GEOGRAPHICALLY WEIGHTED REGRESSION MODELING IN ANALYZING FACTORS INFLUENCING THE URBAN HEAT ISLAND PHENOMENON IN MAKASSAR CITY: SUSTAINABLE MITIGATION EFFORTS

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Abstract: Background:Urban Heat Island (UHI) is a phenomenon of urban microclimate change that has become a significant issue and challenge in environmentally sustainable regional development planning. This study aims to comprehensively analyze the intensity of UHI growth across each district in Makassar City. In addition, the study highlights the importance of identifying the most influential factors contributing to the growth of the UHI phenomenon, with the ultimate goal of generating sustainable mitigation efforts.

Method: The analytical method in this study employs a spatial statistical approach using spatial analysis and Geographically Weighted Regression (GWR) modeling to examine the growth of UHI and the key influencing factors. The GWR analysis includes a Multicollinearity Test of Independent Variables, a Spatial Heterogeneity Test (using the Breusch-Pagan method), Euclidean Distance Calculation, Spatial Weighting with three types of kernels, selection of the best model for GWR analysis, significance testing of variables in each region, and ultimately results in grouping regions based on their influencing variables.

Results: The results of the study show that anthropogenic activities significantly impact environmental temperatures. Consequently, the environmental factors affecting surface temperature vary across districts in Makassar City, with NDVI, elevation, green area, and NDBI identified as significant variables that contribute to either the increase or decrease in temperature as a response to ongoing anthropogenic activities.

Conclusion: These findings form the basis for recommendations to mitigate the Urban Heat Island effect through increased vegetation, population density management, and adaptive spatial planning design based on the spatial

characteristics of each region.
Keywords: Urban Heat Island; Geographically Weighted Regression; Makassar City; Sustainable Mitigation

Introduction

The global urbanization rate is a factor that significantly triggers transformation in the urban environment and triggers the Urban Heat Island phenomenon [1, 2, 3]. Recent research results have explained that UHI occurs due to thermal disparities between urban and rural areas caused by changes in land cover, anthropogenic activities and emissions, and urban material conditions (4, 5, 6). In Indonesia, especially in the Makassar City area, the impacts caused by the UHI phenomenon are now at an alarming stage with the risk of major impacts on urban environmental ecosystems, energy consumption/use, and morbidity related to increased urban heat [7]. Empirical data through previous research results have discussed the increasing number of built-up areas due to the conversion of green land in metropolitan areas, contributing significantly to the increase in surface temperatures reaching 2.5-4.2°C in the last decade [8]. Similar to what happened in Makassar City, the urban area that is increasingly needed with built-up land cover has a significant impact on the reduction of green open space by 22% in the period 2010-2022. Therefore, it is very important to conduct an in-depth study related to the factors that influence green open space in Makassar City [9, 10, 11, 12].

To analyze the spatial variation of UHI, Geographically Weighted Regression (GWR) is an effective method, as it accommodates the heterogeneity of relationships between variables at each location [13]. This method enables the modeling of relationships between dependent variables (such as surface temperature) and independent variables (such as NDVI, population density, and NDBI) while accounting for spatial heterogeneity [14]. Unlike global regression, GWR can reveal local relationships that are undetectable by conventional methods, making it particularly suitable for UHI studies in areas with diverse environmental characteristics such as Makassar. A study by Zhao et al., (2018) confirmed that GWR provides higher accuracy in predicting urban temperature distribution compared to traditional linear models. Therefore, the application of GWR can offer new insights into the dominant factors driving UHI in the city of Makassar [15].

Factors such as the Normalized Difference Vegetation Index (NDVI), surface water area, population density, percentage of green open space (GOS), and the Normalized Difference Built-up Index (NDBI) have consistently been shown to influence UHI in recent studies [16, 17). NDVI and GOS are negatively correlated with surface temperature, as vegetation supports evapotranspiration and provides shading effects [18]. Conversely, NDBI, which represents built-up areas, tends to intensify UHI due to the heat-absorbing and heat-retaining properties of urban materials [19]. Spatial data from Makassar show that areas with population densities exceeding 10,000 people/km² and GOS below 10%, such as Tamalate and Panakkukang, experience surface temperatures 3–5°C higher than those in green-covered areas [11]. These findings align with the study by Hsu et al., (2021) which emphasizes that the interaction between demographic factors and land use is a primary driver of UHI in tropical cities [20].

The humid tropical climate characteristics of Makassar further exacerbate the UHI phenomenon through several distinctive mechanisms. Comparative studies in Southeast Asian tropical cities indicate that the combination of intense solar radiation and high humidity creates ideal conditions for the amplification of UHI (21, 22). Research shows that tropical cities experience thermal inertia, where nighttime temperatures remain elevated due to retained heat released by urban materials [23]. A similar phenomenon occurs in Makassar, where nighttime temperatures in the city center decrease by only 2–3°C from daytime levels due to the dominance of impervious surfaces [24]. In addition, the reduction of water surfaces due to land-use conversion worsens the UHI effect by eliminating natural cooling through evaporation. Data from the Makassar Environmental Agency indicate that 15% of the city's lakes and rivers have been encroached by settlements over the past decade, resulting in a decreased capacity for thermal regulation [24]. This highlights the urgency of integrating hydrological factors into UHI analysis.

Sustainable UHI mitigation strategies must be tailored to local contexts [25, 26]. For instance, the application of cool roofs and reflective materials has proven effective in reducing surface temperatures in arid cities (27, 28, 29). However, the effectiveness of these strategies is highly context-dependent, as demonstrated by comparative studies on the performance of green roofs across different climate zones [30]. In the context of Makassar, coastal ecosystem-based approaches such as mangrove rehabilitation and the optimization of green open space (GOS) based on local characteristics show significant potential [31]. Given Makassar's coastal geography, ecosystem-based strategies like mangrove restoration and the enhancement of urban green space may be more suitable [32]. A study by Chen & Lin, (2021) also emphasizes the importance of equitable green space distribution to reach densely populated areas—still a major challenge in Makassar [33]. Therefore, spatial mapping using GWR can help identify priority areas for targeted mitigation interventions.

This study aims to analyze the factors influencing Urban Heat Island (UHI) in Makassar using a Geographically Weighted Regression (GWR) approach, focusing on the variables NDVI, Water Surface Area, Population Density, Percentage of Green Area, and NDBI. The selection of these variables is based on previous findings that highlight their significant contribution to UHI in Southeast Asian cities [33]. Surface temperature data will be derived from Landsat 9 satellite imagery with a spatial resolution of 30 meters to ensure analytical accuracy [34]. The results of the GWR analysis are expected to reveal local variations in the relationships between environmental factors and UHI—for example, how the influence of NDBI may be stronger in urban centers than in suburban areas. These findings will serve as the basis for evidence-based spatial planning policy recommendations to mitigate the impacts of UHI in Makassar.

This study not only contributes to the academic literature on spatial modeling of UHI in tropical regions but also offers practical implications for urban planners in Makassar. Given the city's high urbanization rate (approximately 3.2% per year), a deep understanding of UHI dynamics is crucial for achieving sustainable development. The recommendations from this research—such as the optimization of green open spaces based on heat zoning and the regulation of reflective material use—can be integrated into Makassar's Regional Spatial Plan. Moreover, the GWR approach employed in this study can be replicated in other Indonesian cities with similar characteristics, making this research nationally relevant. Through a combination of advanced spatial analysis and ecology-based policy, the impacts of UHI in Makassar can be significantly mitigated.

Methodology

2.1 Type and Location Research

This study was conducted in Makassar City by analyzing UHI data from four subdistricts in the city (Figure 1). The selection of data collection locations in each subdistrict was determined through purposive sampling, taking into account land use, land cover, and dominant anthropogenic activities in each area. This approach was employed to ensure the accuracy of the research data, which will be analyzed by considering the factors influencing the development of the UHI phenomenon in Makassar City, South Sulawesi Province.

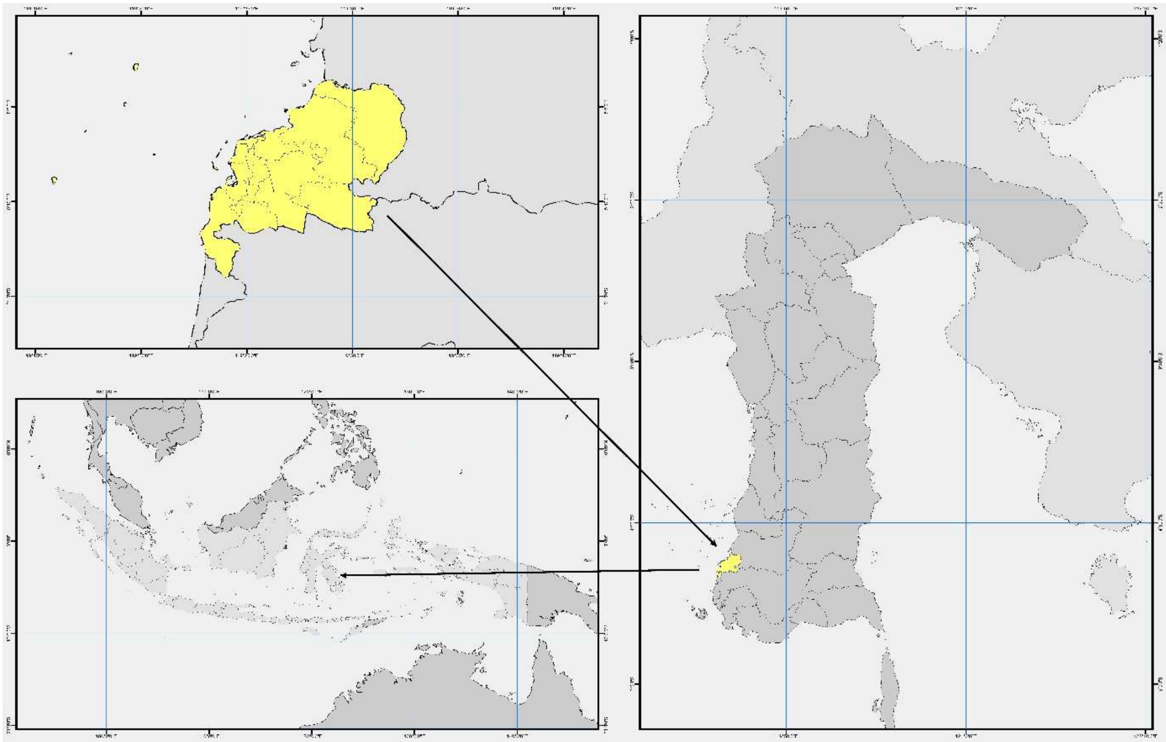


Figure 1. Research Location Map

2.2 Data Sources and Analysis

The Data Sources and Analysis used in this study are as follows.

1) Determine the concentration value for each influential variable

The growth of the Urban Heat Island (UHI) phenomenon is influenced by several variables including NDVI, Elevation, Water Surface Area, Population Density, Percentage of Green Area, and NDBI [35, 36]. The determination of the value of each variable can be seen as follows.

Variable	Formulas
X1-Normalized Difference Vegetation Index (NDVI) (Jiang et al., 2020)	$$\mathrm{NDVI} = \frac{NIR + RED}{NIR - RED}$$ a. Values close to +1: Very healthy and lush vegetation. b. Values around 0: Surfaces devoid of vegetation (bare ground, roads, etc.). c. Negative values: Air, snow, or clouds.
X2-Elevation (Shen et al., 2022)	E (x,y) = Z a. E(x,y): Elevation at coordinates x,yx, yx,y (horizontal). b. ZZZ: Pixel value indicating surface height (elevation) in meters or feet, depending on the DEM data used.

X3-Water Surface Area (Rosleine & Irfandi, 2020)	$$A=\frac{1}{2}\left[\sum_{i=1}^{n}(Xi\ Yi+1-Xi+1Yi)\right]$$ a. A: Area of the polygon. b. (x, y): Coordinates of a point on the boundary of the polygon. c. n: Number of points in the polygon
X4-Population density (Lutz & Samir, 2018)	$$\text{Population density}=\frac{\text{Total population}}{\text{An area}}$$
X5-Percentage of Green Area (X. Zhao et al., 2019)	$$\text{Percentage of Green Area}=\frac{\text{Large green area}}{\text{Total Area}}x\ 100\%$$
X6-NDBI (Normalized Difference Built-up Index) (Jain & Kumar, 2016)	$$\text{NDBI}=\frac{SWIR-NIR}{SWIR+NIR}$$ a. SWIR (Short Wave InfraRed): Short wave infrared band, commonly found in Landsat imagery in band 5 or band 6. b. NIR (Near InfraRed): Near-infrared band, commonly found in Landsat imagery in band 4.

Source: Literature Analysis, 2024

2) Geographically Weighted Regression Modeling to Analyze the Urban Heat Island

The analysis used to analyze the variables that have the most influence on the urban heat island phenomenon in Makassar City includes:

a. Multicollinearity Test of Independent Variables

Multicollinearity detection aims to determine whether there is a linear relationship between predictor variables in a regression model. The detection of multicollinearity can be done using the variance inflation factor (VIF) value criteria. Data is considered multicollinear if the VIF value is more than 10. The VIF value is calculated based on the formula:

$$VIF_K=\frac{1}{1-R_K^2}\ k=1,2,\ldots p$$

With $\boldsymbol{R_K^2}$ the coefficient value of model X's determination is regressed against other predictor variables. Furthermore, LISA (Local Indicators of Spatial Association) Testing is carried out to identify and group areas that show significant spatial relationships.

b. Spatial Heterogeneity Test (With Breusch-Pagan (BP)

Spatial heterogeneity testing aims to determine whether the response variable data is point-type spatial data (spatial heterogeneity). Spatial heterogeneity testing can be done using the Breusch-Pagan (BP) test statistic. The hypothesis of spatial heterogeneity testing is:

H0 : $\boldsymbol{\sigma_2^1}=\boldsymbol{\sigma_2^2}=\cdots=\sigma 2$ (There is no spatial heterogeneity)

H1 : there is at least one $\boldsymbol{\sigma_i^2}\neq\boldsymbol{\sigma^2}$ (i = 1,2,…,n) (There is Spatial Heterogeneity)

Stages for conducting spatial heterogeneity testing with the Breusch-Pagan (BP) test using the equation.

$$\boldsymbol{BP}=\frac{\mathbf{1}}{\mathbf{2}}\boldsymbol{f^T Z(Z^T Z)^{-1} Z^T f}$$

A critical area of hypothesis testing at a significance level α = 5% is to reject H0 at the 5% test level.

c. Calculation of Euclidean Distance

This study uses Euclidean distance to perform Geographically Weighted Regression (GWR) modeling, by utilizing geographic coordinates in the form of latitude and longitude as the basis for calculating distances between regions. Euclidean distance is calculated using the equation:

$$d_{ij} = \sqrt{\left(u_i - u_j\right)^2 + \left(v_i - v_j\right)^2}$$

Where $\boldsymbol{u_i}$ dan $\boldsymbol{u_j}$ is the longitude value, while $\boldsymbol{v_i}$ dan $\boldsymbol{v_j}$ is the latitude value of regions i and j.

d. Spatial Weighting with 3 Kinds of Kernels

In Geographically Weighted Regression (GWR) modeling, the kernel functions to determine spatial weights. $\boldsymbol{w_{ij}}$, namely the influence of observation point j on the estimate at location i, based on the Euclidean distance $\boldsymbol{d_{ij}}$ and bandwidth parameters (b). Three types of kernels are used in this study, namely Gaussian, Bisquare, and Exponential. Bandwidth is applied in two approaches: fixed, where b remains constant for all locations, and adaptive, where b is adjusted according to data density, keeping the number of neighbors the same at each location.

e. Selection of the Best Model for Geographically Weighted Regression analysis

To ensure that the model formed is the best, validation is carried out using model policy measures such as R2, AIC (Akaike Information Criterion), and BIC (Bayesian Information Criterion). R2 measures the proportion of variation in the data that can be explained by the model, with higher values indicating a better model for estimating the data. AIC and BIC are used to compare model quality while taking into account its complexity; models with lower AIC and BIC are considered more efficient.

f. Significance of variables in each region

To identify the influence of variables on the Urban Heat Island (UHI) phenomenon in various regions, Geographically Weighted Regression (GWR) analysis with a t-test is used to test the significance of each variable at each location. This t-test aims to determine whether the coefficient of each independent variable, such as NDVI, elevation, water surface area, population density, percentage of green area, and NDBI, has a significant effect on UHI in the region. Thus, the t-test allows us to determine which variables have a statistically significant impact on the temperature of the region, as well as how this influence varies across locations. The results of this t-test will be visualized in a map that illustrates the distribution of the influence of spatially significant variables, providing a deeper picture of the factors that influence UHI in each region. The following are the results of the significance test for each variable in each region.

g. Results of grouping regions based on influential variables

The results of the t-test conducted on the Geographically Weighted Regression (GWR) analysis are used as a basis for grouping regions based on variables that are significant in influencing the Urban Heat Island (UHI) phenomenon. Each sub-district is grouped based on a combination of variables that are proven to have a significant effect on UHI in the region.3. Results and Discussion

Results And Discussion

3.1 Distribution of the Urban Heat Island Phenomenon in Makassar City

Based on the results of the analysis that has been carried out, it can be seen that the distribution of the Urban Heat Island (UHI) phenomenon in each sub-district area in Makassar City is at the highest concentration in the Rappocini area and the lowest in the Ujung Tanah area. This can be seen in Table 1 below.

Table 2. Concentration of the Urban Heat Island Phenomenon in Each District Area in Makassar City

Subdistrict	X	Y	Urban Heat Island

Tamalanrea	119.5092461	-5.139506389	36,37
Manggala	119.4965139	-5.168028056	37,10
Panakkukang	119.4579097	-5.142606667	38,52
Tallo	119.4368375	-5.122798056	35,84
Rappocini	119.4459719	-5.170747222	39,34
Ujung Tanah	119.4215233	-5.113125833	34,58
Wajo	119.413165	-5.126736944	35,70
Ujung Pandang	119.4189083	-5.142238611	37,15
Bontoala	119.4245356	-5.132859167	36,72
Mariso	119.4101236	-5.158062222	35,85
Mamajang	119.4157011	-5.163935278	37,02
Tamalate	119.4339881	-5.187536389	37,26
Makassar	119.43178	-5.142212778	38,12
Biringkanaya	119.5263017	-5.090474722	37,64

Source: Analysis Results, 2025

Based on the information in Table 1 above, an overview of spatial information related to the distribution of Urban Heat Island concentrations in Makassar City can be seen on the map in Figure 1 below.

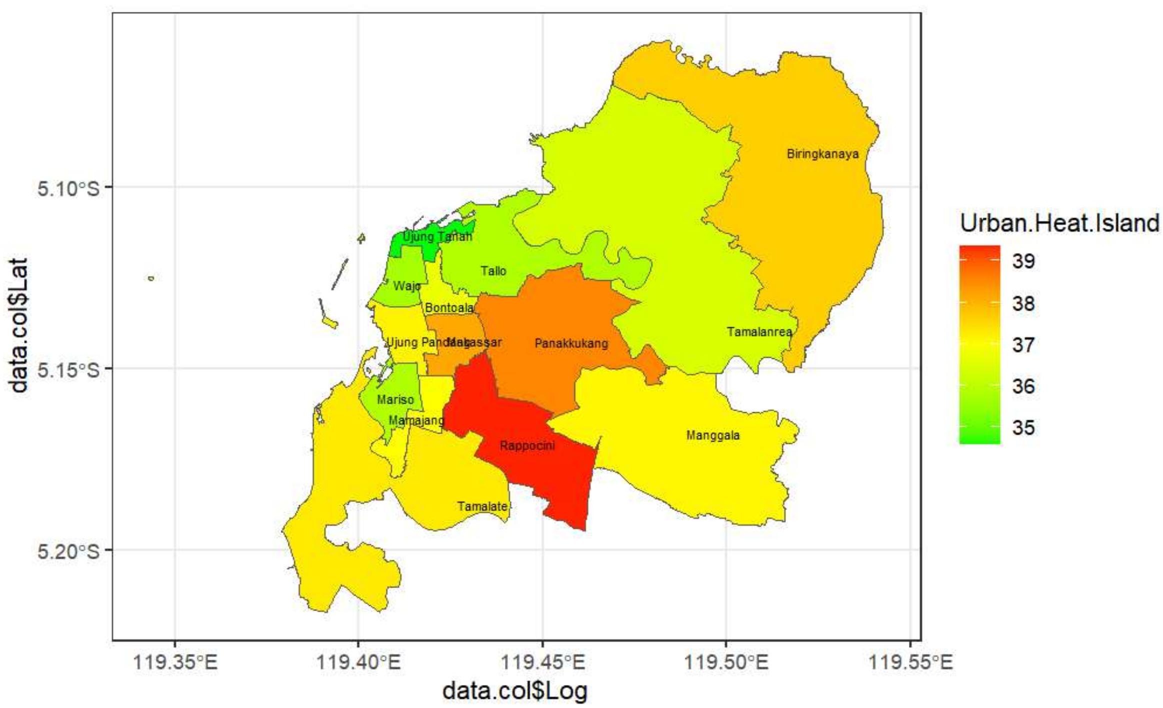


Figure 2. Map of the Distribution of the Urban Heat Island Phenomenon in Makassar City

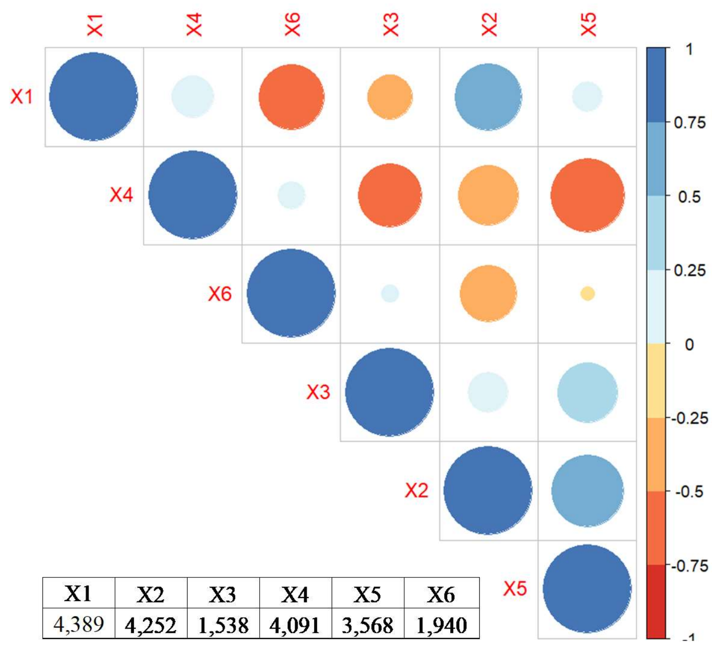
Based on the results of the analysis of the distribution of the Urban Heat Island (UHI) phenomenon that has been carried out, it can be seen that the highest UHI in Makassar City is concentrated in the Rappocini area at 39.34, then in other regions consisting of Panakukang District (38.52), Makassar (38, 12), Biringkanaya (37.64), Tamalate (37.26), Ujung Pandang (37.15), Manggala (37.10), Mamajang (37.02), Bontoala (36.72), Tamalanrea (36.37), Mariso (35.85), Tallo (35.84), Wajo (35.70), and the lowest UHI concentration is in the Ujung Tanah area amounting to 34.58 (See UHI Concentration in Table 2 and UHI Spatial Distribution in Figure 2). In the analysis, the distribution of UHI concentrations in each sub-district varies, influenced by several factors including NDVI, Elevation, Water Surface Area, Population Density, Percentage of Green Area, and NDBI (Bhowmick & Banerjee, 2023; Ghosh & Bandyopadhyay, 2018). So, to analyze the factors that most influence the distribution of UHI concentrations throughout the region, further analysis was carried out, namely by using spatial statistical modeling using the Geographically Weight Regression approach.

3.2 Analysis of Factors, Impacts, and Mitigation Efforts of the Urban Heat Island Phenomenon in Makassar City

To analyze the factors most influential in the Urban Heat Island (UHI) phenomenon in Makassar City, Geographically Weighted Regression (GWR) modeling can be used to spatially analyze which factors contribute to the phenomenon. In Geographically Weighted Regression (GWR) analysis, several assumptions must be met in order to proceed with the analysis and reach the modeling stage. The results of the assumption testing for the Geographically Weighted Regression modeling in analyzing the most influential factors are as follows:

1) Multicollinearity Test of Independent Variables

The identification of multicollinearity aims to determine whether there is a linear relationship between the predictor variables in a regression model. To detect the presence of multicollinearity, the Variance Inflation Factor (VIF) criterion can be used. Data is considered to have multicollinearity if the VIF value exceeds 10. The results of the Multicollinearity Test for Independent Variables can be seen in Figure 3 below.



X1	X2	X3	X4	X5	X6
4,389	4,252	1,538	4,091	3,568	1,940

Figure 3. Results of the Multicollinearity Test for Independent Variables

Based on the information in Figure 3, the Variance Inflation Factor (VIF) values shown in the table indicate that all predictor variables have VIF values of less than 10, which suggests that there is no multicollinearity among these variables. Additionally, the visualization in the diagram shows that there is no strong correlation between the variables, with all correlation values being below 0.5. This condition indicates that all variables meet the criteria to proceed to the regression modeling process, one of which is the Geographically Weighted Regression (GWR) method, which is capable of capturing spatial variations in the relationship between the dependent and predictor variables.

2) Regional Clusters Based on LISA (Local Indicators of Spatial Association)

Regional clustering based on LISA (Local Indicators of Spatial Association) is used to identify local spatial patterns in geographic data. This analysis is conducted to examine inter-regional relationships specifically, such as revealing clusters with high values (High-High) or low values (Low-Low), as well as anomaly patterns like High-Low or Low-High. This approach helps illustrate the spatial distribution of variables, detect concentrations or dispersion of UHI phenomena, and identify regions with similar or significantly different characteristics. The results of the LISA test are as follows:

Table 3. Regional Clusters with Similar Characteristics

Sub-district	mean	median	pysal
Biringkanaya	High-Low	High-Low	High-Low
Bontoala	Low-Low	Low-Low	Low-Low
Makassar	High-Low	High-Low	High-Low
Mamajang	High-High	High-High	High-High
Manggala	High-High	High-High	High-High
Mariso	Low-High	Low-High	Low-High
Panakkukang	High-High	High-High	High-High
Rappocini	High-High	High-High	High-High
Tallo	Low-Low	Low-Low	Low-Low
Tamalanrea	Low-High	Low-High	Low-High
Tamalate	High-High	High-High	High-High
Ujung Pandang	High-Low	High-Low	High-Low
Ujung Tanah	Low-Low	Low-Low	Low-Low
Wajo	Low-Low	Low-Low	Low-Low

Source: Analysis Results, 2025

Based on the information in Table 3 above, it can be observed that Mamajang, Manggala, Panakkukang, Rappocini, and Tamalate fall into the High-High cluster (Hot Spot). Meanwhile, the Low-Low cluster (Cold Spot) includes the sub-districts of Bontoala, Tallo, Ujung Tanah, and Wajo, which have low UHI concentration values and are surrounded by areas with similarly low UHI values. Furthermore, the sub-districts of Biringkanaya, Makassar, and Ujung Pandang fall into the High-Low cluster (Hot Outlier), indicating that these areas have high UHI values but are surrounded by regions with low UHI values, making them heat outliers. The Low-High cluster (Cool Outlier) includes Mariso and Tamalanrea sub-districts, which exhibit low UHI values but are surrounded by areas with high UHI levels. This analysis is consistent with the results of the Moran's I index plot, which shows that sub-districts in the Hot Spot cluster are located at the peak of the curve, while those in the Cold Spot cluster are at the lower end of the curve (Figure 4).

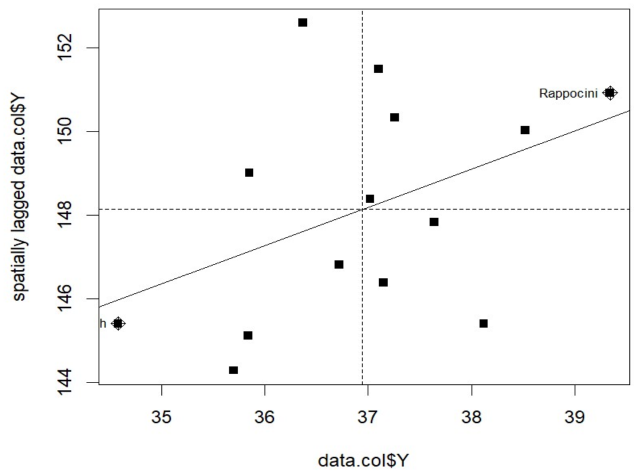


Figure 4. Moran's Index Plot for Each Sub-District in Makassar City

3) Spatial Heterogeneity Test Using Breusch-Pagan (BP)

The spatial heterogeneity test aims to determine whether the response variable data exhibit spatial point-based characteristics (spatial heterogeneity). This test can be performed using the Breusch-Pagan (BP) test statistic. The results of the Breusch-Pagan (BP) test statistic calculation are presented as follows:

```
Breusch-Pagan test

data:  pers
BP = 13.6716, df = 6, p-value = 0.034
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The Breusch-Pagan test results indicate a BP value of 13.6716 with a p-value of 0.0335, which is lower than the 0.05 significance level. This suggests that the residual variance is not constant, indicating the presence of heteroskedasticity in the data. In the context of spatial analysis, heteroskedasticity often reflects spatial variation in the relationships between dependent and independent variables across different locations. Therefore, the Geographically Weighted Regression (GWR) method is highly appropriate for use. GWR allows for the modeling of locally varying relationships by computing separate regressions at each location based on spatial weighting. This method can capture spatial patterns that global regression models cannot detect, making it more effective for analyzing data with spatial heteroskedasticity.

4) Geographically Weighted Regression (GWR) Modeling

This study employed the Euclidean distance method for Geographically Weighted Regression (GWR) modeling, using geographic coordinates (latitude and longitude) as the basis for calculating the distances between regions. The distance calculation produced a 14 × 14 distance matrix, which contains information on the pairwise distances among the 14 study areas, as shown below.

Kecamatan	Biringkanaya	Bontoala	Makassar	Mamajang	Manggala	Mariso	Panakkukang	Rappocini	Tallo	Tamalanrea	Tamalate	Ujung Pandang	Ujung Tanah	Wajo
Biringkanaya	0	0,1102	0,1078	0,1328	0,0831	0,1344	0,0860	0,1136	0,0951	0,0519	0,1340	0,1192	0,1072	0,1188
Bontoala	0,1102	0	0,0118	0,0323	0,0801	0,0290	0,0348	0,0435	0,0159	0,0850	0,0555	0,0109	0,0200	0,0129
Makassar	0,1078	0,0118	0	0,0270	0,0697	0,0268	0,0261	0,0319	0,0201	0,0775	0,0454	0,0129	0,0308	0,0242
Mamajang	0,1328	0,0323	0,0270	0	0,0809	0,0081	0,0473	0,0310	0,0462	0,0967	0,0299	0,0219	0,0511	0,0373
Manggala	0,0831	0,0801	0,0697	0,0809	0	0,0870	0,0462	0,0506	0,0749	0,0312	0,0655	0,0818	0,0929	0,0930
Mariso	0,1344	0,0290	0,0268	0,0081	0,0870	0	0,0502	0,0380	0,0442	0,1008	0,0379	0,0181	0,0464	0,0315
Panakkukang	0,0860	0,0348	0,0261	0,0473	0,0462	0,0502	0	0,0306	0,0289	0,0514	0,0509	0,0390	0,0468	0,0475
Rappocini	0,1136	0,0435	0,0319	0,0310	0,0506	0,0380	0,0306	0	0,0488	0,0706	0,0206	0,0393	0,0626	0,0549
Tallo	0,0951	0,0159	0,0201	0,0462	0,0749	0,0442	0,0289	0,0488	0	0,0743	0,0648	0,0264	0,0181	0,0240
Tamalanrea	0,0519	0,0850	0,0775	0,0967	0,0312	0,1008	0,0514	0,0706	0,0743	0	0,0893	0,0904	0,0916	0,0969
Tamalate	0,1340	0,0555	0,0454	0,0299	0,0655	0,0379	0,0509	0,0206	0,0648	0,0893	0	0,0477	0,0754	0,0643
Ujung Pandang	0,1192	0,0109	0,0129	0,0219	0,0818	0,0181	0,0390	0,0393	0,0264	0,0904	0,0477	0	0,0292	0,0165
Ujung Tanah	0,1072	0,0200	0,0308	0,0511	0,0929	0,0464	0,0468	0,0626	0,0181	0,0916	0,0754	0,0292	0	0,0160
Waio	0.1188	0.0129	0.0242	0.0373	0.0930	0.0315	0.0475	0.0549	0.0240	0.0969	0.0643	0.0165	0.0160	0

Figure 5. Euclidean Distance Matrix for Geographically Weighted Regression (GWR) Modeling

The matrix shown in Figure 5 serves as the basis for determining spatial weights in the GWR model, which aims to analyze the spatial relationships among variables and identify locally significant factors at each location.

In the GWR modeling process, a kernel analysis was also conducted to determine the spatial weights $\boldsymbol{w_{ij}}$, representing the influence of observation point j on the estimation at location i, based on the Euclidean distance $\boldsymbol{d_{ij}}$ and a bandwidth parameter (b). Three types of kernel functions were applied in this study: Gaussian, Bisquare, and Exponential. The bandwidth was implemented using two approaches: fixed, where b remains constant across all locations, and adaptive, where b adjusts according to data density, ensuring a consistent number of neighbors at each location. Cross-validation analysis produced the optimal values for each kernel and bandwidth combination, as presented below.

Table 4. Cross-Validation Results of Kernel and Bandwidth Combinations

Kernel	Bandwidth	Nilai Optimum	Cross-Validation
Gaussian	Fixed	0.1343467	39.16338
	Adaptif	18	39.27265
Bisquare	Fixed	0.0860001	37384.86
	Adaptif	18	45.86974
Eksponensial	Fixed	0.134347	38.43101
	Adaptif	18	38.569

Source: Data Analysis, 2025

Based on the cross-validation results, the Exponential kernel with fixed bandwidth was selected as the optimal model due to its lowest cross-validation score of 38.43101, outperforming other kernel combinations. This low error value indicates a superior predictive accuracy, suggesting that the model effectively captures spatial relationships. The exponential kernel, which assigns decreasing weights exponentially with increasing distance, enhances the model's sensitivity to local variations, making it particularly suited for data with complex spatial heterogeneity. Furthermore, the use of a fixed bandwidth ensures model stability by applying a consistent spatial range for all observations, minimizing fluctuations in local estimates.

To further validate the robustness and performance of the selected GWR model, several model fit statistics were assessed, including R^2 (coefficient of determination), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). These measures provide insight into the explanatory power, parsimony, and overall model quality. The results of this model evaluation are summarized in Table 5 below.

Table 5. Results of the Best Model Selection Analysis

Kernel	Bandwidth	Goodness-of-Fit Measures		
		R^2	AIC	BIC
Gaussian	Fixed	47.1%	43.2515	41.2269
	Adaptif	46.86%	43.2807	41.1987
Bisquare	Fixed	49.94%	109.099	110.192
	Adaptif	58%	41.0171	40.6251
Eksponensial	**Fixed**	**60.08%**	**40.1217**	**39.4306**
	Adaptif	59.34%	40.3091	39.5017

Source: Analysis Results, 2025

Based on the results shown in Table 5 above, the Exponential kernel with a fixed bandwidth demonstrates the best performance, indicated by the highest R^2 value (60.08%) and lower AIC (40.1217) and BIC (39.4306) values compared to other combinations. This suggests that the model is not only better at explaining the variation in the data but also more efficient, avoiding excessive complexity and yielding more accurate estimates. Therefore, the combination of the Exponential kernel and fixed bandwidth is selected as the best model for estimating the parameters influencing UHI in each district of Makassar City.

To analyze the influence of variables on the Urban Heat Island (UHI) phenomenon across different regions, the Geographically Weighted Regression (GWR) approach was used, complemented by t-tests to evaluate the significance of each variable at every location. The t-test aims to identify whether the coefficients of independent variables—such as NDVI, elevation, water surface area, population density, percentage of green areas, and NDBI—have a significant influence on UHI in specific areas. Thus, the t-test provides information on which variables statistically contribute significantly to temperature variation in the region while also showing how these effects vary spatially. The results of this analysis are visualized in the form of maps, illustrating the spatial distribution of each variable's significant influence, thereby offering deeper insight into the determinants of UHI in different locations. The following are the results of the variable significance tests in each district.

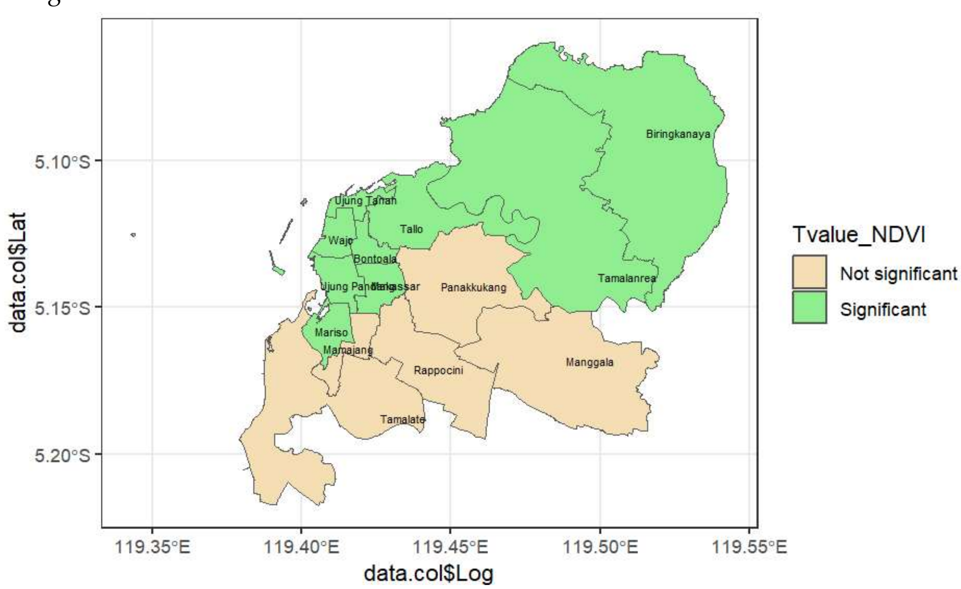

Figure 5. NDVI Variable with Significant Influence on the UHI Phenomenon in Each District of Makassar City

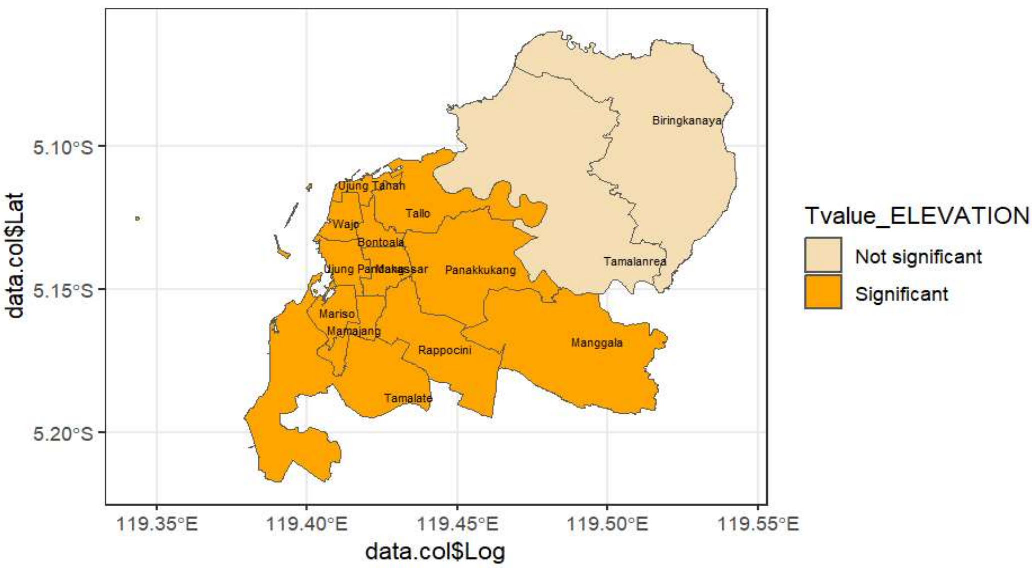

Figure 6. Elevation Variable with Significant Influence on the UHI Phenomenon in Each District of Makassar City

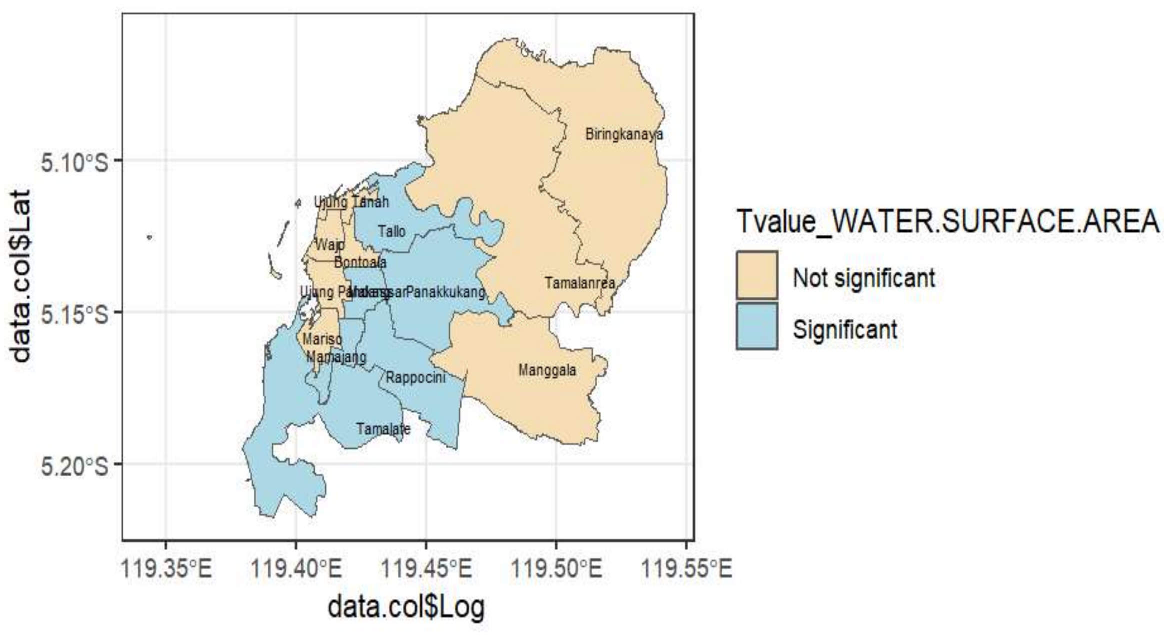

Figure 7. Water Surface Area Variable with Significant Influence on the UHI Phenomenon in Each District of Makassar City

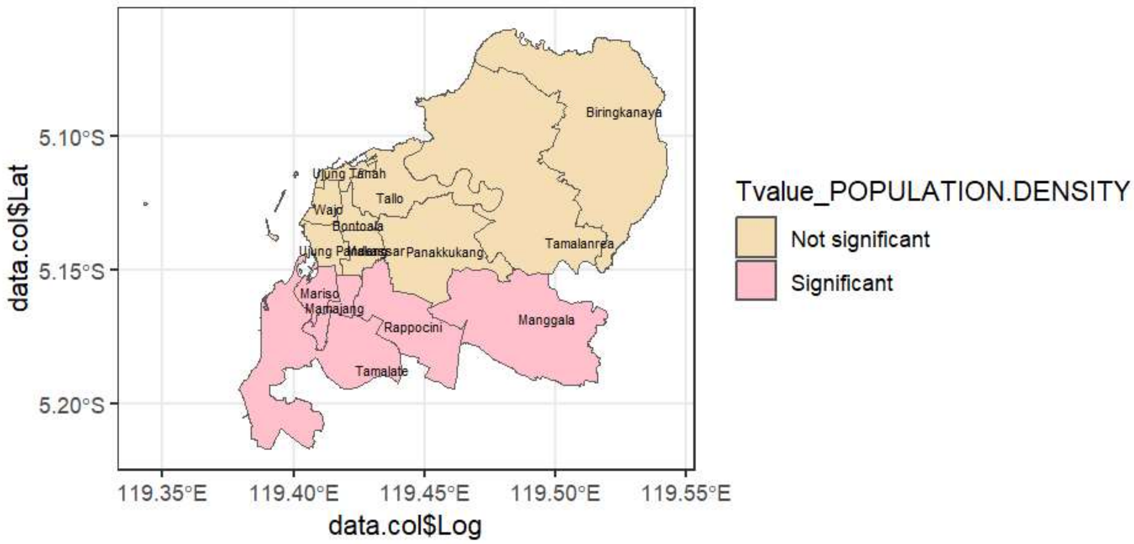

Figure 8. Population Density Variable with Significant Influence on the UHI Phenomenon in Each District of Makassar City

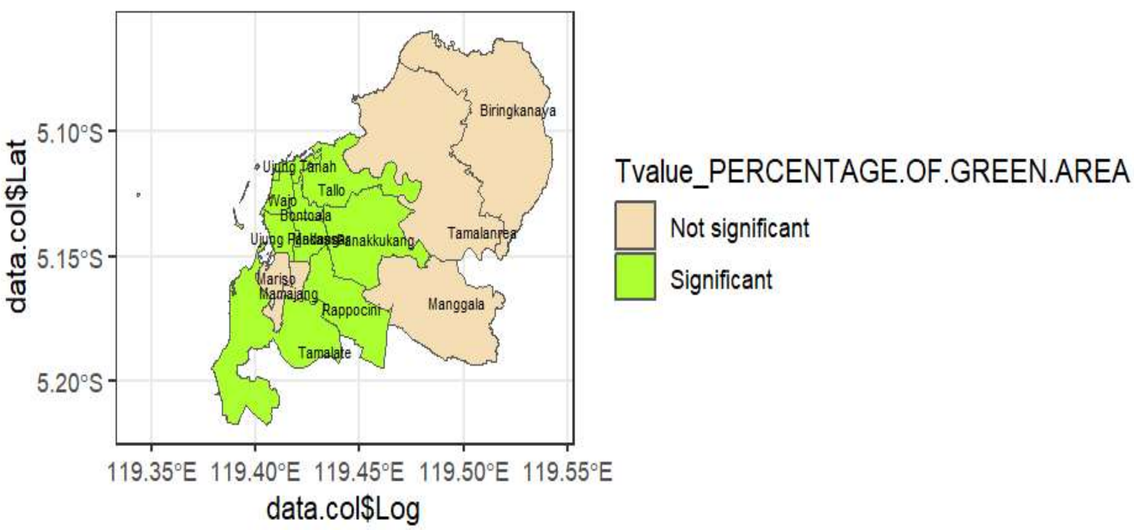

Figure 9. Percentage of Green Area Variable with Significant Influence on the UHI Phenomenon in Each District of Makassar City

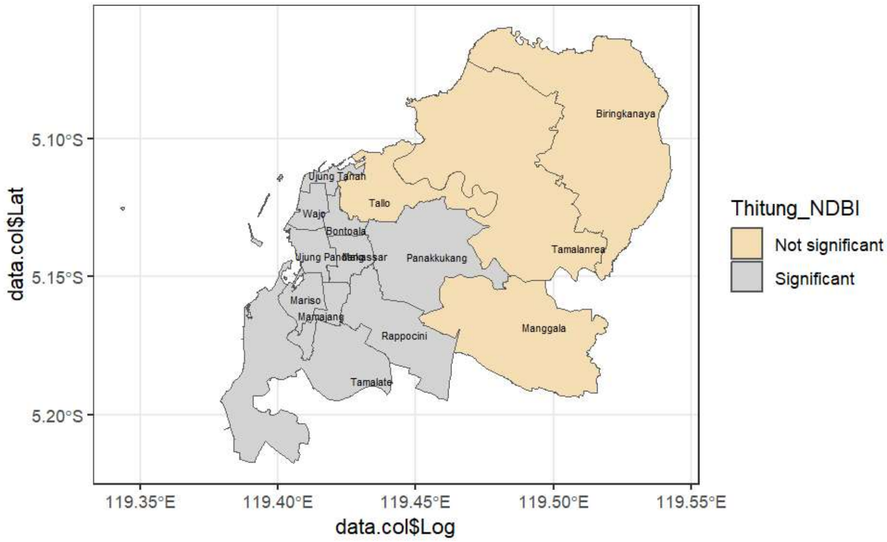

Figure 10. NDBI Variable with Significant Influence on the UHI Phenomenon in Each District of Makassar City

Through the results of the Geographically Weighted Regression (GWR) analysis, it is evident that several research variables have a significant influence on the UHI phenomenon in each district of Makassar City. The NDVI variable (X1) has a significant influence on the UHI phenomenon in several districts, including Biringkanaya, Tamalanrea, Tallo, Ujung Tanah, Wajo, Bontoala, Makassar, Ujung Pandang, and Mariso (Figure 5). This indicates that vegetation density in these areas is relatively low, thus contributing to the Urban Heat Island phenomenon. These findings are consistent with research by Riyadi and Rahayu (2019) which showed that a decrease in vegetation contributes to the intensification of the Urban Heat Island (UHI) effect. Meanwhile, areas such as Tamalate and Manggala, which also have low vegetation density, do not show a significant influence on UHI. This is likely because these areas are less densely populated, and therefore anthropogenic activities do not significantly contribute to UHI in those locations. This is in line with studies by Wahid, Setyono, and Kurniawan (2023) and by Dewi, Taryana, and Astuti (2023), which state that high population density generates environmental emissions (affecting vegetation), thus having a significant impact on the UHI phenomenon [37, 38].

In the elevation variable (X2), the analysis results show that the districts with a significant influence from the elevation variable (X2), contributing to the increase in UHI, include Ujung Tanah, Tallo, Wajo, Bontoala, Ujung Pandang, Makassar, Panakukang, Mariso, Mamajang, Tamalate, Rappocini, and Manggala (Figure 6). Essentially, the influence of elevation on the UHI phenomenon is a complex aspect, affected by various factors [39, 40] . However, this finding indicates that elevation can influence the increase in UHI due to low vegetation density and high population density, leading to high UHI concentrations in the districts of Makassar City.

Meanwhile, the significant influence of the Water Surface Area variable (X3) on the UHI phenomenon in Makassar City includes the districts of Tallo, Panakukang, Makassar, Mamajang, Rappocini, and Tamalate (Figure 7). This indicates that these areas have a relatively small water surface area, thus unable to absorb and store heat in large quantities to mitigate a significant rise in temperature [41, 42, 43]

Furthermore, the Population Density variable (X4) also has a significant influence on the increase of the UHI phenomenon in each district of Makassar City. The areas affected include Biringkanaya, Tamalanrea, Panakukang, Ujung Pandang, Makassar, Bontoala, Wajo, Tallo, and Ujung Tanah (Figure 8).

A significant increase in population in a region influences the rise in surface temperatures, which impacts the UHI phenomenon [44]. This is consistent with the findings of studies showing that the districts of Makassar, Bontoala, Ujung Pandang, Wajo, Ujung Tanah, and Tallo have high population densities, evidenced by the large number of slum settlements in these areas. Meanwhile, the districts of Panakukang and Tamalanrea have moderate population densities, but these areas lack sufficient vegetation to mitigate UHI growth.

In the Green Area Percentage variable (X5), the analysis results show that the districts significantly influenced by this variable (X5) are Ujung Tanah, Tallo, Wajo, Bontoala, Ujung Pandang, Panakukang, Mamajang, Rappocini, and Tamalate (Figure 9). This is consistent with findings that show these areas have a low percentage of green space. Research by Fatturusi, Irsan, and Jati (2023) dan Effendy et al. (2006) also explains that the decrease in green spaces, along with the increase in built-up land, causes a rise in temperature in these areas, which can contribute to the concentration of the Urban Heat Island phenomenon [45, 46].

Additionally, the NDBI variable (X6) also significantly influences several districts in Makassar City, including Ujung Tanah, Wajo, Bontoala, Ujung Pandang, Makassar, Panakukang, Mariso, Mamajang, Rappocini, and Tamalate (Figure 10). This indicates that the built-up areas in these districts are dense and are not supported by adequate vegetation or green space, which triggers an increase in UHI concentration. This is in line with research by Macarof and Statescu (2017), which found a strong linear correlation between NDBI and surface temperature in a study in Iasi, Italy, indicating that areas with high NDBI tend to have higher temperatures [46]. Another study in Surabaya, Indonesia, also showed that the conversion of non-built-up land into built-up areas increases the NDBI value and surface temperature, contributing to the UHI phenomenon [47].

5) Classification of Areas Based on Influential Variables

The results of the t-tests conducted in the Geographically Weighted Regression (GWR) analysis were used as a basis for classifying areas based on the variables that significantly influence the Urban Heat Island (UHI) phenomenon. Each district was classified according to the combination of variables that significantly affect UHI in that area. The following table and figure show the districts included in each group, along with the significant variables that influence UHI in each district (Table 6 and Figure 11). This classification provides a deeper understanding of the factors influencing UHI in each region, which is then visualized through an overlay map to show the spatial distribution of the influence of each variable.

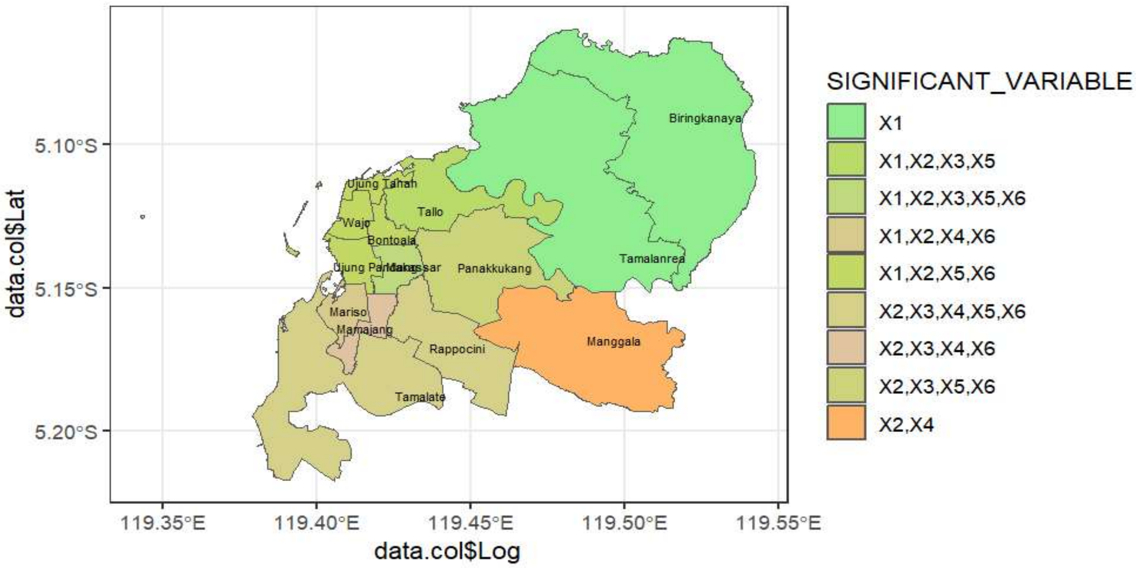

Figure 11. Overlay Map of the Most Influential Variables on UHI

Table 6. Variables Influencing the UHI Phenomenon in Each District of Makassar City

Significant Variable	Subdistrict	Results
X1	Biringkanaya, Tamalanrea	$\hat{\mu}\ (u_1 v_1) = 38{,}2641{+}2{,}2181\mathrm{X}_1$
X2,X4	Manggala	$\hat{\mu}\ (u_5 v_5) = 38{,}8055 - 0{,}2044X_2 - 0{,}0007X_4$
X1,X2,X3,X5	Tallo	$\hat{\mu}\ (u_9 v_9) = 38{,}1403{+}2{,}1970\mathrm{X}_1 - 0{,}1952X_2 - 0{,}0021X_3 + 0{,}0468X_5$
X1,X2,X4,X6	Mariso	$\hat{\mu}\ (u_6 v_6) = 38{,}6512{+}2{,}1740\mathrm{X}_1 - 0{,}2192X_2 - 0{,}0007X_4 - 8{,}1508X_6$
X1,X2,X5,X6	Bontoala, Ujung Pandang, Ujung Tanah, Wajo	$\hat{\mu}\ (u_{13} v_{13}) = 38{,}1471{+}2{,}3243\mathrm{X}_1 - 0{,}2072X_2 + 0{,}0490X_5 - 7{,}9733X_6$
X2,X3,X4,X6	Mamajang	$\hat{\mu}\ (u_4 v_4) = 38{,}6988 - 0{,}2231X_2 - 0{,}0022X_3 + 0{,}0007X_4 - 8{,}3324X_6$
X2,X3,X5,X6	Panakukang	$\hat{\mu}\ (u_7 v_7) = 38{,}4977 - 0{,}2098X_2 - 0{,}0021X_3 + 0{,}0422X_5 - 7{,}8706X_6$
X1,X2,X3,X5,X6	Makassar	$\hat{\mu}\ (u_3 v_3) = 38{,}4468{+}2{,}1570\mathrm{X}_1 - 0{,}2144X_2 - 0{,}0021X_3 + 0{,}0449X_5 - 8{,}2038X_6$
X2,X3,X4,X5,X6	Rappocini, Tamalate	$\hat{\mu}\ (u_8 v_8) = 38{,}9631 - 0{,}2406X_2 - 0{,}0025X_3 - 0{,}0008X_4 + 0{,}0426X_5 - 8{,}9798X_6$

Source: Analysis Results, 2025

The results of this modeling indicate significant variability in the influence of environmental factors on surface temperature across different districts in Makassar City. The analysis shows that in Biringkanaya and Tamalate districts, the model reveals that NDVI (X1) plays a major role in influencing surface temperature, with a significantly positive coefficient—indicating that higher green vegetation values are associated with a greater decrease in surface temperature. Meanwhile, in the districts of Bontoala, Ujung Pandang, Ujung Tanah, and Wajo, other factors such as Elevation (X2), Green Area (X5), and NDBI (X6) exhibit more complex effects on surface temperature. In these cases, increases in elevation and green area help reduce temperature, whereas higher NDBI values (indicating built-up areas) contribute to temperature increases. The model in the Makassar district is more complex, involving interactions among variables such as NDVI (X1), Elevation (X2), Water Surface Area (X3), Population Density (X4), Green Area (X5), and NDBI (X6). The influence of elevation and water surface area appears to contribute to temperature reduction, highlighting the importance of open spaces and environmental management in the area. Using this model, more specific policies can be developed for each district, considering that significant factors in one district may not be significant in another. Therefore, the results of this modeling offer important insights for the Makassar city government in planning interventions to mitigate the Urban Heat Island effect and improve residents' quality of life through more spatially-informed environmental management.

The findings from the conducted research indicate that the intensity of surface temperature in Makassar City has a significant impact on both humans and the environment. This condition will continue to trigger the increase of the Urban Heat Island (UHI) phenomenon, which indirectly causes serious environmental issues. Therefore, it is crucial to implement sustainable efforts to mitigate the Urban Heat Island (UHI). Several steps can be taken as recommendations, including: (1) Increasing Vegetation Density (NDVI) through tree planting and the development of green open spaces aimed at expanding urban green areas, particularly in sub-districts with limited vegetation such as Biringkanaya and Tamalanrea, in order to reduce surface temperatures and minimize UHI effects [48]; (2) Providing vertical vegetation on high-rise buildings through the application of environmentally friendly composting technology in urban centers to lower surface temperatures, which consequently reduces the UHI effect; (3) Managing Population Density through Sustainable Spatial Planning by regulating population density with effective spatial planning to lessen anthropogenic contributions to UHI [49](Darlina et al., 2018); (4) Managing Elevation and Topography through adaptive architectural design by utilizing elevation and topographical features in the design of buildings and infrastructure to help reduce heat accumulation in certain areas, as emphasized by the study of Angkasa et al. (2023), which highlights the use of passive cooling techniques for sustainable UHI mitigation [50]; (5) Reducing Built-Up Areas (NDBI) through the use of green roofs and walls by integrating vegetation into the roofs and walls of buildings to mitigate heat effects from built-up structure [51]; and (6) Increasing Public Awareness and Participation through public education to raise awareness about the importance of green spaces and environmentally friendly practices, which can encourage active community participation in sustainable UHI mitigation efforts. These mitigation efforts can serve as recommendations for the government as policy-makers and for the public as proactive steps in addressing the Urban Heat Island phenomenon.

Conclusion

Based on the results of the conducted research, it is evident that the Urban Heat Island (UHI) phenomenon in Makassar City is unevenly distributed across sub-districts. The highest UHI concentration was identified in Rappocini District with a value of 39.34, while the lowest was recorded in Ujung Tanah District at 34.58. This disparity indicates a significant spatial variation in the distribution of urban surface temperatures. The factors influencing this variation include vegetation index (NDVI), elevation, water surface area, population density, the percentage of green open space, and the built-up index (NDBI). Through the Geographically Weighted Regression (GWR) approach, it was found that several variables have a significant influence on surface temperature intensity, although the distribution of these effects varies by region. For instance, NDVI and green space play a crucial role in reducing surface temperatures in certain districts, while variables such as NDBI and population density tend to increase UHI intensity in areas with high levels of development and anthropogenic activity. The GWR modeling successfully grouped districts based on the combination of significant variables, providing a deeper understanding of the local characteristics contributing to UHI. These findings serve as a critical basis for formulating spatial data-driven mitigation policies, such as enhancing vegetation, implementing adaptive spatial planning, and controlling population density to sustainably reduce the negative impacts of UHI in Makassar City.

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