Comparative Analysis of SAVI and NDVI Correlations with Land Surface Temperature in Mandalika Special Economic Zone Using Landsat 8 Imagery.

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Abstract. The rapid infrastructure development within the Mandalika Special Economic Zone (SEZ) has significantly altered land cover and potentially influenced land surface temperature (LST). This study aims to compare the correlation strength of two remote sensing-based vegetation indices, Normalized Difference Vegetation Index (NDVI) and Soil Adjusted Vegetation Index (SAVI) with LST to determine which index better represents surface temperature variability in areas undergoing rapid development. Landsat 8 imagery from 2014 to 2023 was used to derive NDVI, SAVI, and LST values. Spearman's Rho correlation and simple linear regression were employed to evaluate the strength and consistency of the relationships between vegetation indices and LST. The Shapiro – Wilk test confirmed that all variables were not normally distributed, leading to the use of Spearman's rho correlation. Both indices showed significant negative correlations with LST, with NDVI slightly stronger ($r = -0.555$) than SAVI ($r = -0.536$). Simple linear regression revealed NDVI had a higher R^2 (0.392) and lower residual error than SAVI, indicating a more robust model fit. Although SAVI is more suitable in mixed land cover conditions due to its soil background correction, NDVI provides stronger statistical performance in modeling LST in Mandalika SEZ. These findings support the strategic use of NDVI as a primary indicator in environmental planning and sustainable development monitoring or for Urban Heat Island mitigation policy in developing regions.

Keywords: Landsat8; Land surface temperature (LST); Mandalika; Normalized Difference Vegetation Index (NDVI); Remote sensing; Soil Adjusted Vetation Index (SAVI); Spearman Rho

I. INTRODUCTION

Climate change and the increasing land surface temperature (LST) have emerged as pressing global environmental concerns in recent decades. LST represents the temperature at the Earth's surface resulting from the interaction between solar radiation and land cover characteristics [1]. An increase in LST often indicates environmental degradation, particularly in regions undergoing rapid and extensive land use change [2].

One of the most significant drivers of rising LST is the conversion of natural landscapes into built-up areas through infrastructure development. Replacing vegetated surfaces with heat-retaining materials such as asphalt, concrete, and buildings increases local temperatures, reduces surface moisture, and exacerbates the urban heat island (UHI) effect [3]. Therefore, understanding the relationship between vegetation cover and surface temperature is crucial, and this relationship can be effectively examined using remote sensing-based vegetation indices.

Among the most commonly used vegetation indices are the Normalized Difference Vegetation Index (NDVI) and the Soil Adjusted Vegetation Index (SAVI). NDVI is widely adopted due to its simplicity and effectiveness in detecting vegetation density. However, it may be less accurate in sparsely vegetated or semi-arid regions due to background soil reflectance [4]. SAVI addresses this limitation by incorporating a correction factor to minimize the influence of soil background, making it more suitable for arid or semi-arid environments [5]. Analyzing the correlation between these indices and LST is essential to identify the most reliable indicator for evaluating environmental conditions and heat distribution patterns.

One of the rapidly developing regions in Indonesia is the Mandalika Special Economic Zone (SEZ), located in Lombok, West Nusa Tenggara [6], [7]. Designated as a national strategic project in 2014, Mandalika has been transformed into an international tourism hub through the development of various infrastructures such as race circuits, hotels, resorts, and other commercial facilities.

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While these developments have contributed positively to the local economy, they have also raised concerns about environmental impacts, particularly with regard to rising LST due to changes in land use.

This study utilizes Landsat 8 satellite imagery due to its capability to capture both multispectral and thermal infrared data, allowing for comprehensive, long-term environmental monitoring [8], [9]. Specifically, Landsat 8 Collection 2 Level 2 products were used, which offer surface reflectance and thermal data that are radiometrically and geometrically corrected. Compared to previous collections, Collection 2 provides improved spatial and radiometric accuracy, standardized surface reflectance calibration, and consistent atmospheric correction, making it more suitable for interannual and temporal analysis.

Mandalika represents a unique case study due to its geographic and ecological characteristics. Geographically, it lies in a transitional tropical semi-arid zone characterized by long dry seasons and limited rainfall. However, based on preliminary observations, the region has an average NDVI value of approximately 0.60, indicating moderately dense vegetation cover. This contrasts with typical semi-arid regions, which generally exhibit sparse vegetation (NDVI < 0.5). Furthermore, rapid development over the past decade has resulted in a heterogeneous landscape consisting of natural vegetation, bare land, and impervious built surfaces [10]. The combination of seasonal drought, substantial vegetation cover, and intensive land transformation makes Mandalika an atypical tropical zone—neither fully wet nor fully dry—and offers a novel context for evaluating the performance of vegetation indices in modeling land surface temperature dynamics.

Accordingly, this study aims to compare the effectiveness of NDVI and SAVI in representing vegetation conditions related to LST within the Mandalika SEZ. The results are expected to inform more sustainable spatial planning and environmentally responsible tourism development in Mandalika and potentially serve as a reference for other similar regions in Indonesia.

II. METHODOLOGY

2.1 Study Area

This research focuses on Kuta Village, located in the Pujut District of Central Lombok Regency, within the West Nusa Tenggara Province, Indonesia. The area is part of the Mandalika Special Economic Zone (SEZ), which has undergone significant development, including the construction of the Mandalika Circuit, aimed at boosting tourism and economic growth. The study area lies between the coordinates 8°50'58" to 8°55'18" S and 116°15'4" to 116°19'32" E (Fig.1), making it a suitable site for examining the impact of development on land surface temperature (LST).

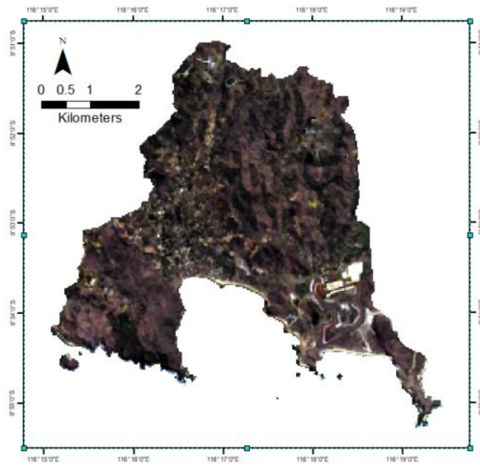

Figure 1. Kuta Village

2.2 Data and Source

To assess changes in land cover, vegetation indices, and LST between 2014 and 2023, this study utilized Landsat 8 satellite imagery. Landsat 8 is equipped with the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS), providing reliable data for environmental monitoring[11], [12], [13]. The satellite offers suitable spatial and temporal resolution for detecting changes in areas experiencing rapid development.

2.3 Image Preprocessing

Image preprocessing was conducted to enhance data quality and ensure accurate analysis. Steps included :

- Image Collection filter date from 2014 to 2023
- Cloud masking using the Quality Assessment (QA) band
- Image subset clipped to the extent of Mandalika SEZ

2.4 Vegetation Index Calculation

Two vegetation indices were calculated using the following formulas :

a) Normalized Difference Vegetation Index (NDVI) [4] :

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

Where :
ρNIR : Surface reflectance for Near Infrared Channel.
ρRED : Surface reflectance for Red Channel.

NDVI is a widely used vegetation index that quantifies vegetation greenness and density based on the difference between near-infrared (NIR) and red reflectance. It is calculated using Equation (1), where higher values typically indicate healthier or denser vegetation cover.
The NDVI values then will be used to classify vegetation density into six categories based on the framework

outlined in Table 1. This classification will enable the mapping and analysis of vegetation patterns, allowing for the identification of areas with varying levels of vegetation cover, from bare or no vegetation to very dense vegetation.

Table 1. NDVI Classification

Value Range	Vegetation Category	Description
< 0.1	No or Bare Vegetation	Open soil surfaces, built-up areas, or water bodies
0.1 – 0.2	Very Sparse Vegetation	Areas with minimal plant cover or early signs of degradation
0.2 – 0.3	Sparse Vegetation	Shrubland or semi-arid dryland
0.3 – 0.5	Moderate Vegetation	Actively cultivated land or seasonal vegetation
0.5 – 0.7	Dense Vegetation	Secondary forest cover, dense plantations
> 0.7	Very Dense Vegetation	Primary tropical forests, lush and closed canopy vegetation

b) Soil Adjusted Vegetation Index (SAVI) [14] :

$$SAVI = \frac{(\rho NIR - \rho RED)}{\rho NIR + \rho RED + L} * (1 + L) \quad (2)$$

Where :
ρNIR : Surface reflectance for Near Infrared Channel.
ρRED : Surface reflectance for Red Channel.
L : Soil brightness correction factor.

SAVI modifies the NDVI formula by introducing a soil brightness correction factor (L) to reduce the influence of background soil reflectance, particularly in sparsely vegetated or mixed land cover areas. It is considered more effective than NDVI in semi-arid environments or regions with exposed soil. In this study, SAVI was calculated using Equation (2).

A value of L = 0.5 was adopted, which is commonly recommended for areas with moderate vegetation cover [15] This choice is supported by the observed average NDVI value of **0.60** across the Mandalika SEZ, indicating predominantly moderate to dense vegetation. Therefore, lower L values (e.g., 0.25–0.3), which are typically suited for sparsely vegetated landscapes, were deemed unnecessary in this context.

A vegetation classification framework categorizes vegetation density based on the SAVI values into six distinct classes based on numerical value ranges, encompassing a spectrum of vegetation cover from areas devoid of vegetation to regions characterized by lush, closed-canopy ecosystems. The classification categories range from No or Bare Vegetation (< 0.1), corresponding to open soil surfaces, built-up areas, or water bodies, to Very Dense Vegetation (> 0.7), exemplified by primary tropical forests or ecosystems with lush, closed-canopy vegetation, with intermediate categories including Very Sparse Vegetation (0.1-0.2), Sparse Vegetation (0.2-0.3), Moderate Vegetation (0.3-0.5), and Dense Vegetation (0.5-0.7), each corresponding to specific land cover types and vegetation characteristics, facilitating the analysis and interpretation of vegetation data as presented in Table 2.

Table 2. SAVI Classification

Value Range	Vegetation Category	Description
< 0.1	No or Bare Vegetation	Open soil surfaces, built-up areas, or water bodies
0.1 – 0.2	Very Sparse Vegetation	Areas with minimal plant cover or early signs of degradation
0.2 – 0.3	Sparse Vegetation	Shrubland or semi-arid dryland
0.3 – 0.5	Moderate Vegetation	Actively cultivated land or seasonal vegetation
0.5 – 0.7	Dense Vegetation	Secondary forest cover, dense plantations
> 0.7	Very Dense Vegetation	Primary tropical forests, lush and closed canopy vegetation

2.5 Land Surface Temperature Derivation

The Land Surface Temperature (LST) in this study was derived from Landsat 8 Level 2 satellite imagery, specifically using the thermal band (Band 10). This dataset provides surface temperature values in Kelvin, which can be converted into more interpretable temperature units. The LST was calculated using the formula [11] :

$$LST = (ST\_B10 * Scale\ Factor) + 149 \quad (3)$$

Land surface temperature (LST) in this study was derived from the ST_B10 band of the Landsat 8 Collection 2 Level 2 dataset using the standard scale factor of 0.00341802 and an offset of 149, as recommended by USGS documentation for converting brightness temperature to surface temperature [11]. This calculation is expressed in Equation (3). The offset value of 149 is empirically derived based on calibration of Landsat thermal sensors to represent surface temperatures more accurately in Kelvin and is embedded in the metadata of Collection 2 Level 2 products. No additional surface emissivity correction was applied, assuming a generalized emissivity embedded within the thermal product. While this may slightly reduce accuracy in heterogeneous areas, the approach maintains consistency with standardized Landsat Level 2 preprocessing and simplifies the LST extraction process.

2.6 Correlation Analysis between LST and Vegetation Indices (NDVI and SAVI)

To determine the relationship between vegetation density and land surface temperature, a statistical correlation analysis was conducted between LST and two vegetation indices : the Normalized Difference Vegetation Index (NDVI) and the Soil Adjusted Vegetation Index (SAVI). This analysis aims to identify which index has a stronger association with surface temperature variations in the Mandalika SEZ

2.7 Spearman's Rho Correlation

Spearman's Rank Correlation, also known as Spearman's rho, is a non-parametric statistical method used to evaluate the strength and direction of a monotonic relationship between two continuous or ordinal variables based on their ranked values [16], [17], [18]. Unlike Pearson correlation, Spearman's method does not assume normality or linearity in the data. The Spearman correlation coefficient (r_s) is calculated using Equation (4) :

$$r_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{4}$$

Where:

- r_s : Spearman's rank correlation coefficient
- d_i : The difference between the ranks of two variables (i.e., $rank_x - rank_y$) for each data pair
- n : The number of data pairs

2.8 Linear Regression

Simple linear regression was employed to determine the extent to which vegetation indices, NDVI and SAVI influence LST. This method aims to establish a mathematical model that describes the relationship between a single independent variable (NDVI or SAVI) and a dependent variable (LST).

The general form of the simple linear regression model is expressed as eEquation (5) [19] :

$$Y = \beta_0 + \beta_1 X + \epsilon \tag{5}$$

Where:

- Y = Land Surface Temperature (LST)
- X = NDVI or SAVI
- β_0 = Intercept (estimated LST when NDVI/SAVI is zero)
- β_1 = Regression coefficient (the change in LST for every 1-unit change in NDVI/SAVI)
- ϵ = Residual error

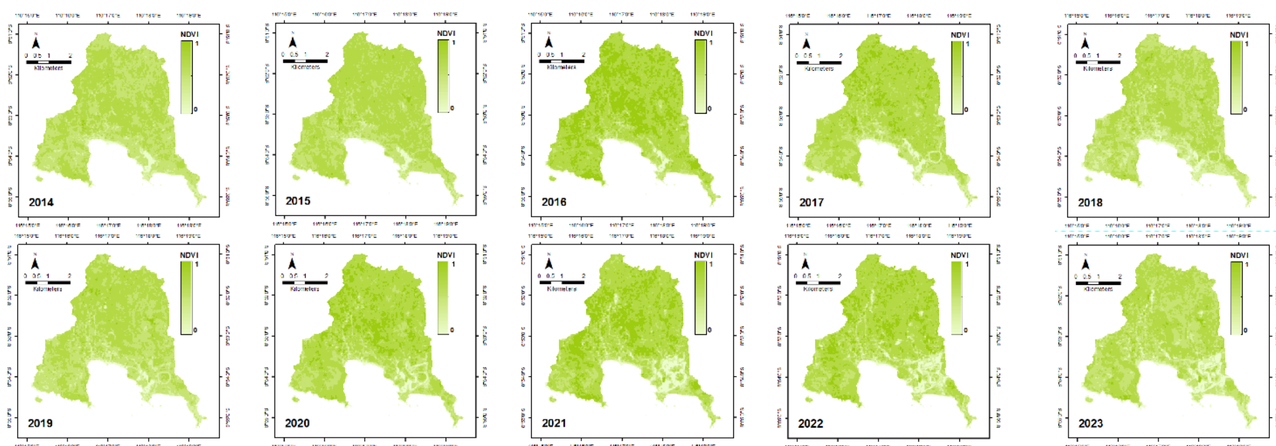

Figure 2. NDVI Kuta Village 2014 – 2023

III. RESULT AND DISCUSSION

3.1 NDVI, SAVI, LST time series

Spatial differences between SAVI (Soil-Adjusted Vegetation Index) and NDVI (Normalized Difference Vegetation Index) values are mainly attributable to their differing sensitivities to bare soil. NDVI generally yields higher values in areas with dense vegetation, but its accuracy decreases in regions where vegetation is sparse or intermixed with exposed soil, due to its susceptibility to soil background noise. In contrast, SAVI incorporates a soil adjustment factor (L), which helps minimize the influence of soil reflectance, making it more stable and reliable in low vegetation density environments.

As illustrated in Figure 2 (NDVI map) and Figure 3 (SAVI map) of Kuta Village, NDVI values are consistently higher than SAVI across most areas. This suggests that NDVI may overestimate vegetation greenness in zones where vegetation is patchy or coexists with bare soil. In such transitional landscapes—common in rural areas characterized by agricultural fields, shrubs, and open terrain—SAVI offers a more conservative and realistic assessment of vegetation cover.

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In terms of surface temperature trends, the average land surface temperature (LST) in 2014 was approximately 37.8 °C, indicating significant surface heating throughout the area. Between 2015 and 2018, LST showed a gradual decline, reaching a low of 34.1 °C in 2017, possibly due to stable vegetation conditions or limited development activity during that period. However, this cooling trend was disrupted in 2019, when the average LST rose again to 37.36 °C, likely due to the commencement of large-scale construction projects, particularly the development of the Mandalika Special Economic Zone (SEZ) and the international racing circuit [20].

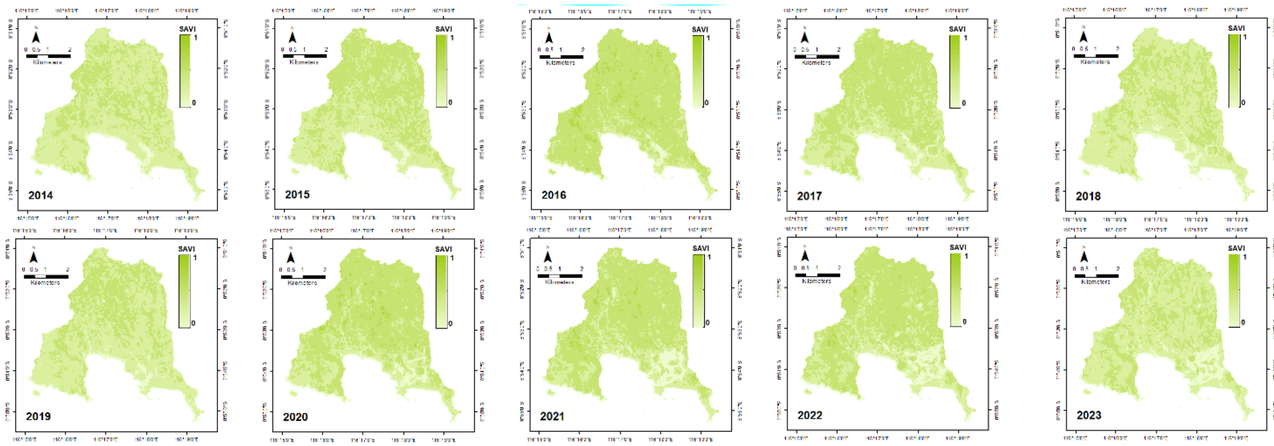

Figure 3. SAVI Kuta Village 2014 – 2023

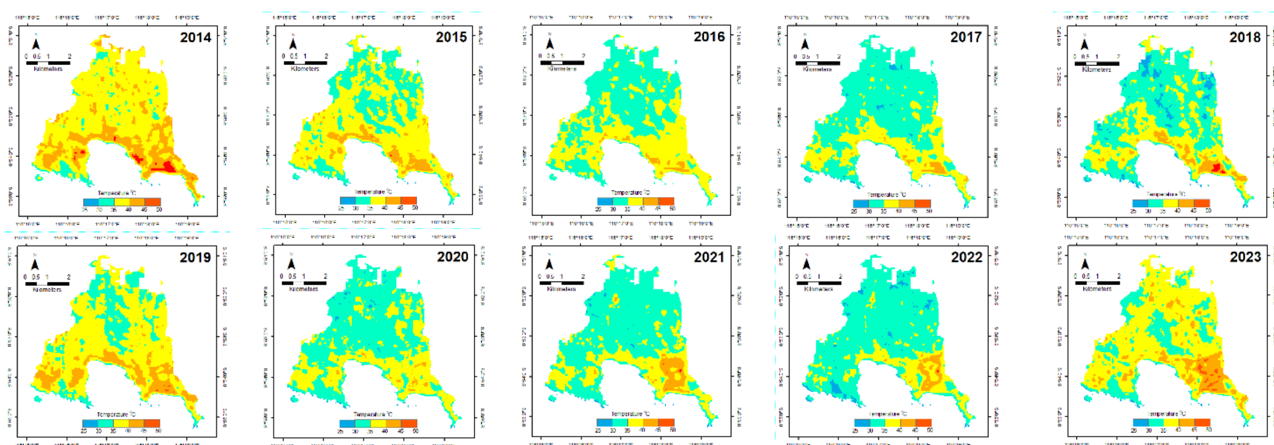

Figure 4. LST Kuta Village 2014 – 2023

From 2020 to 2022, LST averages slightly declined and stabilized around 33.8–34.4 °C, possibly due to temporary reductions in development intensity or the introduction of vegetation in certain parts of the area. However, by 2023, LST increased once more to 36.1 °C, indicating renewed surface heating—especially in southern and southeastern zones near the Mandalika Circuit—driven by ongoing urbanization and expansion of impervious surfaces.

These trends underscore the impact of land-use changes and urban infrastructure development on surface temperature. The recurring rise in LST, especially post-2019, highlights the need for sustainable planning strategies, including the integration of vegetation and green infrastructure, to mitigate surface heating and reduce the urban heat island effect in rapidly developing areas like Kuta Village, as illustrated in Figure 4.

3.2 Descriptive Statistics

Table 3. Descriptive Statistics Result

Variabel	Min	Q1	Median	Mean	Q3	Max
SAVI	0.25	0.34	0.44	0.43	0.50	0.60
NDVI	0.36	0.49	0.61	0.60	0.70	0.79
LST	26.0	32.5	34.7	35.5	38.2	45.0

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The results of the descriptive statistical analysis indicate that the average values of NDVI and SAVI in the Mandalika Special Economic Zone are 0.60 and 0.43, respectively. This suggests that the vegetation cover in most parts of the study area falls within the moderate to high category. Land Surface Temperature (LST) values range from 26 °C to 45 °C, with an average of 35.45 °C, indicating a wide variation in surface temperatures. This variability is likely influenced by differences in vegetation density and land use patterns. The detailed statistics for these indices are presented in Table 3.

3.3 Spearman Rho Correlation

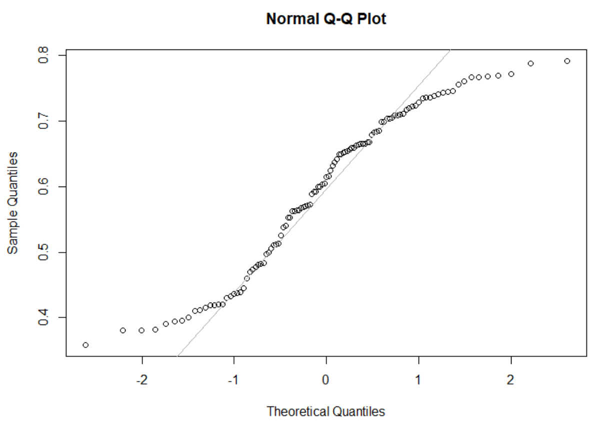

Figure 5. QQ Plot of NDVI

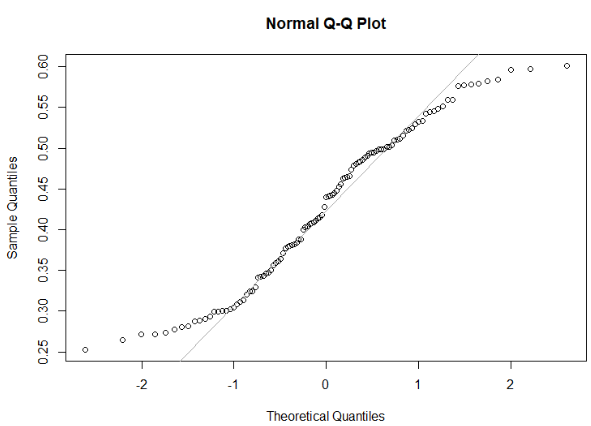

Figure 6. QQ Plot of SAVI

The normality test using the Shapiro–Wilk method for the NDVI, SAVI, and LST variables indicates that none of them are normally distributed (p-value < 0.05). To reinforce this finding, Quantile–Quantile (QQ) plots were also generated for each variable. QQ plots compare the observed data quantiles to those of a theoretical normal distribution. As shown in Fig. 5, Fig. 6, Fig. 7, the data points deviate from the diagonal reference line, particularly in the tails, suggesting substantial departures from normality. This visual evidence supports the use of the non-parametric Spearman's Rho correlation method in analyzing the relationship between vegetation indices and land surface temperature.

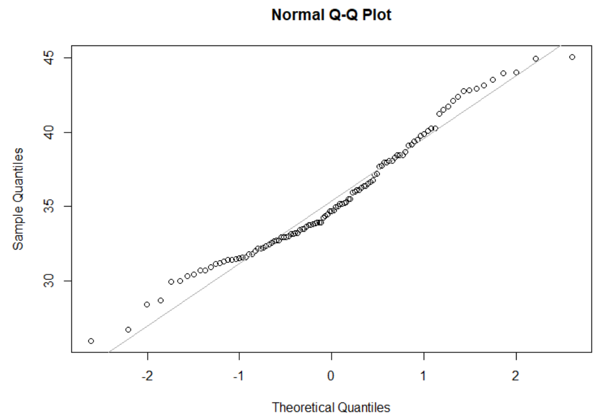

Figure 7. QQ Plot of LST

Therefore, the Spearman's Rho correlation method was employed as a non-parametric approach to assess the relationship between NDVI and SAVI with LST. The Spearman correlation coefficient between NDVI and LST (–0.555) is slightly stronger than that of SAVI (–0.536), with a difference of only 0.019. This margin is relatively small and does not represent a quantitatively significant difference. However, from an ecological perspective, the choice of vegetation index should be adapted to the land characteristics. NDVI tends to be more stable in measuring vegetation cover in areas with moderate to dense vegetation, such as most parts of the Kuta region. On the other hand, SAVI performs better under sparse vegetation conditions or in areas dominated by bare soil. Therefore, although NDVI shows a slightly stronger correlation, this difference should still be interpreted within the biophysical context and the greenness level of the study area. The correlation results are visually represented in Figure 8.

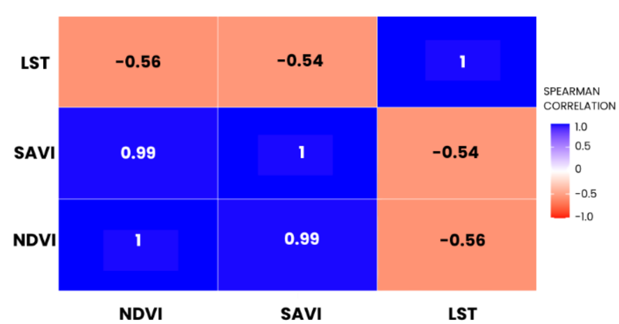

Figure 8. Spearman Correlation Heatmap

3.4 Linear Regression

The results of the simple linear regression analysis between NDVI and LST show that each 1-unit increase in NDVI corresponds to a decrease in LST by approximately 21.186 °C. Meanwhile, a 1-unit increase in SAVI results in a decrease in LST by approximately 24.496 °C. These regression coefficients indicate that both vegetation indices have a negative linear relationship with surface temperature. The detailed regression parameters, including coefficients, R^2 values, and residual standard errors, are presented in Table 4.

Table 4. Linear Regression

Aspect	SAVI Model	NDVI Model
Intercept (β_0)	45.913	48.074
Regression Coefficient (β_1)	-24.496	-21.186
R-squared	0.334	0.392
Residual Std. Error	3.375	3.223
P-value	3.16×10^{-11}	1.93×10^{-13}

The NDVI – LST regression model yields a coefficient of determination (R^2) of 0.392, indicating that approximately 39.2% of the variation in LST can be explained by NDVI. In contrast, the SAVI – LST model has a lower R^2 of 0.334. Additionally, the p-value for the NDVI coefficient is lower than that for SAVI, and the residual standard error is also slightly lower in the NDVI model. These results suggest that, although the regression coefficient of SAVI is numerically larger, the NDVI model performs better in explaining the variation in LST.

Although SAVI is specifically designed for areas with sparse vegetation or mixed bare soil, the results of this study indicate that NDVI demonstrated better statistical performance in explaining surface temperature variation in the Mandalika SEZ. One possible reason is that most of the study area, including Kuta Village, is dominated by medium to dense vegetation cover, as reflected by the average NDVI value of 0.60 and SAVI value of 0.43. Under such conditions, the soil background effect that SAVI is intended to correct becomes relatively minor, allowing NDVI—being more sensitive to vegetation—to produce a statistically stronger and more stable model.

Furthermore, while the higher regression coefficient of SAVI (–24.5) suggests that it is more sensitive to changes in vegetation in affecting LST, this sensitivity may be inconsistent in heterogeneous environments. SAVI incorporates a soil adjustment factor to minimize background noise in sparse vegetation, but in practice, it can be affected by variations in soil reflectance, especially in mixed-cover areas such as roads, construction zones, or exposed land. Consequently, although SAVI mathematically responds more sharply to vegetation change, NDVI offers a more predictable and robust relationship with surface temperature in the spatial context of the Mandalika SEZ, as evidenced by its higher R^2 and lower residual error.

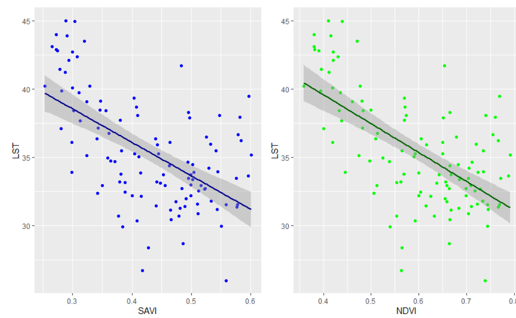

Figure 9. Linear Regression

Based on the scatter plot patterns of both SAVI vs. LST and NDVI vs. LST, a clear downward trend is observed, indicating that higher vegetation index values are associated with lower land surface temperatures (LST). This visual pattern is consistent with the regression results, which yield negative regression coefficients for both indices. The distribution of data points and the regression lines supporting this trend are illustrated in Figure 9.

In the SAVI vs. LST plot, the data points appear more vertically dispersed, particularly in the SAVI range of 0.4 – 0.5. This increased variability in LST within the mid-range of SAVI suggests that other factors besides vegetation may also influence surface temperature in this interval.

In contrast, the NDVI vs. LST scatter plot shows points more tightly clustered around the regression line, indicating that the NDVI-LST model has smaller residual errors. This supports the higher R^2 value obtained for the NDVI model, reinforcing its better performance in explaining variations in LST.

From a policy and spatial planning perspective, these findings emphasize the critical role of vegetation indices in land management and sustainable development. NDVI, with its stronger correlation to surface temperature, can be utilized not only for scientific analysis but also for practical decision-making such as zoning, spatial allocation of green infrastructure, and early detection of thermal risk zones. In rapidly developing areas like Mandalika, incorporating NDVI into local planning systems may help authorities identify hotspots, preserve ecological corridors, and design targeted interventions to mitigate the Urban Heat Island effect while maintaining ecosystem resilience.

3.5 *El Niño–Southern Oscillation*

The annual LST trend in the Mandalika Special Economic Zone (SEZ) exhibits fluctuations that appear to align with ENSO (El Niño–Southern Oscillation) variations. A noticeable decline in LST occurred between 2015 and 2018, despite the presence of a strong El Niño event in 2015 (ENSO index = 1.57). These temporal patterns are illustrated in Figure 10.

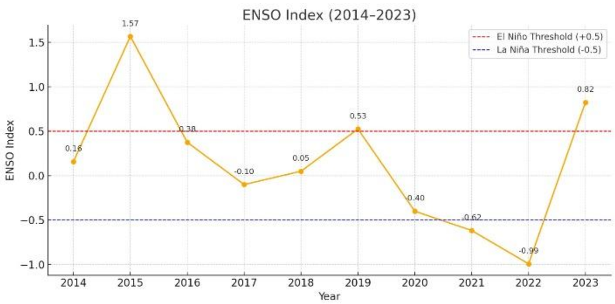

Figure 10. ENSO Index Chart for the Years 2014–2023. Source: Japan Meteorological Agency website

This apparent anomaly may be attributed to a lagged land surface response, where vegetation and soil moisture conditions from the previous wet seasons still contributed to surface cooling. Additionally, infrastructure development in Mandalika had not yet intensified at that time, resulting in lower impervious surface coverage and less heat retention. In tropical semi-arid zones like Mandalika, such delayed biophysical responses are not uncommon and may temporarily mask the thermal impacts of large-scale climate anomalies. LST increased again in 2019 (37.02 °C) and 2023 (36.95 °C), coinciding with moderate El Niño events (ENSO = 0.53 and 0.83). Conversely, LST decreased during the 2020–2022 period, aligning with La Niña phases (ENSO down to –0.99), which typically bring higher rainfall and cooler surface temperatures. These findings indicate that interannual climate variability, particularly ENSO, plays a significant role in influencing land surface temperature dynamics alongside ongoing land use changes.

IV. CONCLUSION

This study demonstrates that land cover changes resulting from the development of the Mandalika Special Economic Zone (SEZ) have had a tangible impact on land surface temperature (LST). Descriptive statistics indicate an average NDVI value of 0.60 and a SAVI average of 0.43, reflecting a dominance of moderate to dense vegetation across the study area. LST values ranged from 26 °C to 45 °C, with a mean of 35.45 °C, suggesting significant spatial variation in surface heating.

Spearman's Rho correlation analysis revealed that both NDVI and SAVI were significantly and negatively correlated with LST, confirming that higher vegetation cover is associated with lower surface temperatures. NDVI had a slightly stronger correlation ($r = -0.555$, $p = 2.48 \times 10^{-10}$) than SAVI ($r = -0.536$, $p = 1.39 \times 10^{-9}$). Similarly, linear regression analysis showed that while the SAVI–LST model produced a steeper slope (-24.496), it had lower explanatory power ($R^2 = 0.334$) compared to the NDVI–LST model (slope = -21.186; $R^2 = 0.392$), suggesting that NDVI provides a more consistent statistical relationship.

Although SAVI is designed to perform better in sparsely vegetated or bare soil regions, the superior performance of NDVI in this study is likely due to the land cover characteristics of the Mandalika SEZ, which is dominated by medium to dense vegetation. In such conditions, the influence of the soil background becomes less significant, diminishing the advantage offered by the SAVI adjustment. Consequently, NDVI proved to be a more reliable predictor of LST in the Mandalika context. Nonetheless, integrating both indices remains valuable for capturing vegetation variation more comprehensively, especially in areas with mixed land cover thus providing a more robust basis for environmental monitoring.

These findings underscore the urgency of implementing green infrastructure in the southern part of the Mandalika SEZ, where the most significant increase in land surface temperature was observed. This may include expanding urban green spaces, restoring vegetative buffers, or introducing nature-based cooling solutions. In addition, it is recommended that NDVI time-series data be integrated into the SEZ's environmental monitoring systems to enable continuous tracking of vegetation dynamics and support proactive land management decisions.

This study has several limitations. The SAVI index was calculated using a fixed soil brightness correction factor ($L = 0.5$) without local optimization, which may limit its accuracy in areas with varying vegetation density. Furthermore, other important environmental factors affecting LST such as surface albedo, soil moisture, and land use were not included in the analysis. Future research is recommended to adopt multivariate approaches to better capture the combined influence of vegetative and non-vegetative drivers on surface temperature variation.

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