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Estimating Urban Land Surface Temperature Using Spatial Machine Learning in Gorontalo City

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ABSTRACT

Urban expansion in tropical cities significantly alters surface thermal conditions, intensifying the urban heat island (UHI) phenomenon. This study aims to estimate and analyze the spatiotemporal dynamics of land surface temperature (LST) in Gorontalo City from 1995 to 2025 using a spatial machine learning (SML) approach based on the Random Forest (RF) algorithm. Multitemporal Landsat 5, 7, 8, and 9 images were processed in Google Earth Engine (GEE) to derive surface reflectance, Normalized Difference Vegetation Index (NDVI), emissivity, and brightness temperature, which were subsequently employed as predictor variables in the LST model. A total of 50 ground validation points were used to assess model performance. The RF model achieved high predictive accuracy with an R^2 of 0.833, RMSE of ±3.33 °C, and MAE of ±2.80 °C, outperforming conventional NDVI-based models. The long-term analysis revealed a consistent increase in LST across urbanized zones, particularly in the city center and northern districts, while areas with higher vegetation cover exhibited lower LST values. The negative correlation between NDVI and LST (R^2 = 0.3132) confirms the critical role of vegetation in mitigating urban thermal intensity. These findings highlight the applicability of the RF-based SML framework for accurate LST estimation and urban climate monitoring, providing a scientific basis for sustainable urban planning and green infrastructure development in tropical cities.

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1. INTRODUCTION

Urban surface temperature plays a vital role in shaping the thermal environment and sustainability of cities, especially in rapidly developing tropical regions. The increase in impervious surfaces due to urbanization has been linked to the intensification of the Urban Heat Island (UHI) phenomenon, elevating ambient temperatures and aggravating issues related to energy consumption, public health, and environmental quality (Moyo et al., 2025; Stewart & Gerald, 2018; Hassan et al., 2021; Liu et al., 2024; Thambawita et al., 2023). Various studies have shown that changes in urban form and land use substantially alter the thermal balance of urban areas, amplifying UHI effects and necessitating comprehensive assessment and management.

Vegetation and water bodies are key elements in mitigating urban surface heating and maintaining urban thermal comfort. The processes of evapotranspiration and shading provided by vegetation have been recognized as effective mechanisms to reduce land surface temperature (LST) (Moyo et al., 2025; Stewart & Gerald, 2018; Hassan et al., 2021; Liu et al., 2024; Thambawita et al., 2023). However, the ongoing conversion of green and blue spaces into built-up land often increases LST and reduces the comfort and health of city dwellers. Research has found that such land cover changes are strongly associated with spatial variations in LST across urban environments.

The relationship between land cover change and LST has become a central concern in urban environmental studies. In the Indonesian context, including Gorontalo, increased built-up areas at the expense of vegetation have led to higher surface temperatures and more varied thermal patterns. Previous research has predominantly used conventional remote sensing methods to analyze this relationship, but these methods often struggle to capture complex spatial and temporal interactions between land cover, vegetation, and temperature (Adi et al., 2022; Arif et al., 2019; Abidin et al., 2021; Arifin et al., 2022; Koto, 2016; Koto & Taslim, 2018).

Technological progress in spatial machine learning (SML) and cloud-based geospatial platforms has provided new opportunities for more accurate assessment of urban thermal dynamics. Advanced algorithms such as Random Forest (RF) have proven effective in modeling nonlinear relationships and integrating diverse predictor variables from multitemporal datasets. Several studies have demonstrated that RF models outperform traditional regression-based approaches for LST prediction, particularly when incorporating variables such as NDVI, brightness temperature, and emissivity, as well as utilizing the computational resources of Google Earth Engine (Sawada, 2020; Kopczewska, 2022; Sheykhmousa et al., 2020; Arunab & Mathew, 2024).

Despite these advancements, research on urban surface temperature in Indonesia remains limited in terms of methodological innovation and temporal scope. Studies in Gorontalo City have not yet integrated SML approaches, long-term satellite data, and field validation to fully elucidate the spatiotemporal dynamics of LST and its controlling factors. As a result, there is a critical need for research that combines these elements to inform urban planning and climate adaptation in the face of rapid urban growth and environmental change (Arif et al., 2019; Abidin et al., 2021; Arifin et al., 2022; Koto, 2016; Koto & Taslim, 2018).

The objective of this study is to estimate and analyze the spatiotemporal dynamics of land surface temperature in Gorontalo City from 1995 to 2025 by applying a Random Forest-based spatial machine learning framework that incorporates multitemporal Landsat imagery and ground validation data. This research introduces a novel approach by integrating long-term satellite observations, advanced machine learning, and rigorous field validation to enhance the understanding of urban thermal environments in tropical cities. By filling methodological and empirical gaps in the existing literature, this study is expected to offer practical recommendations for sustainable urban planning and climate resilience in Gorontalo and comparable urban areas.

2. METHOD

2.1. Materials

The main data sources for this study consist of multitemporal Landsat imagery (Landsat 5, 7, 8, and 9) obtained from the Google Earth Engine (GEE) platform. Supplementary datasets were sourced from the Meteorology, Climatology, and Geophysical Agency (BMKG) and the Central Bureau of Statistics (BPS) of Gorontalo City. Field validation data were collected from 50 observation points across Gorontalo City using calibrated infrared thermometers. These sources ensured comprehensive coverage of both remote sensing and ground-based information for robust analysis.

The selection of multitemporal Landsat datasets, as detailed in Table 1, enables the analysis of long-term trends in land surface temperature and vegetation dynamics in Gorontalo City. The range of acquisition years and sensor types ensures comprehensive temporal coverage and consistency in data quality throughout the study period. This multitemporal approach is essential for capturing both short-term variations and long-term changes associated with urban development and land cover transitions.

Table 1. Landsat imagery spesification

Sensor	Processing	Path/row	Date acquired
Landsat 5 TM	Surface reflectance	113/60	May 5, 1995 Oct 17, 2000
Landsat 7 ETM+	Surface reflectance	113/60	Feb 17, 2005 October 13, 2010
Landsat 8	Surface reflectance	113/60	October 19, 2015 August 29, 2020
Landsat 9	Surface reflectance	113/60	May 31, 2025

2.2. Sample Preparation

All Landsat images underwent a standardized preprocessing workflow, which included cloud masking using the QA band, selection of images with minimal cloud cover, and correction for surface reflectance within the GEE environment. The NDVI was calculated from each image using the normalized difference between near-infrared (NIR) and red bands. Surface emissivity was derived from NDVI values following established NDVI threshold algorithms. Brightness temperature was computed from the thermal bands of the respective Landsat missions. Each dataset was then spatially clipped to the administrative boundaries of Gorontalo City for further analysis.

2.3. Model Development

Land Surface Temperature (LST) was estimated using an NDVI-based algorithm that includes emissivity correction as described by Sobrino et al. (2004). The predictive model employed was Random Forest (RF) regression, utilizing NDVI, brightness temperature, surface emissivity, and spatial coordinates (latitude and longitude) as predictor variables. Data were split into 70% for training and 30% for testing. The RF model comprised 300 decision trees, with bootstrap aggregation implemented. Hyperparameters, including tree depth and minimum samples per split, were optimized using grid search. Model performance was compared with conventional NDVI-based LST estimation methods.

2.4. Parameters

The primary parameters analyzed in this study include NDVI, surface emissivity, brightness temperature, and LST. NDVI was computed using the formula:

$$NDVI = \frac{\rho NIR - \rho R}{\rho NIR + \rho R} \tag{1}$$

Surface emissivity (ε) was estimated based on NDVI values using a threshold approach, and brightness temperature was derived from the respective Landsat thermal bands. LST was then calculated using the NDVI-based approach with emissivity correction (Sobrino et al., 2004):

$$LST = \frac{BT}{1 + (\lambda \times \frac{BT}{\rho}) \times In\varepsilon} \tag{2}$$

where $BT$is the brightness temperature, $\lambda$is the wavelength of emitted radiance, $\rho$is a constant (Planck's law), and ε is surface emissivity. All calculations followed the standard processing pipeline for Landsat-derived LST.

2.5. Model Evaluation

Model performance was evaluated using the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). Validation was conducted using the 50 ground-truth points distributed throughout Gorontalo City. A cross-validation approach was applied to ensure robustness and minimize overfitting in the Random Forest model. Performance of the RF-based model was further compared with conventional NDVI-based LST methods to highlight improvements achieved through spatial machine learning.

3. RESULTS AND DISCUSSION

Indonesia generally experiences a rainy season from October to March, while the dry season occurs from April to September. Western Indonesia experiences its peak rainy season in November and December. Meanwhile, eastern Indonesia experiences its peak rainy season in January-February (Badan Meteorologi dan Klimatologi, 2022) Table 2 shows the seasons experienced according to the time of Landsat image acquiring.

Table 2. Landsat imagery data every 5 years of Gorontalo city (1995-2025)

Sensor	Path/row	Date acquired	Season
Landsat 5 TM	113/60	May 5, 1995	Dry
Landsat 7 ETM	113/60	Oct 17, 2000	Rainy
Landsat 7 ETM (slc off)	113/60	Feb 17, 2005	Rainy
Landsat 7 ETM (slc off)	113/60	Oct 13, 2010	Rainy
Landsat 8 OLI	113/60	Oct 19, 2015	Rainy
Landsat 8 OLI	113/60	Aug 29, 2020	Dry
Landsat 9	113/60	May 31, 2025	Dry

3.1. Landsat

Visualization of Landsat images downloaded from the GEE platform during the period 1995 to 2025 is shown in Figure 1. It appears that the 2005 and 2010 recordings experienced SLC off, meaning that the image satellite sensor installed malfunctioned when scanning the earth's surface, resulting in some areas appearing as horizontal lines that were not recorded or no data was produced.

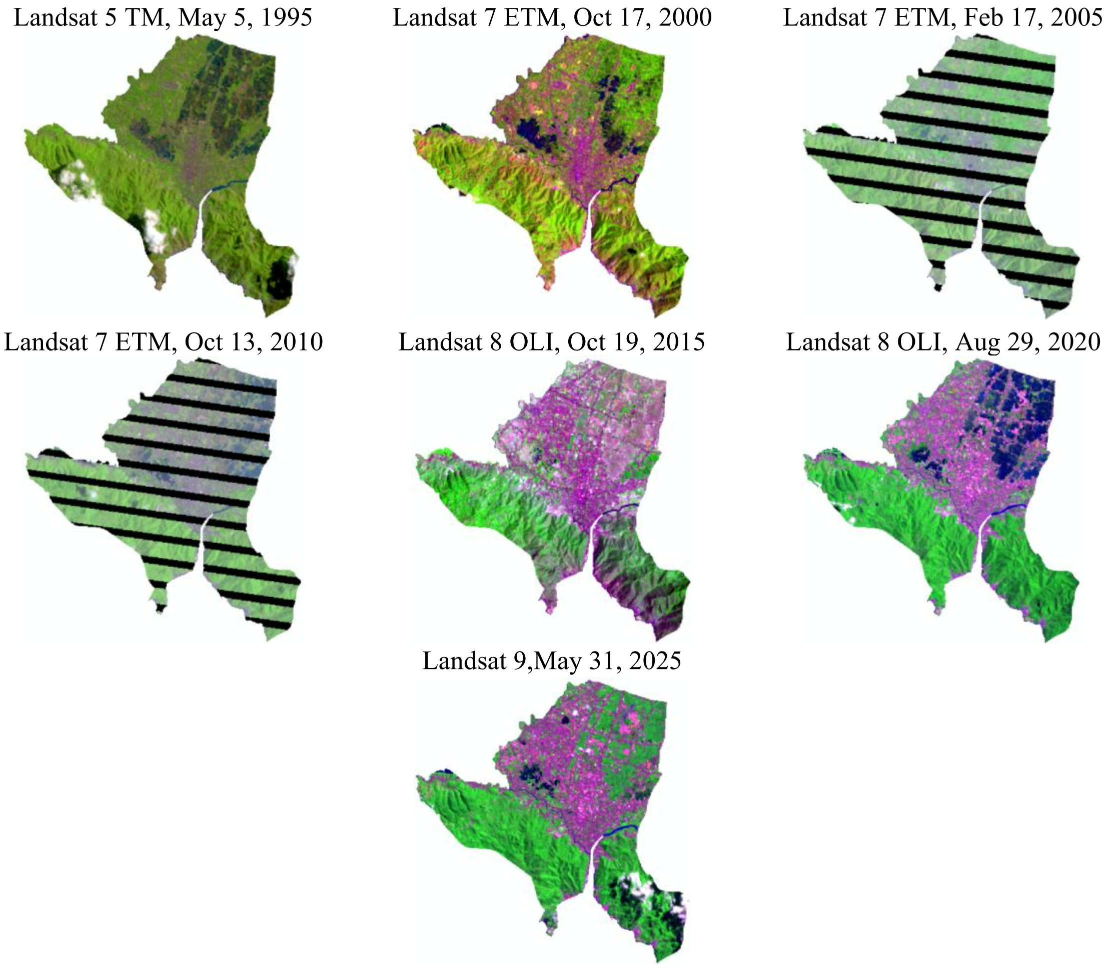

Figure 1. Landsat imagery of Gorontalo city.

3.2. Vegetation (NDVI)

The vegetation index map of Gorontalo City shows NDVI variations from 1995 to 2025. In 1995, vegetation cover was wide with NDVI values between −0.092 and 0.487, indicating minimal urban impact. By 2000, reduced green intensity emerged in the city core and along roads as NDVI values declined due to deforestation and built-up areas. NDVI values for 2005 and 2010 could not be interpreted due to SLC-off issues. In 2015 and 2020, vegetation density decreased in central districts, with the 2025 NDVI pattern showing continued decline in the city center from built-up expansion.

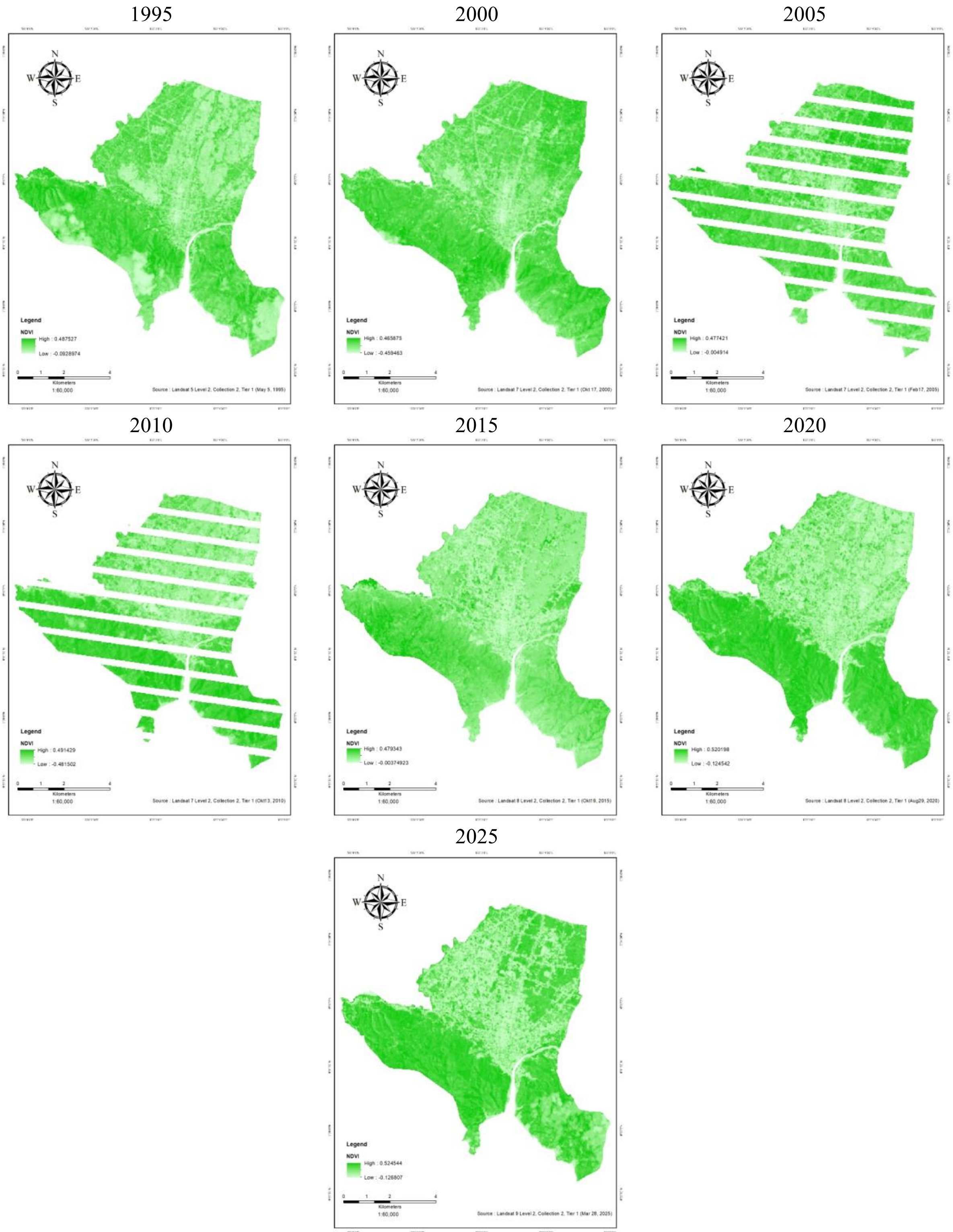

Figure 2. NDVI Map of Gorontalo City.

Figure 3 presents a histogram of pixel value distributions for NDVI derived from Landsat imagery in Gorontalo City over the period 1995–2025. The distribution of NDVI values reveals dynamic and fluctuating patterns that reflect significant changes in vegetation and land cover across three decades. From 1995 to 2005, the histogram is dominated by NDVI values in the 0.1–0.4 range, indicating the prevalence of moderate to dense vegetation cover in the city, particularly in irrigated fields and green open spaces. However, in the following years—especially 2010 and 2020 a shift to a bimodal distribution becomes apparent, signifying the emergence of two primary land cover types: moderately vegetated zones and dense vegetation areas. This shift likely results from the expansion of built-up areas, land conversion, and the continued presence of remnant green spaces.

By 2015, the NDVI histogram transitions to a unimodal pattern, with lower peaks reflecting a marked decline in vegetation density across the city, likely driven by intensified urban development and the reduction of green areas. In 2025, the histogram again displays a bimodal distribution, this time with a dominance of moderate to dense vegetation. These changing patterns suggest that, while urbanization and human activities have led to periods of vegetation loss, there have also been phases of regeneration or successful urban greening initiatives. Overall, the temporal dynamics highlighted by the NDVI histograms emphasize the ongoing transformation of Gorontalo City's urban ecosystem and underscore the importance of continuous monitoring and adaptive land management.

The statistical values for the mean, standard deviation, and quartile for each year are presented in Table 3 below.

Table 3. Statistical summary of NDVI in Gorontalo City, 1995–2025

Year	StdDev	Mean	Quantiles
2025	0.13	0.29	ndvi_p25:0.18 ndvi_p50:0.32 ndvi_p75:0.39
2020	0.14	0.26	ndvi_p25:0.13 ndvi_p50:0.27 ndvi_p75:0.39
2015	0.07	0.19	ndvi_p25:0.15 ndvi_p50:0.19 ndvi_p75:0.24
2010	0.12	0.27	ndvi_p25:0.16 ndvi_p50:0.28 ndvi_p75:0.39
2005	0.08	0.28	ndvi_p25:0.23 ndvi_p50:0.29 ndvi_p75:0.34
2000	0.08	0.28	ndvi_p25:0.23 ndvi_p50:0.29 ndvi_p75:0.34
1995	0.09	0.25	ndvi_p25:0.17 ndvi_p50:0.26 ndvi_p75:0.33

NDVI fluctuations from 1995 to 2025 indicate significant vegetation dynamics, which are likely influenced by: the growth of built-up areas, land conversion, temporary vegetation degradation (e.g., due to human activities or climatic conditions), and vegetation restoration programs. The year 2015 was a critical anomaly with lower NDVI values across all quantiles. This can be attributed to: construction intensity, drought or severe dry season, or local deforestation processes. The 2020–2025 period shows vegetation recovery, marked by an increase in the mean, median, and upper quantile. Vegetation heterogeneity increased in 2020–2025, occurring in areas experiencing urban sprawl.

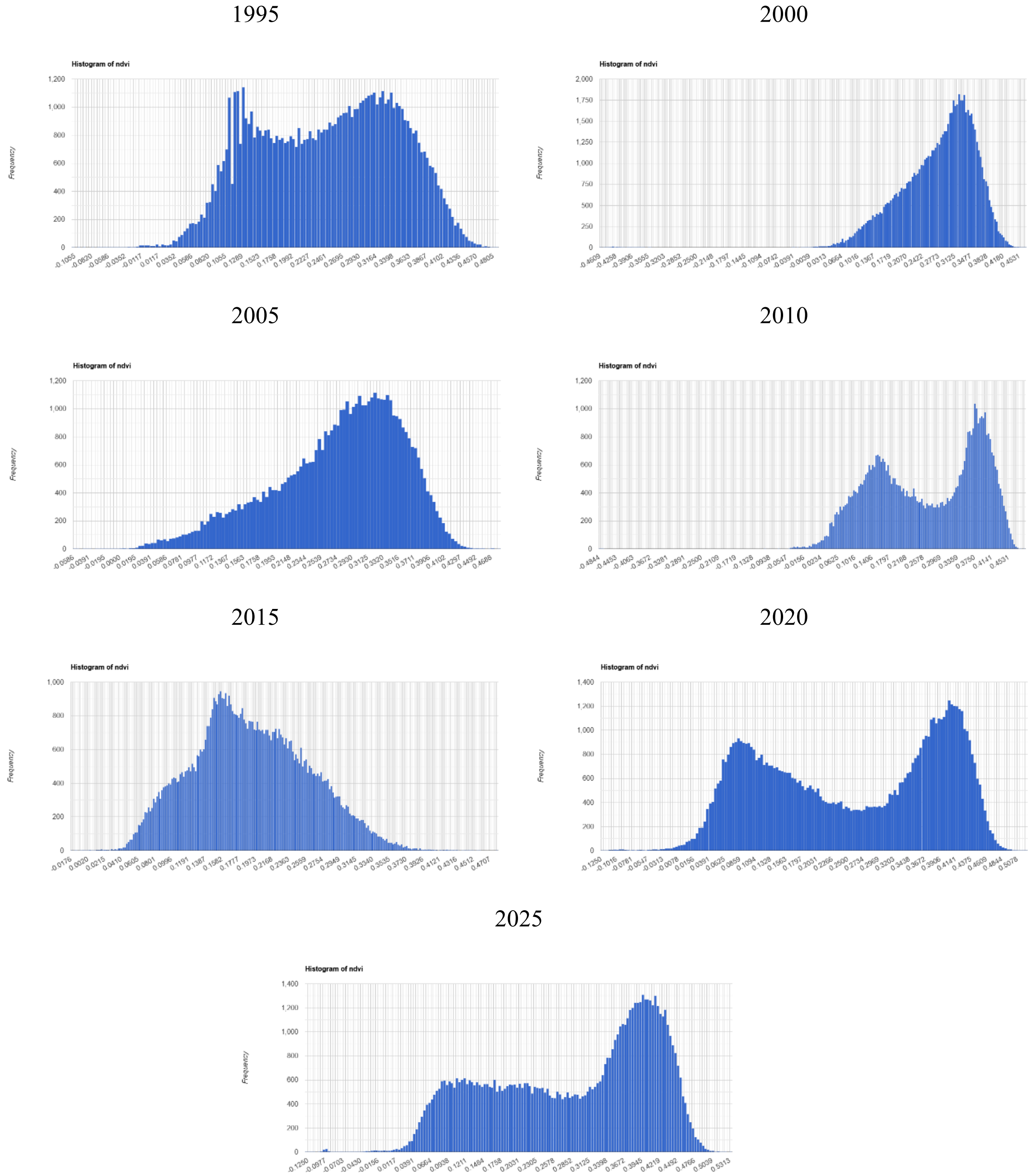

Figure 3. NDVI Map of Gorontalo City.

3.3. Land Surface Temperature

Figure 4 shows Land Surface Temperature (LST) patterns in Gorontalo City from 1995 to 2025. In 1995, LST ranged from 21°C to 35°C, with temperatures above 30°C concentrated in northern and central sectors due to urban development. Cooler zones below 27°C were mainly in southern areas. By 2000, high-temperature regions expanded in central and eastern areas, reflecting increased built-up land. During 2005-2010, despite SLC-off errors in Landsat 7 ETM+ imagery, high-temperature zones spread westward and northward, while cooler areas remained only in vegetated regions. In 2015, areas above 32°C increased significantly in the city center and north. The 2020 pattern showed similar trends, with some cooler zones in the vegetated south. By 2025, most urban areas are projected to exceed 33°C, with low temperatures persisting mainly in southern regions.

These trends clearly demonstrate the dominant impact of urbanization on LST dynamics in Gorontalo City. The consistent increase in LST and the expansion of high-temperature zones are strongly associated with land cover change, particularly the replacement of vegetation with impervious surfaces such as asphalt and concrete, which have low specific heat and albedo and thus intensify surface heating (Patel et al., 2024; Pramudiyasari et al., 2022; Ibrahim & Ash'aari, 2023). Moreover, the scarcity of green spaces and water bodies reduces the city's capacity to mitigate the urban heat island effect (Yenneti et al., 2020). These findings underscore the urgent need for integrated spatial and ecological mitigation strategies to curb UHI effects and support sustainable urban environments in Gorontalo City.

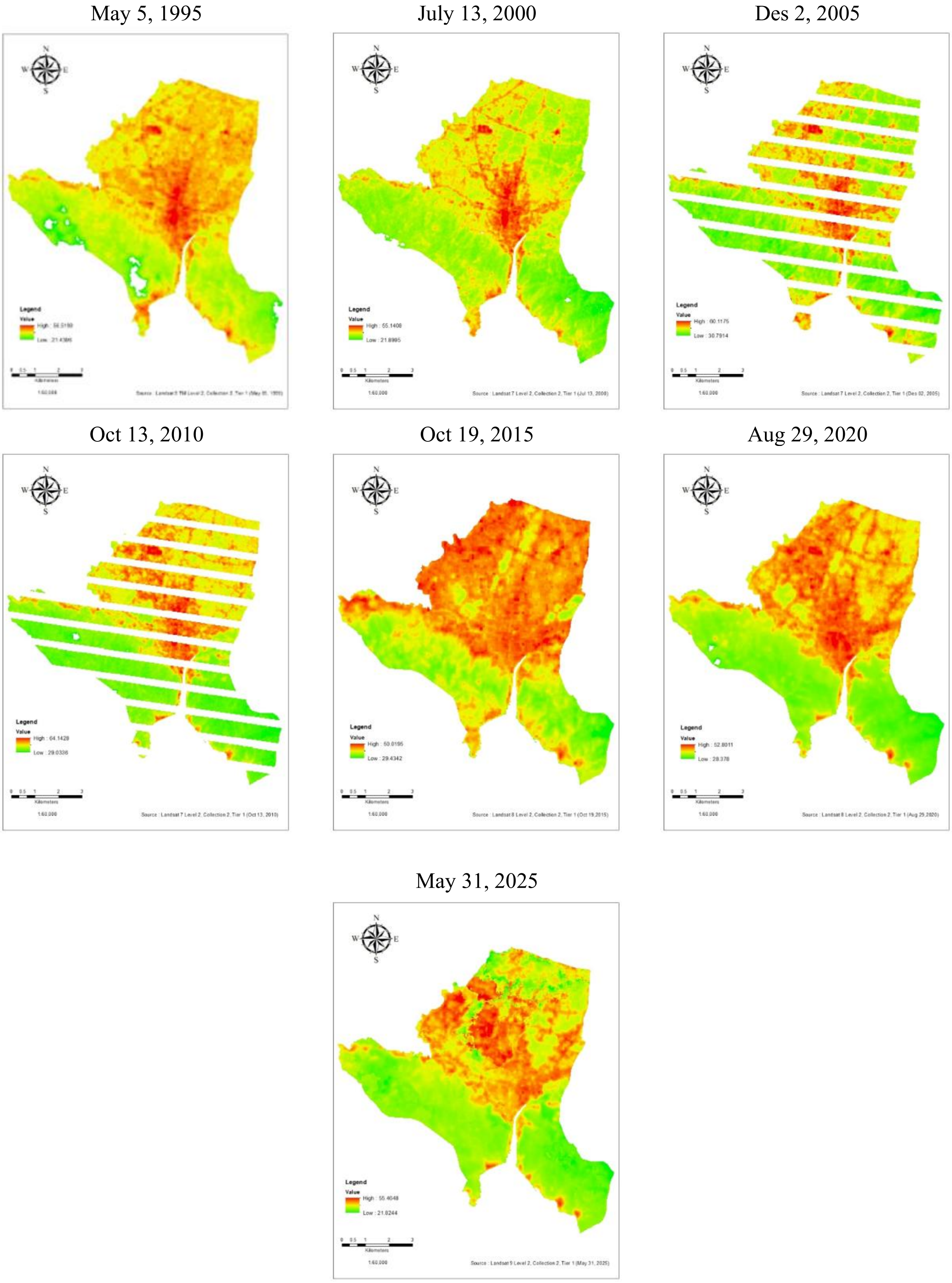

Figure 4. LST Map Gorontalo City

Figure 5 shows the distribution of LST analyzed from Landsat 9 imagery recorded on May 31, 2025. It can be seen that the UHI effect is clearly visible in the city center. The high temperature zone is located in the central to northern parts, indicating areas with high urbanization, minimal vegetation cover, and a predominance of buildings and hard surfaces (asphalt/concrete). The low temperature zone is distributed in the south, southwest, and southeast, which are forest and agricultural areas with higher vegetation. The central eastern zone contains technically irrigated rice fields with two planting seasons per year.

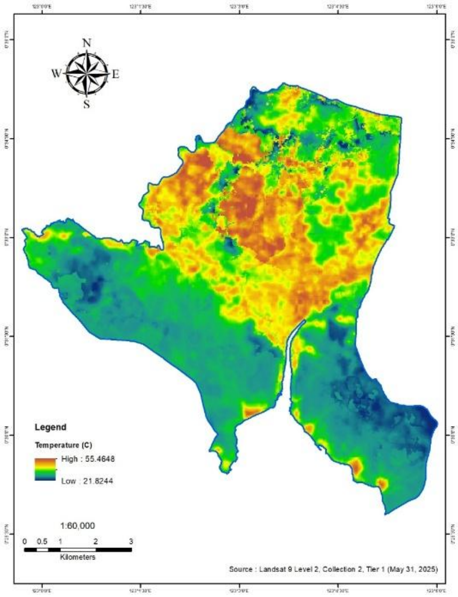

Figure 5. Distibution of LST Gorontalo City.

3.4. Correlation between LST and field temperature measurements

The Random Forest model applied in this study produced an R^2 value of 83.3%, indicating a high level of accuracy in estimating land surface temperature across Gorontalo City. This result demonstrates that the model can effectively capture the variability of LST using the selected predictor variables. The detailed performance of the model is presented in Figure 6.

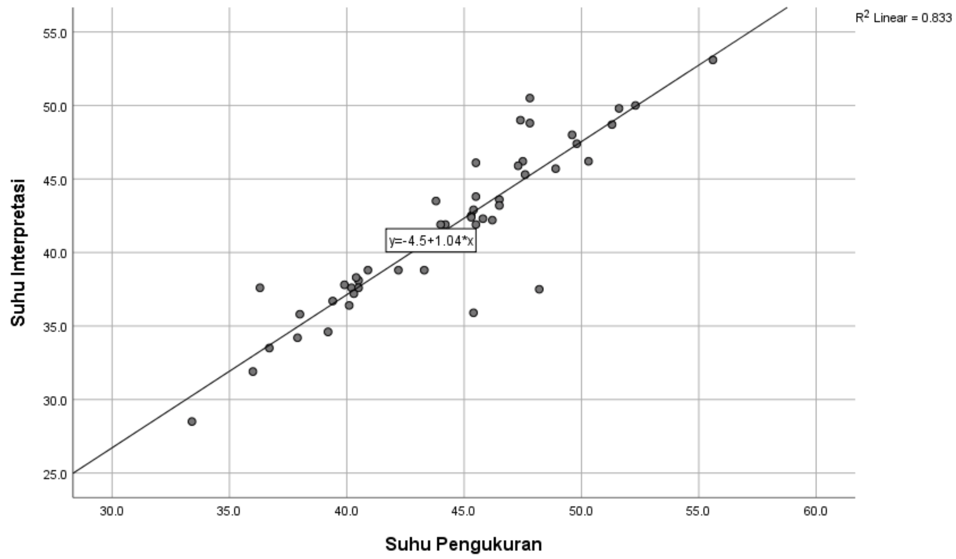

Figure 6. Scatter Plot Graph of The Correlation Between Interpretation Temperature Data And Field Measurement Temperature Data.

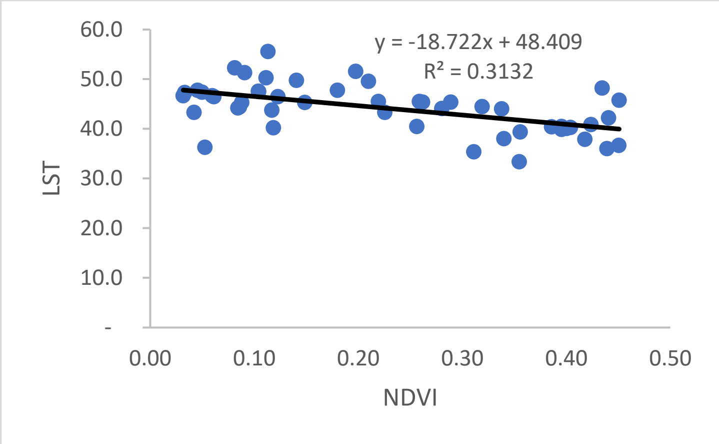

Figure 7. Coefficient Determination NDVI vs LST.

Figure 7 shows that there is a negative relationship between NDVI and LST, although the relationship is not very strong (R2=0.3132). The higher the NDVI value, the lower the LST value. Vegetation plays a role in lowering soil surface temperature. The figure of -18.72 in the x coefficient shows that for every one unit increase in NDVI, LST decreases by approximately 18.70C. The coefficient determination R2=0.3132 shows that approximately 31.32% of the variation in LST can be explained by changes in NDVI, which is classified as a weak to moderate correlation.

3.5. LST and NDVI correlation

In general, the relationship between LST and NDVI shows a negative correlation, meaning that the higher is LST value and lower is NDVI value. In 2005 and 2010, data errors occurred and could not be analyzed. This happened because in those years, Landsat 7 ETM experienced Scan Line Corrector (SLC) off, which is damage to the scanning device when recording the earth's surface, so that in some areas there was no data. Figure 9 shows a downward trend in LST values as NDVI increases, meaning that areas with high vegetation tend to have lower LST values. Conversely, areas with low NDVI (little vegetation or built-up land) tend to have high LST. Figure 8 also illustrates the negative relationship between NDVI and LST, which is a common phenomenon in urban areas. Thus, if NDVI is high, LST is low, and this vegetation can cool the surface temperature. The trend during 1995-2025 shows that it can be used to monitor vegetation degradation, urbanization, or changes in land cover/land use.

The model performance metrics also require further interpretation. The RF model achieved R^2 = 83.3%, RMSE ±3.33°C, and MAE ±2.80°C, indicating strong predictive capability and reliability for urban climate assessment. RMSE of approximately 3°C is within acceptable thresholds for medium resolution thermal remote sensing applications and suggests that the model can effectively support environmental monitoring programs. From an environmental perspective, the relatively low RMSE implies that the model is capable of distinguishing critical thermal gradients across the city, which is essential for identifying high risk UHI zones, planning heat mitigation strategies, and prioritizing areas for green space restoration.

The inverse NDVI-LST relationship, although statistically moderate (R^2 = 0.3132), carries important ecological and urban planning implications. Ecologically, this relationship confirms that vegetation plays a central role in regulating urban surface temperature through evapotranspiration and shading processes. The magnitude of the regression coefficient (-18.7°C per unit NDVI) indicates that even modest increases in vegetation density can substantially reduce surface temperature in Gorontalo's tropical climate.From a planning perspective, the NDVI-LST gradient highlights the urgency of integrating green infrastructure into urban development policies, preserving existing vegetated corridors, and designing urban cooling strategies tailored to areas with persistent high temperatures. The findings are therefore not only consistent with global evidence on the cooling function of vegetation but also provide localized insights essential for climate resilient city planning in Gorontalo.

Seasonal variability is addressed through atmospheric-corrected surface reflectance and ground surface temperature derived from data produced by the Landsat 8 OLI/TIRS sensor. The visible and near-infrared (VNIR) and short-wave infrared (SWIR) bands are processed into orthorectified surface reflectance, and the thermal infrared (TIR) band is processed into orthorectified surface temperature. Emissivity adjustments are based on NDVI, and LST values are normalized using air temperature data from field checks. This ensures that comparisons between periods reflect actual land surface changes rather than seasonal thermal fluctuations.

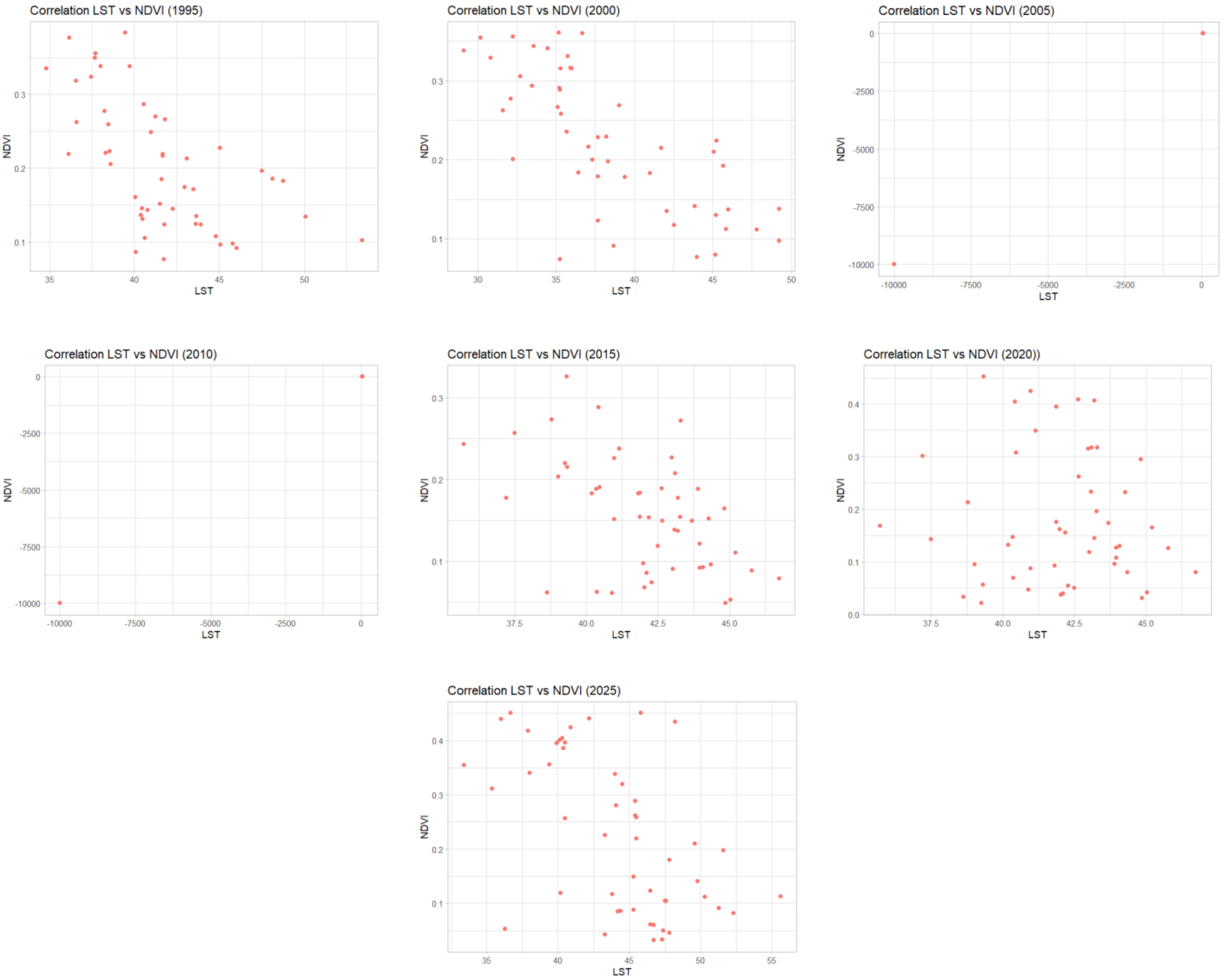

Figure 8. Correlation LST vs NDVI.

4. CONCLUSIONS

This study demonstrates that the integration of multitemporal Landsat imagery with spatial machine learning using the Random Forest algorithm provides an effective and reliable approach for estimating and analyzing long-term dynamics of land surface temperature (LST) in Gorontalo City. The results reveal a consistent upward trend in LST from 1995 to 2025, primarily driven by rapid urbanization and the conversion of vegetated land into built-up areas. High temperature zones have progressively expanded from the northern part of the city in 1995 to encompass almost the entire urban area by 2025, while low temperature zones remain concentrated in the southern and southwestern regions where vegetation and water bodies persist.

The Random Forest model achieved robust predictive accuracy (R^2 = 83.3%, RMSE ±3.33°C, MAE ±2.80°C), validating its capacity to capture the spatiotemporal variability of LST in a complex urban environment. The observed negative correlation between NDVI and LST underscores the critical role of vegetation in mitigating urban heat, as every unit increase in NDVI was associated with a reduction in LST of approximately 18.7°C. These findings highlight the importance of preserving and expanding green spaces as a strategic measure to minimize the urban heat island effect and promote environmental resilience. Limitations of the study include incomplete data due to SLC-off errors in Landsat 7 imagery and potential seasonal bias from the use of images acquired in different seasons. Future research should incorporate higher resolution data and additional socio-economic variables to further enhance spatial accuracy and understanding of LST drivers, thereby strengthening support for climate-resilient urban planning in Gorontalo City and comparable tropical urban settings.

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