing UHI and greenhouse gas effects is the best option for every country [18]. Spatial data methods can be applied to spatial simulations of greenhouse gas effects and urban warming from UHI data analyzed through remote sensing techniques based on raster data with large and medium spatial scales. In summary, this system adopts more advanced and convenient methods to measure UHI and vegetation density in a specific area. Studies [12], [14], [19], [20], [21], [22] have conducted UHI data analysis through remote sensing of Land LST and NDVI values. NDVI is an index used to measure the quantity and quality of vegetation in an area by utilizing the difference in reflectance between near-infrared (NIR) and red in satellite imagery or aerial photos. This index provides information on the presence and density of vegetation and can be used to monitor changes in land conditions [1], [5], [17]. Meanwhile, LST measures the temperature at the Earth's surface. LST refers to the actual temperature felt at the ground surface, including soil, vegetation, water, and human infrastructure [12].

From previous studies, researchers have not identified recommended actions from spatial data analyses related to reducing UHI in the form of programs supporting the reduction of greenhouse gases, either through community empowerment or government programs. The analysis from previous research still focuses on spatial data from satellite imagery, where there is no validation of the data against real conditions for data not captured by satellite images. The use of automated or real-time technology can be combined in this research, where in previous studies [23], [24], [25], researchers developed a system to monitor the environmental health levels. This system utilizes IoT technology by applying a wireless sensor network to obtain data on environmental conditions [26], [27]. A combination of spatial data from remote sensing and wireless sensor network technology, along with climate village programs, can be an interesting research topic. In this study, researchers attempt to develop a system using the UHI Spatial Model for planning climate village programs with data to be analyzed in the city of Banjarmasin.

2. Method

This research is conducted in the administrative area of Banjarmasin city. The type of research is field research, employing a mix-method approach that combines quantitative spatial analysis and qualitative spatial descriptive analysis. This method is used to develop a spatial data model for UHI that can mitigate the impacts of UHI through the climate village program.

Using the UHI Spatial Model, this analysis aims to map high-temperature areas for planning climate village programs. Temperature data collected through WSN is used to validate and enrich the UHI model derived from satellite imagery via code.earthengine.google.com. Spatial mapping methods employ techniques such as satellite image analysis, spatial modeling with algorithms like spatial regression or kriging, integrating data through WSN.

Spatial regression in this study is an analytical method used to model the relationship between response (dependent) variables, such as land surface temperature and humidity, and predictor (independent) variables, such as land cover, building density, or distance to heat sources in the context of UHI analysis for climate village planning. This regression

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analysis considers the spatial structure of data and can help identify factors influencing UHI in climate villages. In the context of spatial analysis considering the spatial structure of data, the following is the Spatial Regression formula:

1) Notation:

   $Y(u)$: Value of the response variable at the prediction location

   $X(u)$: Value of the predictor variable at the prediction location

   $Y(x_i)$: Value of the response variable at observation location i

   $X(x_i)$: Value of the predictor variable at observation location i

   $\varepsilon(u)$: Residual at the prediction location

   β : Regression coefficient

2) Spatial Value Estimation ($Y(u)$):

$$Y(u) = X(u) * \beta + \varepsilon(u) \quad (1)$$

3) Regression Coefficient (β):

$$\beta = (X'WX)\hat{}-1X'WY \quad (2)$$

In this formula, Y(u) is the value of the response variable to be predicted at the prediction location. X(u) is the value of the predictor variable used to predict the response variable at the prediction location. $Y(x_i)$ and $X(x_i)$ are the values of the response and predictor variables at observation location i. ε(u) is the residual, which is the difference between the actual observed value and the predicted value using the regression model.

The steps in Spatial Regression in this study involve collecting observation data for response and predictor variables at multiple locations. Next, a regression model is built using the provided formula. With the obtained regression model, the response variable values are predicted at the prediction locations using the predictor variable values present at those locations. In the UHI spatial regression analysis using WSN for climate village planning, the steps include:

1) Collecting WSN data: Installing temperature sensors at various locations in the climate village to measure LST and humidity.

2) Building the regression model: Developing a spatial regression model considering predictor variables such as land cover, building density, or distance to heat sources. This regression model will estimate the relationship between predictor variables and LST in the climate village.

3) Evaluating and interpreting the model: Evaluating the regression model to understand the relative influence of predictor variables on LST.

4) Predicting LST: Using the developed regression model to predict LST at locations not covered by WSN.

Descriptive spatial analysis in the UHI spatial model for climate village planning using WSN involves explaining and visualizing spatial patterns and basic statistics from LST data collected by WSN sensors and satellite imagery data from code.earthengine.google.com. The steps in descriptive spatial analysis for this study are as follows:

1) Collect LST data from WSN sensors located at various points in the climate village.

2) Ensure data quality and integrity by checking sensor reliability and performing data validation.

3) Inspect and clean the data: Identify outliers, missing values, or inconsistent data, and take necessary actions such as imputing missing values.

4) Transform data if necessary: For example, perform data transformations to meet normality assumptions, such as logarithmic transformations.

5) Create LST maps: Use spatial visualization tools like Geographic Information Systems or Google Earth Engine to create maps that depict spatial patterns in the climate village.

6) Generate thematic maps showing LST levels in different areas of the climate village, highlighting possible spatial variations.

7) Calculate descriptive statistics: Compute basic statistics such as mean, median, standard deviation, quartiles, and range from the LST data.

8) Analyze spatial variables: Use spatial statistical tools like variograms to understand the spatial patterns, spatial dependency, and spatial variation of LST in the climate village.

9) Interpret maps and statistics: Understand spatial patterns of LST, identify hot or cold zones, and analyze relationships with environmental factors like land cover or building density.

10) Identify areas requiring intervention: Based on the descriptive spatial analysis, identify areas that need special attention in climate village planning, such as areas with very high temperatures that require UHI mitigation measures.

Descriptive spatial analysis offers an initial insight into the spatial patterns of UHI in climate villages, aiding planners in identifying factors that may influence LST and determining necessary interventions for climate village planning. LST, measured or estimated using remote sensing data from satellites, refers to the actual temperature at the surface of the ground, vegetation, and buildings in this dataset (da Silva Espinoza et al., 2022). It is utilized to analyze and model temperature distribution patterns in urban areas. LST is derived from satellite imagery data that captures the thermal radiation emitted from the Earth's surface. In this study, LST serves as an input variable for modeling, complemented by data on ground temperature and humidity from a DS18B20 sensor, air temperature and humidity from a DHT11 sensor, and thermal camera data. Calculating LST involves adjusting the brightness temperature and considering surface emissivity values, which are 0.979 for water bodies, 0.965 for built-up areas, 0.964 for open lands, and 0.986 for vegetated areas. The USGS provides the formula for surface temperature, ensuring precise measurement and analysis.

$$Ts = \frac{Tb}{1 + \lambda\left(\frac{Tb}{a}\right)\text{In}\left(\mathcal{E}\right)} \quad (3)$$

Note:

Ts = Surface temperature (K)

Tb = Brightness temperature (K)

λ = The mean value of the channel wavelength (11.5 μm)

a = hc/k (148380 K)

h = Constanta planck (6.26 x 10-34 Js)

c = Speed of light (2.998 x 108 ms-1)

k = Constanta Stefan Boltzman (1.38 x 10-23 JK-1)

UHI data can be obtained by extracting LST data from Landsat 9 satellite imagery. UHI maps can be generated by modifying existing equations and incorporating the following formula (Jain et al., 2020):

$$UHI = T_{mean} - (\mu + 0{,}5\ \alpha) \quad (4)$$

Note:

UHI = Urban Heat Island

Tmean = LST (ºCelcius)

μ = Average value LST (ºCelcius)

α = Veviation Value Standart LST (ºCelcius)

In addition to UHI analysis, VHI can be assessed using the TCI and the VCI. VHI provides a comprehensive evaluation of vegetation health by integrating both TCI and VCI. The TCI reflects the relative temperature conditions affecting vegetation, while the VCI represents the relative greenness or vegetation density. By combining these indices, VHI offers valuable insights into the overall health and stress levels of vegetation, facilitating better management and planning for sustainable land use and environmental conservation.

VHI is calculated by combining the TCI and the VCI. The formula for VHI is as follows:

$$VHI=\alpha\cdot VCI+(1-\alpha)\cdot TCIVHI=\alpha\cdot VCI+(1-\alpha)\cdot TCI \quad (5)$$

where:

αα is the weight assigned to VCI, typically set to 0.5 to give equal weight to both indices.

VCI is the Vegetation Condition Index.

TCI is the Temperature Condition Index.

Before calculating the VHI, it is essential to determine the TCI and VCI. These indices provide crucial information on the temperature and vegetation conditions, respectively, which are necessary for a comprehensive assessment of vegetation health. The formulas for TCI and VCI are as follows:

$$VCI = \frac{NDVI - NDVImin}{NDVImax - NDVImin} * 100 \quad (6)$$

$$TCI = \frac{LSTmax - LST}{LSTmax - LSTmin} * 100 \quad (7)$$

Note:

NDVI : Normalized Difference Vegetation Index.

NDVImax : Maximum NDVI value observed over a given period.

NDVImin : Minimum NDVI value observed over a given period.

LST : Land Surface Temperature.

LSTmax : Maximum LST value observed over a given period.

LSTmin : Minimum LST value observed over a given period.

This formula allows the VHI to integrate the effects of both temperature and vegetation conditions, providing a more comprehensive assessment of vegetation health.

3. Result and Discussion

3.1. Analysis Using Spatial Data

In this study, we have analyzed LST data in Banjarmasin city on South Kalimantan using Google Earth Engine. The analysis results reveal significant LST variations across different areas, providing crucial insights into the UHI phenomenon in the region. We analyze the phenomenon in region of interest from Climate Village Program.

3.1.1. Land Surface Temperature (LST)

Based on data obtained from Landsat 9 and Sentinel-2 satellite imagery we analyzed data LST in Banjarmasin City with google earth engine, we get the visualitation can be seen in figure 1.

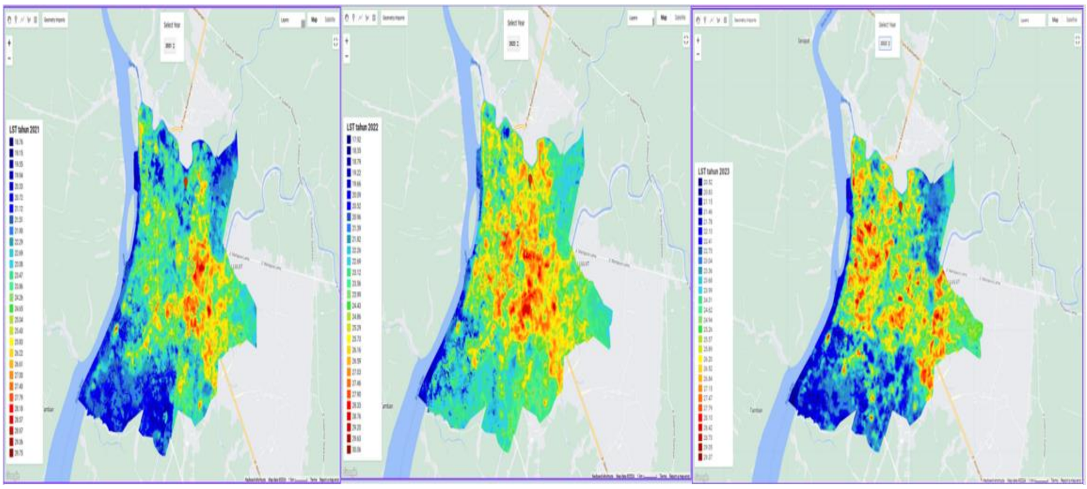

Figure 1. Analysis Result using Spatial Google Earth Engine

The result analysis spatiol with google earth engine shows minimum and maximum values that reflect the temperature differences between urban and rural areas. The minimum LST values are recorded in areas with denser vegetation cover, while the maximum LST values are observed in areas with high urbanization levels. Based on The Table, a graph was constructed to model the relationship between field-measured land surface temperatures derived from Sentinel-2 imagery and those measured directly on the ground. The coefficient of determination (R^2) obtained was 0.835, indicating a very strong correlation.

Based on LST, data in the Banjarmasin area for the years 2021, 2022, and 2023, significant temperature variations are evident, with a range from 17.92°C to 30.09°C. The LST maps indicate that the city center of Banjarmasin is the hottest area, with temperatures reaching 29°C to 30°C, while the outskirts with vegetation cover show lower temperatures, ranging from 18°C to 21°C. The significant UHI phenomenon is clearly observed in the city center, exhibiting higher surface temperatures compared to the greener peripheral areas. Over the three years analyzed, there are temperature fluctuations that might be attributed to climate change, urbanization, and environmental management. These results underscore the importance of enhancing green spaces and implementing sustainable spatial planning to mitigate UHI effects and create a more comfortable and healthier environment for residents.

This temperature variation indicates a significant UHI effect, where urban areas tend to be hotter compared to their greener surroundings. These findings provide empirical evidence of the importance of spatial planning and the enhancement of green spaces in urban areas to mitigate UHI impacts and improve environmental quality.

3.1.2. Urban Heat Island

Based on the data obtained, the key findings related to the UHI phenomenon in Banjarmasin are as follows: areas with high levels of urbanization, such as the city center of Banjarmasin, exhibit higher LST values, while regions with denser vegetation cover display lower LST. The temperature differential between the city center and the greener areas demonstrates a significant UHI intensity shown in figure 2.

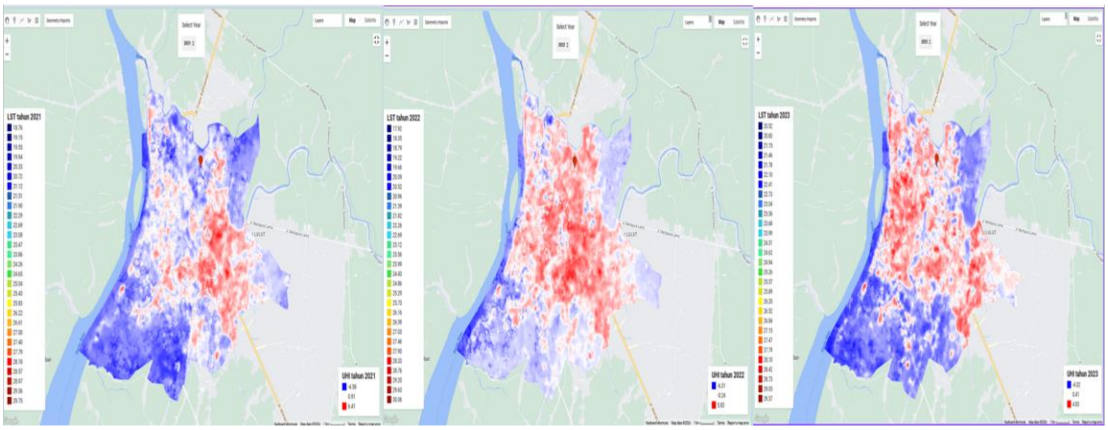

Figure 2. Urban Heat Island Distribution in Region of Interest Banjarmasin City

Based on UHI from analysis result in figure 2, Banjarmasin for the years 2021, 2022, and 2023, it is evident that the city center consistently shows high UHI intensity, with values reaching 6.41 in 2021, 5.83 in 2022, and 4.83 in 2023. In contrast, areas with vegetation cover in the outskirts exhibit lower UHI intensity, with values as low as -4.58 in 2021, -6.31 in 2022, and -4.02 in 2023. This pattern confirms that the significant UHI phenomenon in the city center of Banjarmasin is due to dense urbanization, while areas with more vegetation help mitigate the UHI impact. Enhancing green spaces and implementing sustainable spatial planning are crucial to reducing the negative effects of UHI and creating a more comfortable and healthier environment for residents.

3.1.3. Normalized Difference Vegetation Index

Based on the data obtained from the following satellite imagery from sentinel-2, the NDVI analysis indicates that areas with denser vegetation cover in Banjarmasin exhibit lower LST values, while urbanized areas with sparse vegetation show higher LST values. This pattern highlights the inverse relationship between NDVI and LST, where higher NDVI values correspond to cooler surface temperatures due to the presence of vegetation. The significant contrast between the city center and the outskirts emphasizes the role of green spaces in mitigating the UHI effect. The NDVI data reinforces the importance of increasing vegetation cover and implementing sustainable urban planning to enhance the quality of the urban environment and reduce the negative impacts of UHI shown in figure 3.

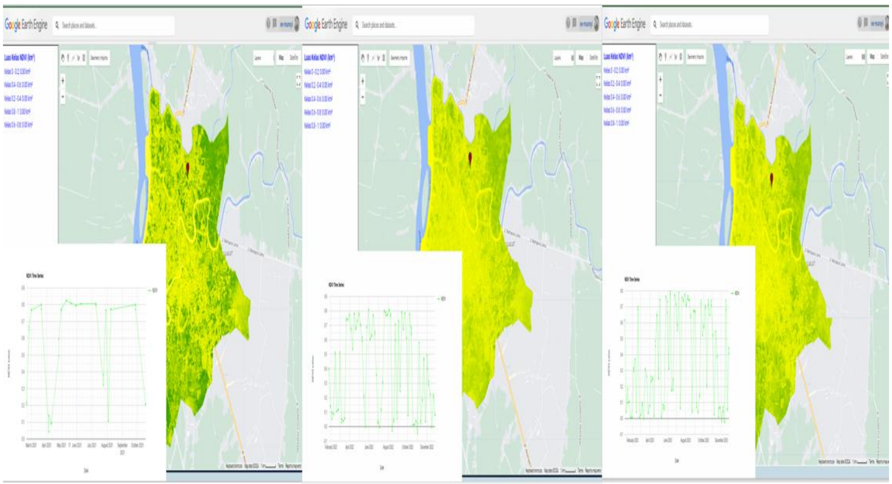

Figure 3. Distribution Pattern of Normalized Difference Vegetation Index

Based on the figure 3, showing NDVI maps and time series graphs for the Banjarmasin area from 2021 to 2023, it is evident that most of the region has high NDVI values, indicating healthy and dense vegetation. NDVI values range from 0 to 1, with most areas falling within the 0.4 to 1 class, signifying good vegetation cover. The time series graphs show fluctuations in NDVI values throughout the year, with peaks during certain months indicating the healthiest vegetation conditions. The observed declines in NDVI values during some months are likely due to seasonal factors such as rainfall or drought. This data demonstrates that vegetation in the Banjarmasin area is generally in good condition, playing a crucial role in mitigating the UHI effect and maintaining ecosystem balance.

3.1.4. Vegetation Health Index

Based on the data obtained from NDVI, LST, and UHI analyses, the following are the key findings related to the VHI in Banjarmasin. The NDVI analysis indicates that most areas exhibit high values, ranging from 0.4 to 1, signifying healthy and dense vegetation. LST data reveal that regions with denser vegetation cover have lower LST, while highly urbanized areas display higher temperatures. The UHI phenomenon is notably significant in the city center of Banjarmasin, where LST reach maximum values compared to the greener outskirts. The stark temperature difference between the city center and the greener areas highlights the high UHI intensity, underscoring the importance of enhancing green spaces and implementing sustainable spatial planning to mitigate the adverse effects of UHI and improve the living environment for residents can seen in figure 4..

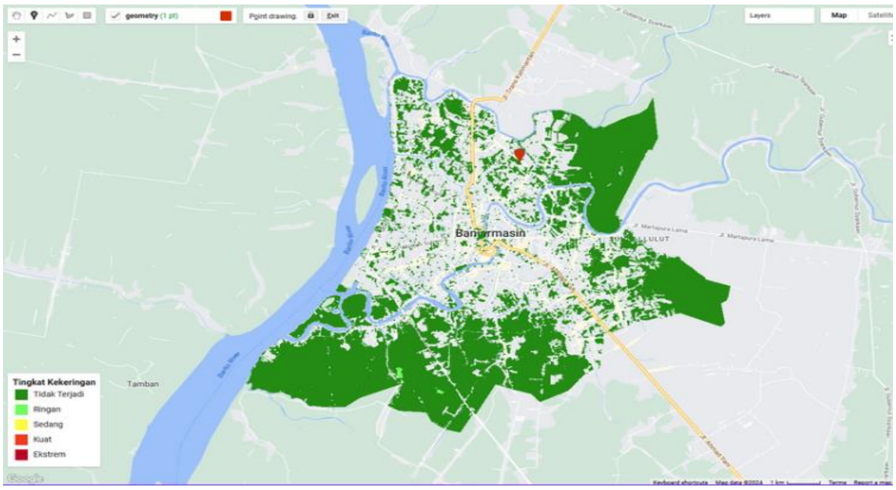

Figure 4. Distribution Pattern of Normalized Difference Vegetation Index

Based on the figure 4 showing the drought level map in the Banjarmasin area, it is evident that most areas are marked in green, indicating no drought conditions. The predominance of green signifies healthy and well-watered vegetation. Areas with lighter colors indicate mild to moderate drought levels, with very few areas showing severe or extreme drought. This data is relevant to the UHI phenomenon, where areas with healthy and well-watered vegetation (indicated by green) tend to have lower LST, thus reducing UHI intensity. Consequently, this map emphasizes the importance of vegetation cover in mitigating UHI effects and maintaining urban environmental health where:

3.1.4.1. Vegetation Conditions in Urban Areas:

Low VHI Values: Areas with high urbanization levels, such as the city center of Banjarmasin, exhibit lower VHI values. This reflects poor vegetation health or limited vegetation cover. The average VHI value in urban areas reaches 9,75. Low VHI values correlate with higher LST, reinforcing the UHI effect in these areas.

3.1.4.2. Vegetation Conditions in Green Areas:

High VHI Values: Regions with denser vegetation cover show higher VHI values, indicating healthy vegetation conditions. The average VHI value in green areas reaches 55,39.Temperature Reduction: Areas with high VHI values have lower LST, helping to mitigate the UHI effect.These findings highlight the crucial role of vegetation cover in reducing the UHI effect and promoting a healthier urban environment. Timeline for trending data shown in figure 5.

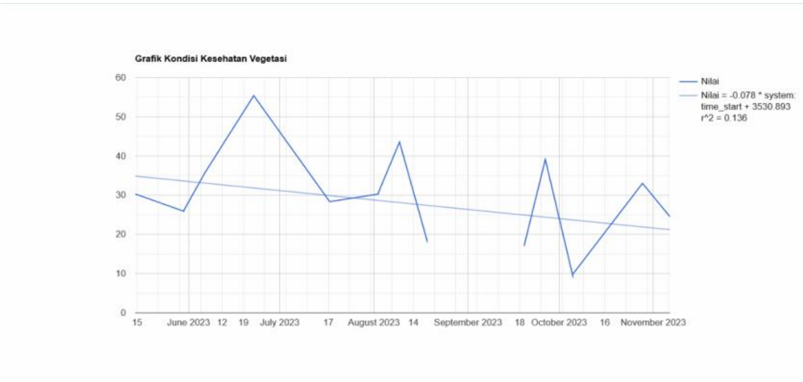

Figure 5. Vegetation health condition graph

Based on vegetation health data from June to November 2023, significant fluctuations are observed, with a peak in July and a sharp decline in the other months. This indicates that vegetation health in the region is influenced by seasonal factors or changing environmental conditions. The second dataset shows LST and UHI maps for the years 2021, 2022, and 2023. These maps reveal that the city center of Banjarmasin consistently experiences a significant UHI phenomenon each year, with the highest intensity in densely urbanized areas, marked by red for high UHI intensity and blue for lower UHI intensity.

To reduce UHI intensity and improve environmental health within the climate village program, several types of land cover are recommended, including green open spaces, natural vegetation, urban agriculture, as well as green roofs and green walls. Creating or expanding urban parks and urban forests, planting trees and shrubs in urban areas, and installing green roofs and green walls on buildings can significantly lower LST. Community gardens and urban agriculture not only increase vegetation cover but also provide local food sources and enhance community engagement in environmental stewardship.

3.2. The impact of the Climate Village Program on the Urban Heat Island

The Climate Village Program is a local initiative aimed at enhancing climate change adaptation and mitigation through community-level actions. The following are the key findings related to the UHI phenomenon in climate village program can be seen in figure 6.

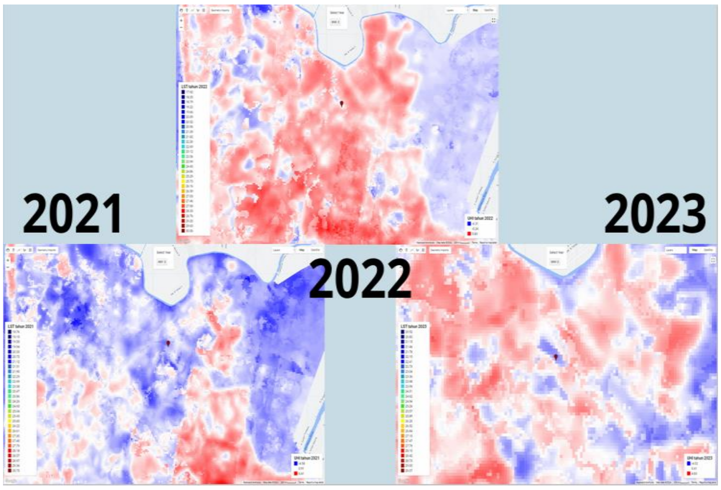

Figure 6. Distribution Pattern of UHI in Climate Village Program

The provided images from figure 6 depict UHI data for the years 2021, 2022, and 2023, focusing on a specific point marker representing a Climate Village Program Area in Banjarmasin City with Coordinat [114.60164316191577,-3.296326363850163]. The data illustrates that in 2021, the UHI intensity around the point marker was relatively high, as indicated by the significant red coloration. In 2022, the UHI intensity shows a reduction, with a noticeable shift towards blue, indicating cooler surface temperatures around the Climate Village Program area. By 2023, the data reveals a further decrease in UHI intensity, with the area around the point marker exhibiting even more pronounced blue regions, signifying effective mitigation of heat through the program's interventions. This progressive cooling trend highlights the success of the Climate Village Program in reducing UHI effects over the observed period, demonstrating the impact of increased vegetation and sustainable urban planning practices in lowering surface temperatures and improving urban environmental quality.

3.3. Measurement using Wireless Sensor Networks

The implementation of the Climate Village Program has demonstrated a positive impact on reducing LST. The average LST in climate village program Villages is consistently recorded as lower compared to the surrounding urban areas. This reduction in temperature is primarily attributed to the increase in vegetation cover through tree planting and greening efforts. To enhance our understanding and validate these findings, we using the real-time data analysis using WSN. WSN are deployed in the Climate Village Program Banjarmasin city to continuously monitor LST. The sensors used function to provide real-time, detailed monitoring of temperature variations. This data helps assess the cooling impact of increased vegetation and identify areas that may require additional green infrastructure. We developed a real-time monitoring system by integrating data from the Indonesian Meteorology, Climatology, and Geophysics Agency API to obtain information related to temperature, humidity, and rainfall. The following is the dashboard display of the system we built can be seen in figure 7.

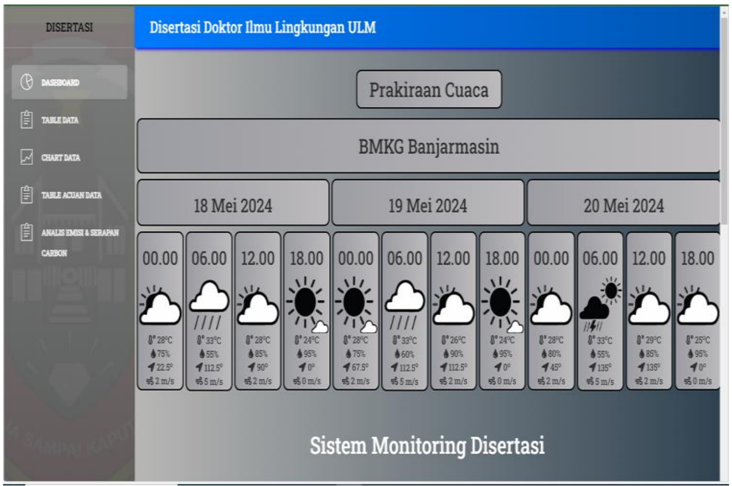

Figure 7. Distribution Pattern of UHI in Climate Village Program

In this system, real-time data from the sensors used for field data collection in the climate village program are also displayed. These data are employed for validation and comparison with spatial data acquired from Landsat 9 and Sentinel-2 satellite imagery. The following is the display of real-time sensor data. The process of data acquisition using a WSN begins with various sensor modules, including temperature and air humidity sensors, soil moisture sensors, and CO2 sensors. These sensors measure relevant environmental parameters such as temperature, air humidity, soil moisture, and CO2 levels. The data collected by these sensors is then gathered by an AVR microcontroller, which acts as the initial data processing unit, reading the sensor data and preparing it for transmission via a wireless network module. The wireless network module transmits the processed data to a cloud storage system, allowing for remote access and real-time data analysis. This data sensing process, encompassing the collection and transmission of temperature, air humidity, soil moisture, and CO2 data, ensures continuous environmental monitoring. The collected data is stored in the cloud, enabling real-time analysis and visualization through various interfaces such as graphs, pie charts, and indicator dashboards. These visual interfaces provide a comprehensible overview of current environmental conditions, facilitating informed decision-making based on the real-time data obtained shown in figure 8.

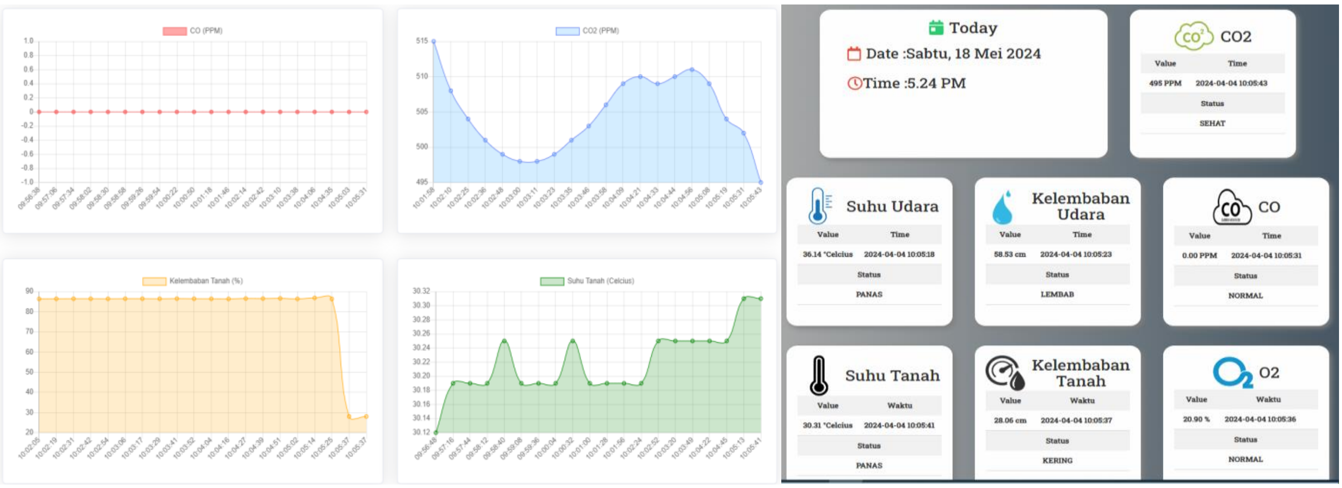

Figure 8. Distribution Pattern of UHI in Climate Village Program

The placement of the device is specifically in the Kampung Iklim area of Banjarmasin, with coordinates [114.60164316191577, -3.296326363850163]. The displayed data provide an overview of environmental conditions at the recorded time and date. The high air and soil temperatures, along with the dry soil moisture, indicate conditions that may not be ideal for plants or living organisms that require a cooler and more humid environment. However, the levels of CO2, CO, and O2 indicate that air quality is still in a healthy and normal condition. The WSN device we developed can be seen in the following figure 9.

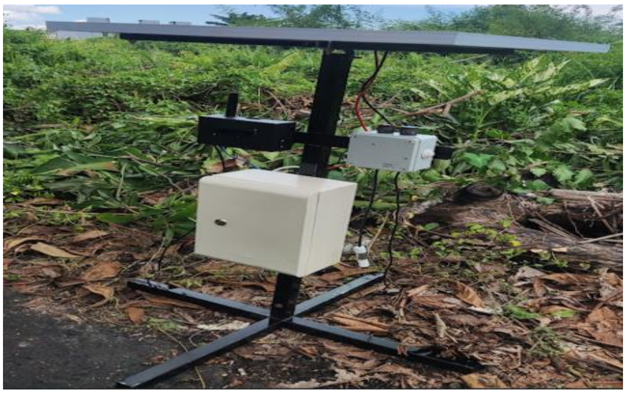

Figure 9. WSN Device in Climate Village Program

4. Conclusion

The he conclusions of this study indicate that increasing vegetation cover can significantly reduce the Urban Heat Island phenomenon in the Banjarmasin area. The analysis of LST data obtained from Landsat 9 and NDVI using Sentinel-2 satellite imagery reveals significant surface temperature variations between urban areas and those with higher vegetation cover. Highly urbanized areas, such as the city center of Banjarmasin, exhibit higher surface temperatures compared to the greener outskirts. These findings underscore the importance of sustainable spatial planning and the enhancement of green spaces to mitigate the negative impacts of UHI and improve the quality of the urban environment.

Moreover, this study emphasizes the importance of validating spatial data using field data obtained through wireless sensor networks. WSN technology allows for real-time monitoring of environmental conditions, providing more accurate data for the analysis and planning of climate village programs. The integration of spatial data from satellite imagery with field sensor data enables the identification of specific zones requiring intervention to mitigate the effects of UHI. Thus, the integrated approach proposed in this study can serve as a model for other cities facing similar ecological and climatic challenges.

5. Conclusion

Based on the research, the IndoBERT model demonstrated improved capability in classifying types of corruption offenses after being trained with a tokenized dataset. The training process was conducted over ten cycles using TensorFlow's 'fit' method. The 'early stopping' technique was applied at the seventh epoch after achieving a validation accuracy above 82%, to prevent overfitting and maintain effective performance. The IndoBERT model was then implemented in a web application hosted on a DigitalOcean VPS server, which is accessible via a provided link and features four main pages, including a page for text classification of corruption cases. Results from User Acceptance Testing indicate that the application functions well and meets all requirements, providing an informative and secure platform for users to learn about and identify potential corruption cases.

For future research, several recommendations include increasing the amount of training and testing data to reduce overfitting, integrating algorithms such as GRU and LSTM to improve accuracy, optimizing code, and using higher-capacity servers to enhance classification efficiency and speed. Additionally, integrating the application with anti-corruption agencies can enrich the content and functionality of the app, and employing different web development frameworks could create a more appealing and interactive user interface. These improvements could significantly enhance the application's utility and user experience, making it a more effective tool in the fight against corruption.

6. Declarations

6.1. Author Contributions

Conceptualization: M., A.N., A.J., and M.R.F.; Methodology: A.N.; Software: M.; Validation: M., A.N., A.J., and M.R.F.; Formal Analysis: M., A.N., A.J., and M.R.F.; Investigation: M.; Resources: A.N.; Data Curation: A.N.;

Writing Original Draft Preparation: M. and M.R.F.; Writing Review and Editing: A.N. and M.; Visualization: M.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] S. Jevrejeva, L. Jackson, R. Riva, A. Grinsted, and J. C. Moore, "Coastal Sea Level Rise With Warming Above 2 °C," *Proc. Natl. Acad. Sci.*, vol. 113, no. 47, pp. 13342–13347, 2016, doi: 10.1073/pnas.1605312113.

[2] G. A. Meehl et al., "How Much More Global Warming and Sea Level Rise?," *Science (80-.).*, vol. 307, no. 5716, pp. 1769–1772, 2005, doi: 10.1126/science.1106663.

[3] H. K. Jabbar, M. N. Hamoodi, and A. N. Al-Hameedawi, "Urban heat islands: a review of contributing factors, effects and data," *IOP Conf. Ser. Earth Environ. Sci.*, vol. 1129, no. 1, p. 12038, 2023, doi: 10.1088/1755-1315/1129/1/012038.

[4] S. Jain, S. Sannigrahi, S. Sen, S. Bhatt, S. Chakraborti, and S. Rahmat, "Urban heat island intensity and its mitigation strategies in the fast-growing urban area," *J. Urban Manag.*, vol. 9, no. 1, pp. 54–66, 2020, doi: 10.1016/j.jum.2019.09.004.

[5] X. Deng, F. Gao, S. Liao, Y. Liu, and W. Chen, "Spatiotemporal evolution patterns of urban heat island and its relationship with urbanization in Guangdong-Hong Kong-Macao greater bay area of China from 2000 to 2020," *Ecol. Indic.*, vol. 146, no. September 2022, p. 109817, 2023, doi: 10.1016/j.ecolind.2022.109817.

[6] C. M. Souza et al., "Reconstructing three decades of land use and land cover changes in brazilian biomes with landsat archive and earth engine," *Remote Sens.*, vol. 12, no. 17, pp. 1-12, 2020, doi: 10.3390/RS12172735.

[7] A. Price, E. C. Jones, and F. Jefferson, "Vertical Greenery Systems as a Strategy in Urban Heat Island Mitigation," *Water, Air, Soil Pollut.*, vol. 226, no. 8, p. 247, 2015, doi: 10.1007/s11270-015-2464-9.

[8] C. W. Chen, "Internet of Video Things: Next-Generation IoT with Visual Sensors," *IEEE Internet Things J.*, vol. 7, no. 8, pp. 6676–6685, 2020, doi: 10.1109/JIOT.2020.3005727

[9] H. Xia, Y. Chen, C. Song, J. Li, J. Quan, and G. Zhou, "Analysis of surface urban heat islands based on local climate zones via spatiotemporally enhanced land surface temperature," *Remote Sens. Environ*., vol. 273, no. 11, p. 112972, 2022, doi: https://doi.org/10.1016/j.rse.2022.112972.

[10] Y. Lu, M. A. Rahman, N. W. Moore, and A. J. Golrokh, "Lab-Controlled Experimental Evaluation of Heat-Reflective Coatings by Increasing Surface Albedo for Cool Pavements in Urban Areas," vol. 8, no. 7, 2021, doi: 10.3390/coatings12010007.

[11] B. Halder, J. Bandyopadhyay, and P. Banik, "Evaluation of the Climate Change Impact on Urban Heat Island Based on Land Surface Temperature and Geospatial Indicators," *Int. J. Environ. Res*., vol. 15, no. 5, pp. 819–835, 2021, doi: 10.1007/s41742-021-00356-8.

[12] Munsyi, A. Sudarsono, and M. U. H. Al Rasyid, "Secure Data Exchange Based on Wireless Sensor Network for Environmental Monitoring Using Dynamical Attributed Based Encryption," *Int. J. Adv. Sci. Eng. Inf. Technol*., vol. 11, no. 4, pp. 1306–1315, 2021, doi: 10.18517/ijaseit.11.4.8546.

ISSN 2723-6471

[13] BHARTENDU SAJAN, SHRUTI KANGA, SURAJ KUMAR SINGH, VARUN NARAYAN MISHRA, and BOJAN DURIN, “Spatial variations of LST and NDVI in Muzaffarpur district, Bihar using Google earth engine (GEE) during 1990-2020,” *J. Agrometeorol.*, vol. 25, no. 2 SE-Research Paper, pp. 262–267, May 2023, doi: 10.54386/jam.v25i2.2155.

[14] Z. KHAN and A. JAVED, “Correlation between land surface temperature (LST) and normalized difference vegetation index (NDVI) in Wardha Valley Coalfield, Maharashtra, Central India,” *Nov. Geod.*, vol. 2, no. 3 SE-Research articles, p. 53, Sep. 2022, doi: 10.55779/ng2353.

[15] S. Kandel, B. Gyawali, J. Sandifer, S. Shrestha, and S. Upadhaya, “Assessment of Urban Heat Islands (UHIs) Using Satellite-Derived Normalized Difference Vegetation Index (NDVI), and Land Surface Temperature (LST) in Three Metropolitan Cities of Nepal,” *Banko Janakari*, vol. 32, no. 2, pp. 37–51, 2022, doi: 10.3126/banko.v32i2.50895.

[16] Y. Liao et al., “Surface urban heat island detected by all-weather satellite land surface temperature,” *Sci. Total Environ.*, vol. 811, no. 4, p. 151405, 2022, doi: https://doi.org/10.1016/j.scitotenv.2021.151405.

[17] S. Fernández-Barrés et al., “Urban environment and health behaviours in children from six European countries,” *Environ. Int.*, vol. 165, no. March, pp. 1-9, 2022, doi: 10.1016/j.envint.2022.107319.

[18] K. Onačillová, M. Gallay, D. Paluba, A. Péliová, O. Tokarčík, and D. Laubertová, “Combining Landsat 8 and Sentinel-2 Data in Google Earth Engine to Derive Higher Resolution Land Surface Temperature Maps in Urban Environment,” *Remote Sens.*, vol. 14, no. 16, 2022, pp. 8–16, doi: 10.3390/rs14164076.

[19] K. H. Pangestu, A. Jauhari, and U. Udiansyah, “Analisis Korelasi Nllal Ndvl (Normallzed Difference Vegetatlon Index) dengan Vegetatlon Denslty di Khdtk Unlversitas Lambung Mangkurat,” *J. Sylva Sci.*, vol. 6, no. 3, p. 384, 2023, doi: 10.20527/jss.v6i3.9214.

[20] R. Rahmadanti, A. Jauhari, D. M. Asy’ari Program, and S. Kehutanan, “Distribution of Urban Heat Island at Banjarbaru Using Remote Sensing,” *J. Sylva Sci.*, vol. 05, no. 2, pp. 194–202, 2022.

[21] S. Taslim, D. M. Parapari, and A. Shafaghat, “Jurnal Teknologi Full paper Urban Design Guidelines to Mitigate Urban Heat Island (UHI) Effects In Hot-,” *J. Teknol.*, vol. 4, no. 7, pp. 119–124, 2015.

[22] S. Jain, S. Sannigrahi, S. Sen, S. Bhatt, S. Chakraborti, and S. Rahmat, “Urban heat island intensity and its mitigation strategies in the fast-growing urban area,” J. *Urban Manag.*, vol. 9, no. 1, pp. 54–66, 2020, doi: 10.1016/j.jum.2019.09.004.

[23] N. da Silva Espinoza et al., “Assessment of urban heat islands and thermal discomfort in the Amazonia biome in Brazil: A case study of Manaus city,” *Build. Environ.*, vol. 227, no. August 2022, p. 109772, 2022, doi: 10.1016/j.buildenv.2022.109772.

[24] F. Musco et al., Planning and climate change: Concepts, approaches, design. 2016. doi: 10.1007/978-3-319-10425-6.

[25] H. Bahi, H. Radoine, and H. Mastouri, “Urban Heat Island: State of the Art,” in *2019 7th International Renewable and Sustainable Energy Conference (IRSEC)*, vol. 7, no. 1, pp. 1–7, 2019. doi: 10.1109/IRSEC48032.2019.9078329.

[26] H. Ashraf, T. A. El Seoud, S. Sodoudi, and A. El Zafarany, “Anisotropic Surface Urban Heat Island in Cairo, Egypt: A Spatiotemporal Analysis of Local Climate Change from 2000 to 2021,” *Civ. Eng. Archit.*, vol. 11, no. 1, pp. 331–350, 2023, doi: 10.13189/cea.2023.110127.

[27] W. B. Adi, Sukuryadi, J. S. Adiansyah, Ibrahim, and H. I. Johari, “Analisis Pola Spasial Fenomena Urban Heat Island (Uhi) Berdasarkan Faktor Emisivitas Lahan,” *Geography*, vol. 10, no. 2, pp. 6–7, 2022, [Online]. Available: http://journal.ummat.ac.id/index.php/geography/article/view/9740