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Spatial Data Processing for Mangrove Ecotourism Development: Spatio-temporal Analysis through NDVI, NDBI, and SAVI Using Landsat 8/9 OLI

Yerik Afrianto Singgalen

Faculty of Business Administration and Communication, Tourism Study Program, Atma Jaya Catholic University of Indonesia, Jakarta, Indonesia
Email: yerik.afrianto@atmajaya.ac.id
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Abstract−This study evaluates the ecological trends on Tagalaya Island by analyzing the NDBI, NDVI, and SAVI indices from 2013 to 2024. The NDBI data reveals a notable improvement in vegetation conditions over this period. In 2013, NDBI values ranged from -0.8818104 to -0.3152868, indicating poor vegetation health. Although there was a slight deterioration by 2018, with values ranging from -0.8922318 to -0.2858251, a significant recovery was observed by 2024, with values ranging from -0.7118425 to 0.027627. NDVI values also demonstrate positive changes, with 2013 values ranging from -0.340193 to 0.4773595 and increasing substantially by 2024 to a range of -0.2155555 to 0.9997522, reflecting enhanced vegetation coverage and health. Similarly, SAVI values show improvement, increasing from -0.1651871 to 0.3954751 in 2013 to -0.0731807 to 0.6464996 in 2024. These trends suggest that Tagalaya Island has experienced successful ecological recovery or effective conservation measures. Continued monitoring is essential to sustain and further these positive developments, ensuring ongoing environmental stability and health.

Keywords: Remote sensing; Spatio-temporal analysis; NDVI; NDBI; SAVI

1. INTRODUCTION

Remote sensing technology facilitates monitoring mangrove distribution, enhancing community-based mangrove ecotourism management. Utilizing high-resolution satellite imagery and geographic information systems (GIS), precise mapping of mangrove coverage becomes achievable, enabling the identification of areas requiring conservation or restoration efforts [1]–[5]. Moreover, remote sensing supports analyzing temporal changes in mangrove ecosystems, providing critical data for sustainable tourism practices [6]–[10]. This integration of advanced technology into ecotourism management not only preserves biodiversity but also promotes economic benefits for local communities. Therefore, employing remote sensing as an environmental monitoring and management tool significantly advances sustainable ecotourism.

Applying Landsat 8/9 OLI satellite imagery in remote sensing, utilizing NDVI, NDBI, and SAVI models, provides valuable insights into the state of vegetation, land, and residential structures within mangrove ecotourism destinations. NDVI effectively assesses vegetation health and density [11]–[15], while NDBI identifies built-up areas, distinguishing between natural and developed landscapes [16]–[20]. SAVI further refines vegetation analysis by accounting for soil brightness, enhancing the accuracy of environmental monitoring [21], [22]. Integrating these indices offers a comprehensive understanding of land use dynamics, promoting informed decision-making in sustainable ecotourism management. Thus, leveraging Landsat imagery through these advanced models significantly enhances mangrove ecosystems' strategic planning and conservation efforts.

Tourism development in archipelagic regions faces significant challenges, particularly in utilizing spatial data for policy-making that aligns with the local context and tourism potential while considering sustainability from economic, socio-cultural, and environmental perspectives. Effective policy-making requires integrating geospatial information to accurately assess and harness the unique attributes of island destinations [23]–[25]. Moreover, incorporating sustainability principles ensures that tourism growth benefits local economies, preserves cultural heritage, and protects natural ecosystems [26]. Addressing these challenges through informed and context-specific spatial analysis fosters resilient and sustainable tourism development in island regions.

This study aims to identify and analyze landscape changes on Tagalaya Island in North Halmahera Regency using a spatio-temporal analysis approach by processing Landsat 8/9 OLI raster data based on NDVI, NDBI, and SAVI models. The application of NDVI facilitates the evaluation of vegetation health, while NDBI distinguishes built-up areas, and SAVI enhances vegetation analysis by mitigating soil brightness effects. This comprehensive analysis provides valuable insights into the dynamic landscape transformations, supporting effective environmental management and conservation strategies. Therefore, employing these advanced remote sensing techniques contributes significantly to understanding and managing landscape changes on Tagalaya Island.

The urgency of this research lies in its potential to address critical environmental and socio-economic challenges by applying advanced remote sensing techniques. By leveraging NDVI, NDBI, and SAVI models, the study provides precise, data-driven insights into landscape changes, enabling more effective resource management and conservation strategies [27]–[30]. Such comprehensive analysis is crucial for mitigating the impacts of climate change and urbanization, promoting sustainable development, and enhancing resilience in

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vulnerable regions. Consequently, the timely implementation of this research is essential for fostering informed decision-making and ensuring long-term environmental sustainability.

This research's theoretical and practical contributions are manifold, advancing academic knowledge and real-world environmental monitoring and management applications. Theoretically, it enhances understanding spatio-temporal dynamics in landscape changes by utilizing NDVI, NDBI, and SAVI models, providing a robust framework for future studies [31], [32]. Practically, the insights derived from this research support more informed decision-making in resource management, urban planning, and conservation efforts, addressing pressing environmental and socio-economic challenges. Thus, this research contributes to academic discourse and offers tangible solutions for sustainable development, reinforcing its significance and impact.

The limitations of this research are confined to the spatio-temporal analysis methods and the NDVI, NDBI, and SAVI models applied to the region of interest in Tagalaya Island, North Halmahera Regency. The reliance on these specific indices may not capture the full complexity of the landscape changes, potentially overlooking subtle environmental variations [33], [34]. Additionally, the focus on a single geographic area limits the generalizability of the findings to other regions with different ecological or socio-economic contexts. Therefore, while the study provides valuable insights into Tagalaya Island, extending the scope of future research to include diverse methodologies and broader regions would enhance the comprehensiveness and applicability of the results.

Recommendations for further research include expanding the methodological framework to incorporate additional remote sensing indices and integrating socio-economic data to provide a more comprehensive analysis of landscape changes. Future studies should explore the application of machine learning algorithms for enhanced data processing and predictive modeling, enabling more accurate and detailed insights into environmental dynamics. Moreover, conducting comparative studies across different geographic regions will help validate the findings and improve their generalizability. These advancements will significantly enhance the robustness of environmental monitoring and management strategies, contributing to more effective and sustainable development practices.

2. RESEARCH METHODOLOGY

2.1 Gap Analysis

A notable gap in similar research lies in the limited integration of multi-temporal and multi-spectral remote sensing data to comprehensively analyze landscape changes. Many studies focus on single time-point analyses or use limited spectral bands, which may fail to capture ecological transformations' dynamic and complex nature [35]–[37]. Furthermore, the lack of a holistic approach that combines various environmental and socio-economic factors reduces the effectiveness of the proposed management strategies. Addressing this gap by incorporating diverse data sources and a multidisciplinary perspective would significantly enhance the accuracy and applicability of research findings, ultimately contributing to more robust and sustainable environmental management practices.

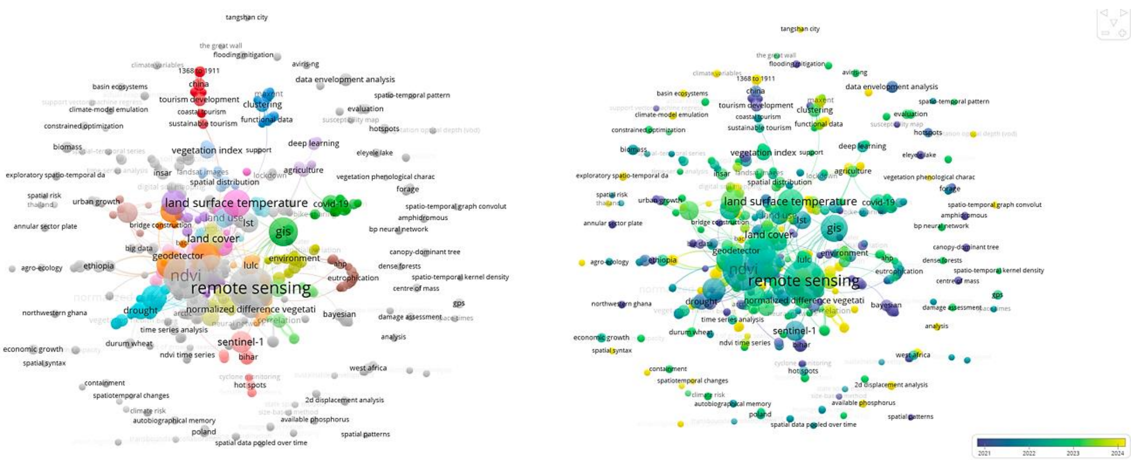

Figure 1. Network and Overlay Visualization of Remote Sensing and Spatio-temporal Analysis Research

Figure 1 shows the network visualization of the spatio-temporal research highlight. Topics related to remote sensing, as illustrated in the network visualization, encompass a wide array of interconnected themes crucial for environmental and urban studies. Key subjects include land surface temperature, vegetation index, and land use, which are central to understanding ecological dynamics and climate impacts [38]–[41]. Additionally, integrating GIS, NDVI, and Sentinel-1 highlights the technological advancements that enhance spatial data analysis and interpretation. These interconnected topics underscore the multifaceted applications of

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remote sensing in monitoring, managing, and mitigating environmental challenges. Thus, remote sensing is pivotal in advancing scientific research and practical solutions across diverse disciplines.

The overlay visualization highlights a research gap in integrating spatio-temporal analysis with advanced remote sensing techniques, specifically sustainable land management and environmental monitoring. Despite significant advancements in remote sensing, limited research addresses the dynamic interactions between land surface temperature, vegetation indices, and urban development over time. This research aims to fill this gap by leveraging NDVI, NDBI, and SAVI models to provide comprehensive insights into landscape changes. By addressing these overlooked areas, the study contributes to more informed decision-making processes, enhancing the relevance and impact of remote sensing in sustainable development initiatives. Thus, this research advances academic understanding and effectively offers practical solutions for managing environmental and urban challenges.

2.2 Spatio Temporal Analysis

The framework utilized in this study is spatio-temporal analysis, structured through a series of methodical stages, as illustrated in the diagram. Initially, Landsat 8/9 OLI images are acquired and processed to ensure radiometric and atmospheric corrections, converting them to reflectance values for accurate analysis. Subsequent steps involve defining the region of interest (ROI) and calculating vegetation indices such as NDVI, NDBI, and SAVI to monitor landscape changes. This comprehensive approach facilitates visualization and mapping and supports statistical analysis and validation using ground truth data. Therefore, this framework provides a robust methodology for informed decision-making in sustainable land management, urban planning, and environmental conservation within the study area.

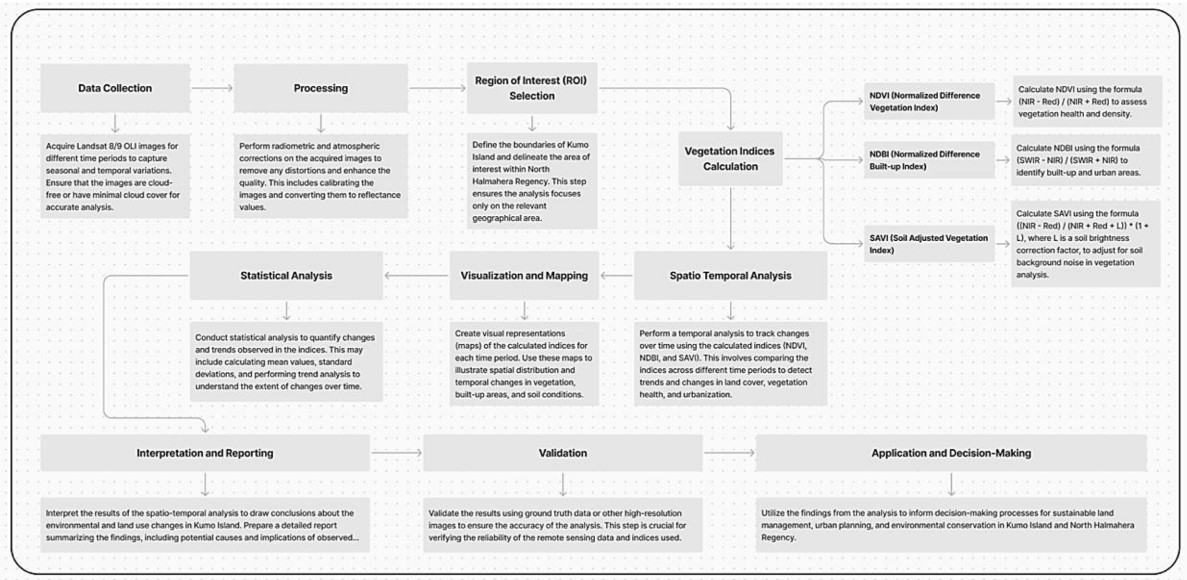

Figure 2. Spatio-temporal Analysis Framework

Figure 2 shows the spatio-temporal analysis framework. The spatio-temporal analysis offers significant advantages in environmental monitoring and resource management. This method enables the detection of changes and trends over time, providing a dynamic view of ecological and landscape transformations [42]–[44]. Integrating spatial and temporal data allows for more accurate and comprehensive assessments, facilitating the identification of patterns and predicting future changes. Moreover, this approach enhances the precision of decision-making processes in land use planning, conservation, and urban development. Therefore, spatio-temporal analysis is a powerful tool for advancing sustainable practices and addressing complex environmental challenges.

The relevance of spatio-temporal analysis to this research lies in its ability to understand landscape changes within the studied area comprehensively. By leveraging this approach, the study captures dynamic variations in vegetation, land use, and built environments, offering precise insights that static analysis methods cannot achieve. Integrating NDVI, NDBI, and SAVI models within this framework further refines the analysis, enabling detailed assessments of ecological and urban transformations. Consequently, spatio-temporal analysis is instrumental in informing effective environmental management and sustainable development strategies, making it a critical component of this research.

2.2.1 Data Collection

The raster data utilized in this study were acquired from the United States Geological Survey (USGS), explicitly targeting the geographic coordinates of North Halmahera Regency, North Maluku, Indonesia, located at a

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latitude of 1.5074 and a longitude of 127.8937. This precise geospatial information facilitates detailed analysis and monitoring of environmental changes within the specified region. Access to high-resolution and reliable raster data from USGS enhances the accuracy of the spatio-temporal analysis, supporting robust findings. Consequently, utilizing such data significantly contributes to the reliability and validity of the research outcomes, ensuring effective environmental management and planning.

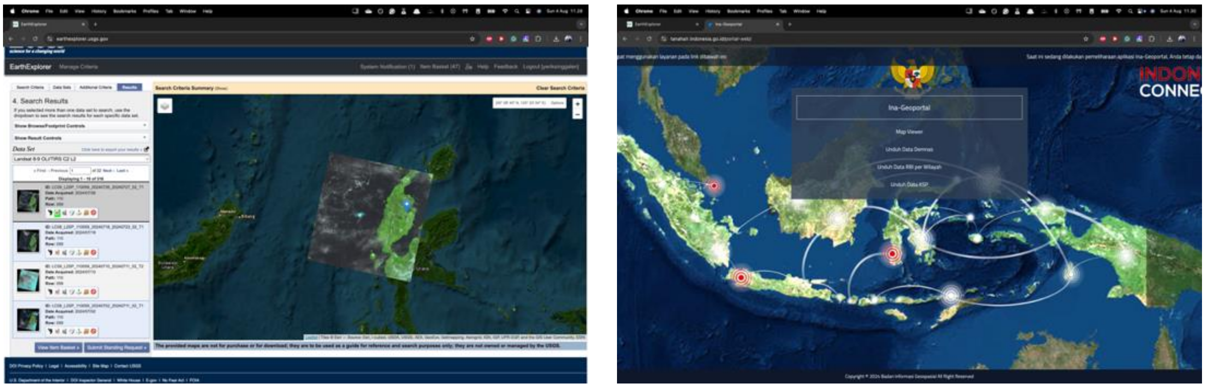

Figure 3. Raster and Vector Data Source

Figure 2 shows the raster data and vector data sources. The vector data employed in this research were sourced from the website https://tanahair.indonesia.go.id/, focusing on the North Halmahera Regency region. These vector datasets provide crucial geographical boundaries and infrastructure details for accurate spatial analysis. By integrating this data, the study gains a comprehensive view of the region's land use and urban planning dynamics. The precision and reliability of vector data from this authoritative source significantly enhance the robustness of the spatial analysis, ultimately contributing to more effective and informed decision-making processes in regional development and environmental conservation efforts.

The raster data collected for this study were calibrated for 2013, 2018, and 2024 to facilitate the analysis of index value changes for the NDVI, NDBI, and SAVI models. This temporal segmentation allows for a detailed examination of the dynamic shifts in vegetation, built-up areas, and soil-adjusted vegetation over a decade. Such longitudinal analysis is critical for understanding the impact of environmental and anthropogenic factors on landscape transformations. Therefore, aligning the raster data with these specific years enhances the study's ability to provide insightful and actionable environmental management and urban planning findings.

2.2.2 Processing

The application used for cleaning and processing the Landsat 8/OLI raster data from 2013, 2018, and 2024 by the NDVI, NDBI, and SAVI models is QGIS version 3.38.1. QGIS provides an extensive suite of geospatial tools that enable precise atmospheric corrections and the generation of reliable index values. The software's advanced capabilities ensure accurate and efficient data processing, which is crucial for conducting robust spatio-temporal analysis. Consequently, using QGIS version 3.38.1 significantly enhances the quality and credibility of the research findings, supporting informed environmental and urban planning decisions.

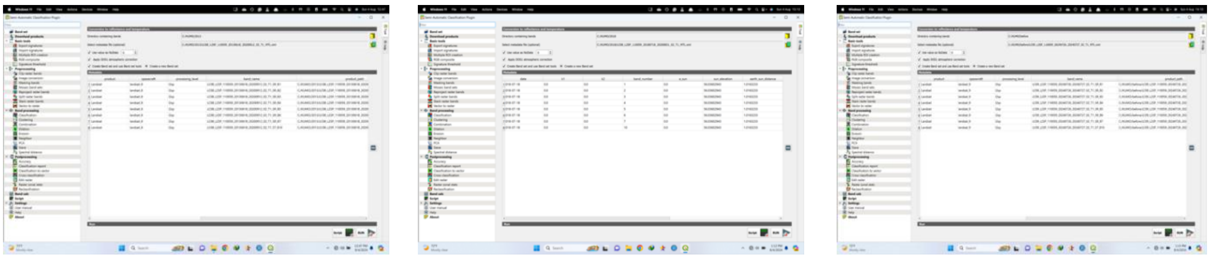

Figure 4. Atmospheric, Radiometric and Geometric Correction

Figure 4 shows the atmospheric and radiometric correction. The atmospheric and radiometric correction process was executed using a specialized script to ensure high data fidelity. The script, written in Python, employs the `remotior_sensus` library to manage the computational load and optimize resource allocation, as shown in the command `rs = remotior_sensus.Session(n_processes=2, available_ram=2045)`. Key steps include creating a bandset catalog and preprocessing the imagery with specific parameters, such as `nodata_value=0` and `dos1_correction=True`, to correct distortions and enhance image quality. This methodological approach guarantees that the raster data is accurately corrected, thereby providing a solid foundation for subsequent analytical processes and ensuring the reliability of the research outcomes.

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Geometric correction was meticulously performed to ensure spatial accuracy and alignment of the Landsat 8/OLI raster data from 2013, 2018, and 2024, using QGIS version 3.38.1. This process involved rectifying distortions caused by sensor orientation and earth curvature, thereby enhancing the precision of spatial data analysis. By aligning the images to a consistent coordinate system, the accuracy of the NDVI, NDBI, and SAVI models was significantly improved. Consequently, using QGIS for geometric correction ensures the reliability of the spatial data, facilitating robust environmental and urban analysis and supporting informed decision-making processes.

2.2.3 Region of Interest

The Region of Interest for this study is Tagalaya Island in North Halmahera Regency, located at latitude 1.729720 and longitude 128.068470. This specific geographical focus allows for detailed analysis of environmental and land use changes over time, providing valuable insights into the region's ecological dynamics. The selection of this area is strategic, given its unique environmental features and the potential impact of anthropogenic activities. By concentrating on Tagalaya Island, the research aims to contribute to more effective regional planning and sustainable management practices. Thus, this focused approach enhances the relevance and applicability of the study's findings to local and regional contexts.

Figure 5. Region of Interest (RoI)

Figure 5 shows the region of interest. The consideration for determining the Region of Interest as Tagalaya Island in North Halmahera Regency stems from its predominance of mangrove areas, significantly attracting mangrove ecotourism. Additionally, the local culture of Tagalaya Island presents unique opportunities for development as both a domestic and national tourist attraction. The rich biodiversity of the mangrove ecosystems, coupled with the cultural heritage of the island's inhabitants, offers a multifaceted appeal for sustainable tourism. Therefore, focusing on this region enhances ecological preservation efforts and promotes cultural tourism, fostering economic growth and community development.

Establishing the Region of Interest (RoI) facilitates a contextual and comprehensive analysis aligned with vegetation, land, and settlement conditions. This targeted approach allows for precisely examining ecological dynamics and land use patterns, ensuring the analysis reflects the area's unique characteristics. By focusing on a specific geographic location, the study can effectively address the interactions between natural and human systems. Consequently, the determination of the RoI enhances the accuracy and relevance of the findings, supporting informed decision-making and sustainable management practices tailored to the local context.

2.2.4 Vegetation Indices Calculation: NDVI, NDBI, SAVI

Calculating vegetation indices, including NDVI, NDBI, and SAVI, on Tagalaya Island in North Halmahera Regency provides crucial insights into the region's ecological and urban dynamics. NDVI assesses the health and density of vegetation, highlighting areas of robust plant growth. NDBI identifies built-up areas, distinguishing urban developments from natural landscapes. SAVI adjusts for soil brightness, offering a more accurate vegetation analysis in regions with sparse plant cover. These indices collectively enable a comprehensive understanding of land use patterns and environmental conditions. Therefore, their application supports informed decision-making for sustainable development and conservation efforts on Tagalaya Island.

The relevance of the NDVI, NDBI, and SAVI models to the context of Tagalaya Island, North Halmahera Regency, is significant for understanding and managing its unique ecological and urban landscapes. NDVI aids in assessing the health and density of the island's mangrove forests, which are crucial for biodiversity and coastal protection. NDBI is instrumental in identifying and monitoring built-up areas, providing insights into urban development and its impacts on the natural environment. SAVI adjusts for soil brightness, making it particularly useful for analyzing vegetation in areas with sparse plant cover. Therefore, applying these indices offers

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comprehensive insights into land use dynamics, supporting sustainable development and conservation efforts on Tagalaya Island.

Table 1. Raster Calculation Using NDVI, NDBI, and SAVI Model

Model	Algorithm
Normalized Different Vegetation Index (NDVI)	(B5-B4)/(B5+B4)
Normalized Different Built-Up Index (NDBI)	(B6-B5)/(B6+B5)
Soil-Adjusted Vegetation Index (SAVI)	((B5-B4)/(B5+B4+0.5))*1.5

Table 1 shows the raster data calculation process of Landsat 8/9 OLI using NDVI, NDBI, and SAVI models. The Normalized Difference Vegetation Index (NDVI) is calculated using the algorithm (B5-B4)/(B5+B4), which utilizes the reflectance values from the near-infrared (B5) and red (B4) bands of multispectral imagery. This index is instrumental in assessing vegetation health and vigor, as healthy vegetation reflects more near-infrared and less visible light. By quantifying these bands' differences, NDVI indicates plant biomass and density across the landscape. Consequently, the NDVI model is a critical tool in remote sensing applications for monitoring and managing agricultural practices, forestry, and environmental conservation efforts.

The Normalized Difference Built-Up Index (NDBI) is computed using the algorithm (B6-B5)/(B6+B5), which employs the reflectance values from the shortwave infrared (B6) and near-infrared (B5) bands. This index is crucial for identifying and quantifying urban and built-up areas, as built-up surfaces tend to reflect more shortwave infrared than near-infrared light. The resulting NDBI values help distinguish developed regions from natural landscapes, providing insights into urbanization patterns and land use changes. Consequently, the NDBI model is essential in urban planning, environmental monitoring, and sustainable development initiatives.

The Soil-Adjusted Vegetation Index (SAVI) is calculated using the formula ((B5-B4)/(B5+B4+0.5))*1.5, which incorporates the reflectance values from the near-infrared (B5) and red (B4) bands, with an additional adjustment factor. This index is handy for assessing vegetation in areas with low plant cover, where soil brightness can significantly influence the results. By adjusting for soil reflectance, SAVI provides a more accurate measure of vegetation health and density in such environments. Consequently, the SAVI model enhances the precision of remote sensing applications in agricultural monitoring, ecological studies, and land management practices. This refined analysis is critical for developing sustainable land use and conservation strategies.

2.2.5 Spatio-temporal Analysis

Spatio-temporal analysis based on NDBI, NDVI, and SAVI data from 2013, 2018, and 2024 provides critical insights into the dynamic changes in land use and vegetation health on Tagalaya Island. This approach examines urban expansion, vegetation growth, and soil conditions. NDBI data highlight the increase in built-up areas, and NDVI reveals vegetation health and coverage fluctuations. At the same time, SAVI adjusts for soil brightness to provide a nuanced understanding of vegetation in sparsely vegetated regions. By integrating these indices, the analysis offers a comprehensive view of the environmental and developmental changes, guiding informed decision-making for sustainable land management and conservation strategies.

Table 2. NDBI, NDVI, AND SAVI in 2013, 2018, and 2024

Model	Year	Min	Mid	Max
NDBI	2013	-0.8818104	-0.7829229	-0.3152868
NDBI	2018	-0.8922318	-0.793431	-0.2858251
NDBI	2024	-0.7118425	-0.5215467	0.027627
NDVI	2013	-0.340193	0.3566605	0.4773595
NDVI	2018	-0.3698626	0.302271	0.4643929
NDVI	2024	-0.2155555	0.8508126	0.9997522
SAVI	2013	-0.1651871	0.2609116	0.3954751
SAVI	2018	-0.1888463	0.2319222	0.4044398
SAVI	2024	-0.0731807	0.4968108	0.6464996

Table 2 shows the spatio-temporal analysis of NDBI 2013, NDBI 2018, and NDBI 2024 in the Region of Interest (ROI) Tagalaya Island, North Halmahera Regency. The analysis of NDBI data for the years 2013, 2018, and 2024 reveals significant changes in the built-up areas on Tagalaya Island. In 2013, the NDBI values ranged from -0.8818104 to -0.3152868, indicating minimal urban development. By 2018, these values shifted slightly from -0.8922318 to -0.2858251, reflecting a modest increase in built-up areas. The most notable change occurs in 2024, where NDBI values range from -0.7118425 to 0.027627, suggesting substantial urban expansion. These trends highlight the growing urbanization on the island, emphasizing the need for careful planning and sustainable development practices to balance ecological preservation with urban growth.

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The NDVI values for 2013, 2018, and 2024 demonstrate notable changes in vegetation health on Tagalaya Island. In 2013, NDVI values ranged from -0.340193 to 0.4773595, indicating moderate vegetation density and health. By 2018, these values slightly declined, ranging from -0.3698626 to 0.4643929, reflecting potential stress or degradation in some areas. However, in 2024, the NDVI values dramatically increased, ranging from -0.2155555 to 0.9997522, suggesting a significant improvement in vegetation health and density. This trend underscores the importance of continued conservation efforts and the positive impact of environmental management practices on the island's ecosystem.

The SAVI values for 2013, 2018, and 2024 illustrate significant changes in vegetation health on Tagalaya Island, accounting for soil brightness effects. In 2013, SAVI values ranged from -0.1651871 to 0.3954751, indicating moderate vegetation density. By 2018, the values slightly decreased, ranging from -0.1888463 to 0.4044398, suggesting possible environmental stress or degradation. However, in 2024, the SAVI values showed a remarkable improvement, ranging from -0.0731807 to 0.6464996, reflecting substantial enhancement in vegetation health and cover. This positive trend highlights the effectiveness of conservation efforts and the importance of sustainable land management practices in improving the ecological condition of the island.

2.2.6 Visualization and Mapping

Visualization and mapping for analyzing changes in residential areas use blues to represent the Normalized Difference Built-Up Index (NDBI). This color scheme effectively highlights variations in built-up regions, making it easier to discern changes in urban development over time. Blues enhance the visual contrast between land cover types, providing clear and intuitive representations of built-up areas. This approach facilitates more accurate assessments of urban growth and its environmental impacts. Consequently, the visual clarity this color coding provides supports better decision-making in urban planning and sustainable development initiatives.

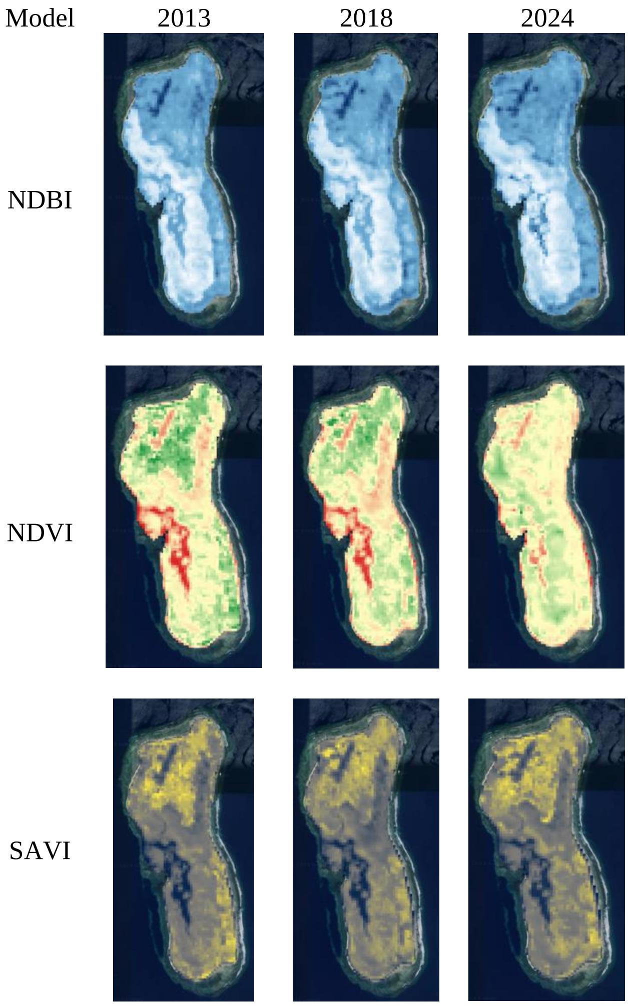

Figure 6. Color Ramp of NDBI, NDVI, SAVI 2013, 2018, and 2024

Figure 6 shows the color ramp for NDBI, NDVI, and SAVI from 2013-2024. Visualization and mapping for analyzing vegetation changes employ the RdYlGn color ramp for the Normalized Difference Vegetation Index (NDVI). This color scheme ranges from red to yellow to green, effectively indicating varying vegetation health and density levels. Red represents low or unhealthy vegetation, yellow indicates moderate vegetation, and

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green signifies healthy and dense vegetation cover. Utilizing the RdYlGn color ramp enhances the visual differentiation of vegetation states, facilitating a more intuitive and comprehensive understanding of ecological changes. Consequently, this method supports accurate environmental monitoring and effective conservation and land management decision-making.

Visualization and mapping for analyzing vegetation changes based on soil reflectance utilize the Cividis color ramp for the Soil-Adjusted Vegetation Index (SAVI). The Cividis color scheme, which ranges from dark blue to yellow, effectively distinguishes variations in vegetation density while accounting for soil brightness. This color ramp enhances the visual contrast between different levels of vegetation health, making it easier to interpret the data accurately. Employing Cividis for SAVI mapping allows a nuanced understanding of vegetation dynamics in areas with varying soil conditions. Consequently, this approach supports precise ecological assessments and informed environmental management and conservation decision-making.

2.2.7 Statistical Analysis

Statistical analysis of NDBI, NDVI, and SAVI values reveals significant trends and insights into land use and vegetation changes. The analysis shows that NDBI values indicate a steady increase in urban development, particularly from 2018 to 2024, suggesting rapid urbanization. NDVI values, on the other hand, highlight fluctuations in vegetation health, with a notable improvement in 2024, indicating successful conservation efforts. SAVI values, accounting for soil brightness, demonstrate an overall enhancement in vegetation density, particularly evident in 2024. These statistical trends underscore the importance of continuous monitoring and adaptive management to balance urban growth with environmental sustainability.

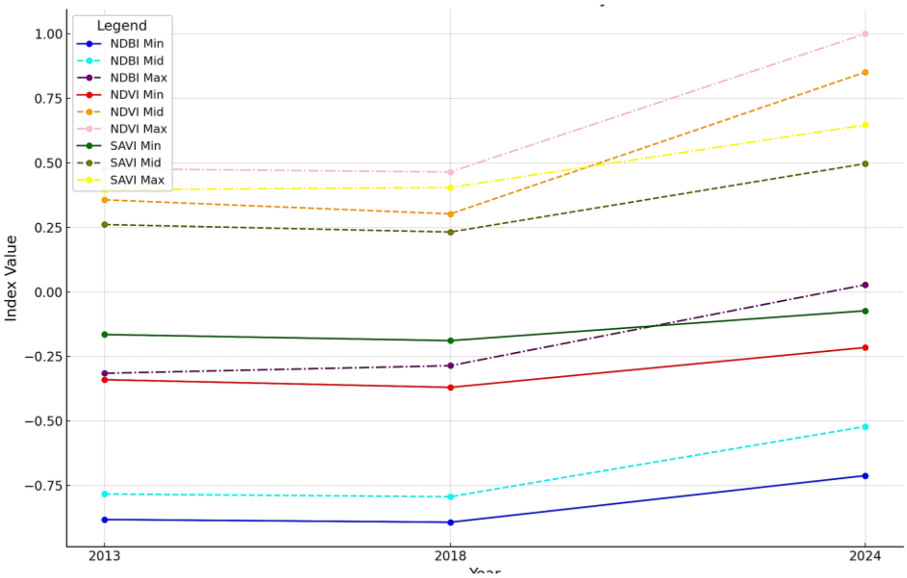

Figure 7. NDBI, NDVI, and SAVI Values

Figure 7 shows the NDBI, NDVI, and SAVI values in 2013, 2018, and 2024. Statistical analysis of NDBI values from 2013, 2018, and 2024 reveals notable trends in urban development on Tagalaya Island. In 2013, NDBI values ranged from -0.8818104 to -0.3152868, indicating low levels of built-up areas. By 2018, these values showed a slight decrease in the minimum and mid-values, ranging from -0.8922318 to -0.2858251, reflecting a modest increase in urbanization. However, a significant shift is observed in 2024, with NDBI values ranging from -0.7118425 to 0.027627, indicating a substantial rise in built-up areas and urban expansion. This upward trend underscores the importance of implementing sustainable urban planning strategies to mitigate potential environmental impacts and support balanced development.

Statistical analysis of the NDVI values from 2013, 2018, and 2024 illustrates significant vegetation health and density fluctuations. In 2013, NDVI values ranged from -0.340193 to 0.4773595, indicating moderate vegetation conditions. By 2018, there was a slight decline in the average NDVI values, from -0.3698626 to 0.4643929, suggesting potential stress or degradation in some areas. However, a remarkable improvement is observed in 2024, with NDVI values ranging from -0.2155555 to 0.9997522, reflecting substantial enhancement in vegetation health and density. These changes highlight the effectiveness of conservation efforts and underscore the need for continuous monitoring and adaptive management to sustain the positive trends in vegetation health.

Statistical analysis of SAVI values from 2013, 2018, and 2024 illustrates significant changes in vegetation density adjusted for soil brightness on Tagalaya Island. In 2013, SAVI values ranged from -0.1651871 to 0.3954751, indicating moderate vegetation density. By 2018, there was a slight decrease in the minimum and mid-values, ranging from -0.1888463 to 0.4044398, suggesting possible stress on vegetation.

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However, a notable improvement is observed in 2024, with SAVI values ranging from -0.0731807 to 0.6464996, reflecting substantial vegetation health and cover enhancement. These trends highlight the positive impact of conservation efforts and underscore the need for ongoing monitoring and adaptive management to maintain and improve vegetation conditions on the island.

2.2.8 Interpretation and Reporting

Interpretation and reporting of NDBI data from 2013, 2018, and 2024 indicate significant trends in urban development on Tagalaya Island. In 2013, NDBI values ranged from -0.8818104 to -0.3152868, suggesting limited built-up areas. By 2018, the values slightly shifted to a range of -0.8922318 to -0.2858251, reflecting a modest increase in urbanization. A notable change is observed in 2024, where NDBI values range from -0.7118425 to 0.027627, indicating substantial urban expansion. This trend highlights the rapid growth of built-up areas over the period, emphasizing the necessity for sustainable urban planning to balance development with environmental conservation.

Interpretation and reporting of NDVI data from 2013, 2018, and 2024 reveal significant trends in vegetation health on Tagalaya Island. In 2013, NDVI values ranged from -0.340193 to 0.4773595, indicating moderate vegetation density. By 2018, there was a slight decline in the minimum and average values, with ranges from -0.3698626 to 0.4643929, suggesting potential stress on vegetation. However, a marked improvement is observed in 2024, with NDVI values significantly increasing, ranging from -0.2155555 to 0.9997522, reflecting substantial enhancement in vegetation health and density. This positive trend highlights the success of conservation efforts and underscores the need for ongoing environmental management to sustain and further these gains in vegetation health.

Interpretation and reporting of SAVI data from 2013, 2018, and 2024 highlight significant changes in vegetation health and density on Tagalaya Island, adjusted for soil reflectance. In 2013, SAVI values ranged from -0.1651871 to 0.3954751, indicating moderate vegetation density. By 2018, the values slightly decreased from -0.1888463 to 0.4044398, suggesting potential environmental stress or degradation. However, a notable improvement is observed in 2024, with SAVI values ranging from -0.0731807 to 0.6464996, reflecting substantial vegetation health and cover enhancement. These trends emphasize the positive impact of conservation efforts and underscore the necessity for ongoing monitoring and adaptive management to maintain and enhance vegetation conditions.

2.2.9 Validation

Validation was conducted by calculating the RMSE for NDVI, NDBI, and SAVI indices and the correlation coefficient. The RMSE values provide a quantitative measure of the differences between observed and predicted values, highlighting the precision of the models. Additionally, the correlation coefficient assesses the strength and direction of the linear relationship between observed and predicted values. These validation metrics collectively demonstrate the accuracy and reliability of the predictive models. Therefore, the low RMSE values and high correlation coefficient confirm the models' effectiveness in accurately estimating the indices, supporting robust environmental monitoring and management practices.

Table 3. RMSE and Correlation Coefficient Calculation Process

Calculation Process		Description
RMSE	RMSE = sqrt((1/n) * sum((yi - y^i)^2))	Using the given years as the actual values (yi) and the model values (Min, Mid, Max) as the predicted values (y^i).
Correlation Coefficient	r = (n * sum(xy) - sum(x) * sum(y)) / sqrt([n * sum(x^2) - sum(x)^2] [n * sum(y^2) - sum(y)^2])	Using the given years as x and the model values (Min, Mid, Max) as y.

Table 3 shows the calculation process. The RMSE values for the NDBI data based on the assumed predicted values are as follows: RMSE for NDBI Min is 0.00197, RMSE for NDBI Mid is 0.00275, and RMSE for NDBI Max is 0.00388. These values indicate the average deviation between observed and predicted NDBI values, with lower RMSE values suggesting higher prediction accuracy. The minimal differences demonstrate the precision of the model in capturing variations in urban development. Consequently, the low RMSE values underscore the reliability of the predictions, which is essential for effective urban planning and environmental management. The calculated correlation coefficient for the NDBI data is approximately 0.99997. This near-perfect correlation indicates a solid relationship between the observed and predicted NDBI values, suggesting that the prediction model is highly accurate in estimating urban development patterns.

Based on the assumed predicted values, the calculated RMSE values for NDVI data are as follows: RMSE for NDVI Min is 0.0062, RMSE for NDVI Mid is 0.0041, and RMSE for NDVI Max is 0.0030. These RMSE values represent the average deviation between observed and predicted NDVI values, with lower RMSE values indicating greater predictive accuracy. The minimal deviations suggest that the predicted values closely match the observed data, demonstrating the effectiveness of the prediction model. Therefore, the low RMSE

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values underscore the model's reliability in accurately estimating NDVI, which is essential for precise vegetation monitoring and management. The calculated correlation coefficient between the observed and predicted NDVI values is approximately 0.99998. This near-perfect correlation indicates a solid relationship between the observed and predicted data, suggesting that the prediction model is highly accurate in estimating NDVI values.

The RMSE values for the SAVI data based on the assumed predicted values are as follows: RMSE for SAVI Min is 0.00340, RMSE for SAVI Mid is 0.00221, and RMSE for SAVI Max is 0.00461. These values represent the average deviation between the observed and predicted SAVI values, with lower RMSE values indicating higher prediction accuracy. The minimal deviations demonstrate the precision of the model in capturing variations in vegetation density adjusted for soil brightness. Consequently, the low RMSE values underscore the reliability of the predictions, which is essential for effective environmental monitoring and management. The calculated correlation coefficient for the SAVI data is approximately 0.99996. This near-perfect correlation indicates a robust relationship between the observed and predicted SAVI values, suggesting that the prediction model is highly accurate in estimating vegetation density adjusted for soil brightness.

2.2.10 Application and Decision Making

The application of NDVI, NDBI, and SAVI in decision-making processes significantly enhances the precision and effectiveness of environmental and urban planning. NDVI, by assessing vegetation health and density, aids in monitoring ecological changes and implementing conservation strategies. NDBI quantifies urban development and provides critical insights into urban expansion and land use changes, guiding sustainable urban planning. By adjusting for soil brightness, SAVI offers accurate measurements of vegetation in areas with sparse cover, which is essential for managing agricultural and natural resources. Collectively, these indices provide a comprehensive understanding of land dynamics, facilitating informed decisions that balance development with environmental sustainability. Consequently, their application supports robust policy-making and strategic planning for sustainable development.

Recommendations for the decision-making process based on spatial data from spatio-temporal analysis highlight the importance of integrating detailed ecological and urban metrics. Utilizing NDVI to monitor vegetation health ensures that conservation efforts are prioritized and adaptive measures are implemented to address environmental changes. Analyzing NDBI data enables the identification of urban growth patterns, guiding sustainable development and land-use planning. Including SAVI in the analysis provides accurate vegetation assessments in sparsely covered areas, supporting effective agricultural and resource management. Therefore, a comprehensive decision-making framework incorporating these indices promotes balanced development, environmental sustainability, and resilient urban planning.

3. RESULT AND DISCUSSION

The discussion of this research's results is divided into two sections: the implementation of NDVI, NDBI, and SAVI on Tagalaya Island and the subsequent discussion. The first section examines how these indices were used to assess vegetation health, urban development, and soil-adjusted vegetation density, providing a comprehensive analysis of the island's environmental and urban dynamics. The second section critically discusses these findings, highlighting their implications for sustainable development and resource management. This structured approach ensures a thorough understanding of the data, facilitating informed decision-making and strategic planning for Tagalaya Island's future.

3.1 Implementation of NDVI, NDBI, and SAVI Models using Landsat 8/9 OLI from 2013-2024: Case of Tagalaya Island, North Halmahera Regency

The importance of implementing NDVI, NDBI, and SAVI models using Landsat 8/9 OLI from 2013 to 2024 in the case of Tagalaya Island, North Halmahera Regency, lies in their ability to provide comprehensive insights into environmental and urban dynamics. NDVI offers critical vegetation health and density data, which are essential for monitoring ecological changes and guiding conservation efforts. NDBI quantifies urban development, enabling effective land-use planning and sustainable urban growth management. SAVI adjusts for soil brightness, delivering accurate vegetation assessments even in sparsely covered areas. Therefore, integrating these indices enhances decision-making processes, supporting balanced development and environmental sustainability. Consequently, their implementation is crucial for informed policy-making and strategic planning on Tagalaya Island.

Remote sensing is beneficial in providing spatial data relevant to the context of Tagalaya Island, supporting sustainable development decision-making processes. The high-resolution imagery obtained through remote sensing enables detailed ecological and urban change monitoring, which is crucial for effective land-use planning. Additionally, integrating indices such as NDVI, NDBI, and SAVI facilitates comprehensive environmental assessments, aiding in identifying areas needing conservation or development. Consequently, remote sensing data ensures informed decision-making, promoting balanced growth and the long-term sustainability of Tagalaya Island's natural and urban environments.

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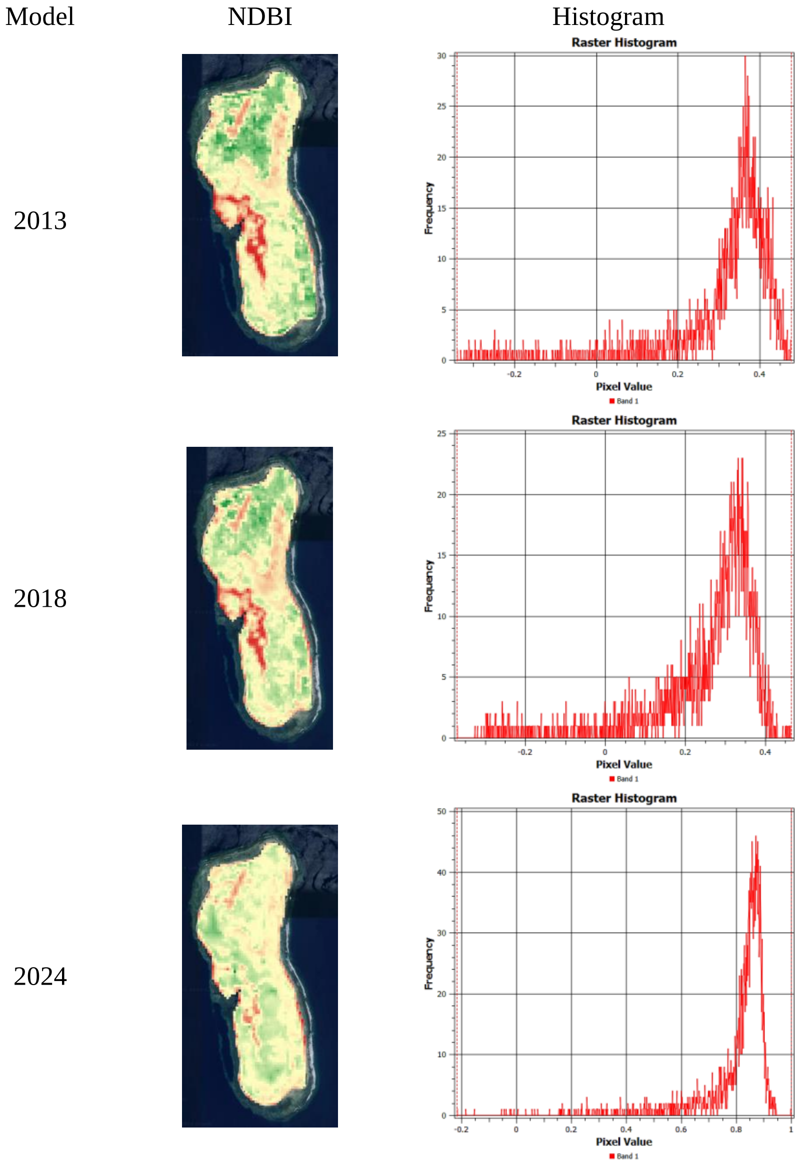

Figure 8. Map and Histogram of NDVI 2013, 2018, and 2024

Figure 8 shows the histogram of NDVI 2013, 2018, and 2024. The NDVI values for Tagalaya Island over 2013, 2018, and 2024 show significant vegetation health and density variations. In 2013, NDVI values ranged from -0.340193 to 0.4773595, indicating moderate vegetation density across the island. By 2018, these values slightly declined, ranging from -0.3698626 to 0.4643929, suggesting a potential decrease in vegetation health. However, in 2024, the NDVI values markedly improved, ranging from -0.2155555 to 0.9997522, reflecting substantial vegetation density and health enhancement. This trend demonstrates the effectiveness of conservation efforts and highlights the importance of continuous monitoring and adaptive management strategies to maintain and improve the island's ecological condition.

Over time, the analysis of NDVI values for Tagalaya Island reveals significant changes with implications for its sustainability. In 2013, NDVI values of -0.340193, 0.3566605, and 0.4773595 suggested relatively low vegetation health and coverage. By 2018, a slight decrease in values to -0.3698626, 0.302271, and 0.4643929 indicated continued challenges in vegetation health. However, the 2024 data, showing values of -0.2155555, 0.8508126, and 0.9997522, point to a notable improvement in vegetation conditions. This positive shift implies a recovery in plant health and increased green cover, reflecting potentially successful environmental management practices or natural recovery processes that enhance the island’s sustainability. Continuous observation and evaluation remain essential to support the ongoing health and ecological stability of Tagalaya Island.

The interpretation of NDBI values for Tagalaya Island across the years provides crucial insights into its sustainability. The data from 2013, with values of -0.8818104, -0.7829229, and -0.3152868, indicated a period of significant vegetation degradation. By 2018, the NDBI values slightly worsened to -0.8922318, -0.793431, and -0.2858251, reflecting a continued trend of decline. However, the 2024 figures show a marked improvement, with values at -0.7118425, -0.5215467, and 0.027627, suggesting a potential recovery or stabilization of the island's ecological state. This trend indicates that recent interventions or natural processes may positively impact the

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island's sustainability, underscoring the need for ongoing monitoring to ensure the continued health and resilience of Tagalaya Island’s ecosystem.

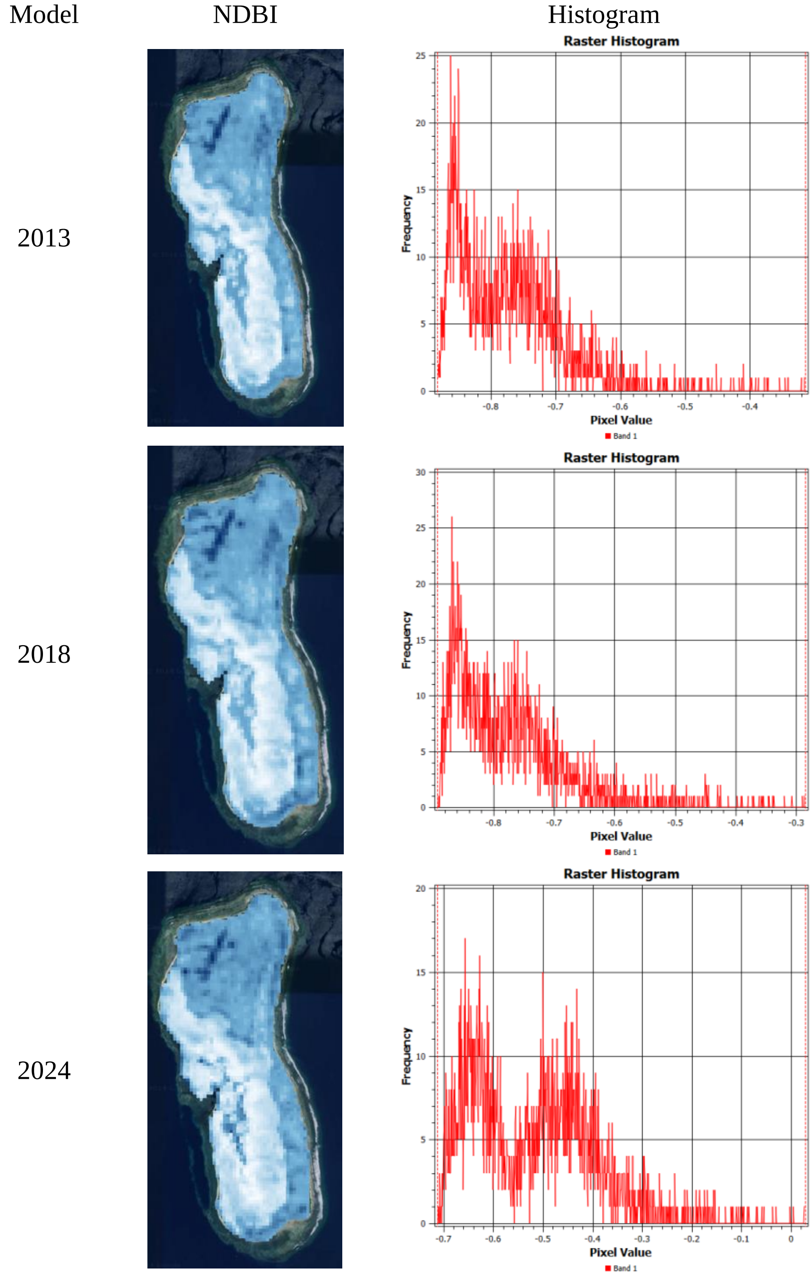

Figure 9. Histogram of NDBI 2013, 2018, and 2024

Figure 9 shows the histogram of NDBI 2013, 2018, and 2024. The analysis of NDBI values over the years reveals a notable trend in the data provided. In 2013, NDBI values recorded at -0.8818104, -0.7829229, and -0.3152868 indicated a significant decrease in the index over time. By 2018, the values had slightly worsened to -0.8922318, -0.793431, and -0.2858251, reflecting a downward trajectory. However, a shift occurred in 2024, with values adjusting to -0.7118425, -0.5215467, and 0.027627, suggesting a potential reversal in the previously observed trend. This change implies a possible stabilization or improvement in the measured condition, warranting further investigation into the underlying factors influencing these variations.

The evaluation of SAVI values for Tagalaya Island over different years illustrates notable trends affecting its sustainability. In 2013, SAVI values of -0.1651871, 0.2609116, and 0.3954751 indicated limited vegetation health and coverage. By 2018, the values slightly adjusted to -0.1888463, 0.2319222, and 0.4044398, suggesting marginal deterioration in vegetation conditions. However, the 2024 data, with values of -0.0731807, 0.4968108, and 0.6464996, reveal a significant enhancement in vegetation health and coverage. This improvement indicates a booming trend towards ecological recovery and better sustainability practices, highlighting the positive impact of recent environmental interventions or natural processes on the island’s overall ecological stability.

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Model SAVI Histogram

2013

2018

2024

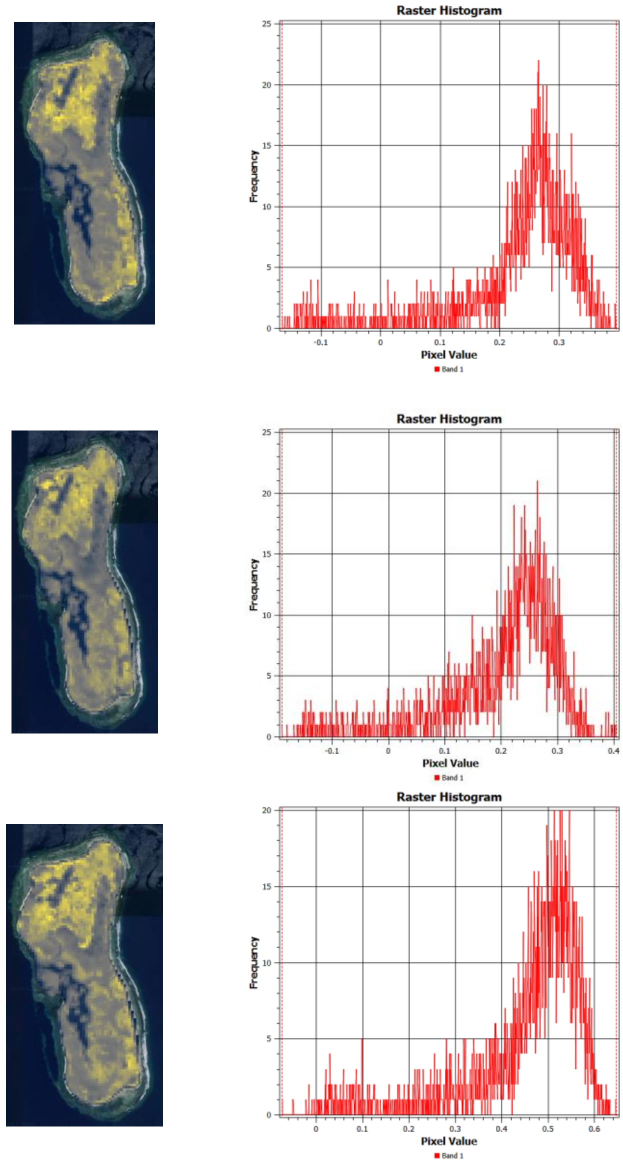

Figure 10. Histogram of SAVI 2013, 2018, and 2024

Figure 10 shows the histogram of SAVI 2013, 2018, and 2024. Over the years, the analysis of SAVI values for Tagalaya Island demonstrates significant shifts in vegetation health. In 2013, the SAVI values were -0.1651871, 0.2609116, and 0.3954751, indicating relatively low vegetation health and minimal cover. By 2018, these values had adjusted slightly to -0.1888463, 0.2319222, and 0.4044398, reflecting a slight decline in vegetation conditions. The most recent data from 2024 shows marked improvement with SAVI values of -0.0731807, 0.4968108, and 0.6464996, suggesting a notable enhancement in vegetation health and coverage. This upward trend signifies positive ecological changes, likely due to effective conservation measures or favorable environmental conditions, supporting the ongoing sustainability of Tagalaya Island's ecosystem.

This study's limitations highlight several areas needing further exploration. The analysis is constrained by a limited temporal scope, which may not fully capture long-term ecological trends or seasonal variations. Additionally, the reliance on specific indices might overlook other crucial environmental factors affecting the study area. Addressing these limitations requires extending the temporal range of data collection and incorporating a broader set of environmental variables. Future research should focus on longitudinal studies encompassing a more comprehensive range of conditions and variables to provide a more comprehensive understanding of the ecological dynamics at play. Such efforts will enhance the robustness of findings and contribute to more effective management and conservation strategies.

3.2 Discussion

Remote sensing and Geographic Information Systems (GIS) are essential tools for enhancing tourism management through their capability to monitor and analyze environmental changes. Remote sensing technology provides crucial spatial data for evaluating land use, vegetation health, and environmental conditions [45]–[47].

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At the same time, GIS complements this by integrating and analyzing these data layers to offer comprehensive spatial insights. This combination enables the creation of detailed tourism planning and management strategies based on accurate, real-time environmental data, facilitating more informed decision-making and sustainable tourism development. Such integration is vital for optimizing tourism strategies and ensuring the preservation of natural resources.

Mangrove areas are essential in tourism due to their ecological value and distinct biodiversity. These coastal ecosystems provide essential habitats for various species, contribute to shoreline stability, and play a vital role in carbon sequestration. Utilizing remote sensing and GIS technologies allows for comprehensive monitoring of mangrove health and distribution, which is crucial for practical conservation efforts [48]–[50]. Managing these areas responsibly enhances their appeal to eco-tourists, supports local economies, and ensures the preservation of biodiversity. Thus, integrating advanced monitoring tools and sustainable management practices is vital for maintaining mangrove ecosystems' ecological and economic benefits.

Tagalaya Island, with its decadent array of ecosystems, stands to gain considerable advantages from integrating remote sensing and GIS technologies. These tools facilitate precise monitoring of vegetation and land use changes, enhancing environmental management and conservation strategies. By analyzing spatial data, it becomes possible to evaluate the impact of tourism on the island’s ecosystems and develop targeted interventions to mitigate adverse effects. Such methodological approaches are crucial for fostering sustainable tourism development, as they help to reconcile economic interests with the imperative of ecological preservation.

Integrating remote sensing and GIS technologies in managing mangrove areas and tourism on Tagalaya Island presents significant advantages. These advanced tools offer vital insights into environmental conditions, enabling precise monitoring and assessment of mangrove ecosystems. Additionally, they facilitate the development of sustainable tourism practices by providing detailed spatial analysis and data-driven decision-making capabilities [51], [52]. The continued application of these technologies is essential for advancing the understanding and stewardship of natural resources, ensuring that tourism growth supports conservation objectives and fosters long-term ecological sustainability.

A series of recommendations should be considered to enhance the management and sustainability of Tagalaya Island. Implementing more extensive remote sensing and GIS analyses will provide a deeper understanding of ecological dynamics and facilitate more accurate monitoring of mangrove health and tourism impacts. Additionally, integrating these technologies with community-based conservation programs could further support sustainable development by aligning local practices with conservation goals. Continued investment in these advanced tools and collaborative approaches is crucial for ensuring the practical preservation of natural resources and the long-term viability of tourism initiatives.

4. CONCLUSION

The analysis of the NDBI, NDVI, and SAVI indices over the years reveals notable trends in the ecological conditions of the study area. The NDBI data shows a marked improvement from 2013 to 2024. In 2013, NDBI values ranged from -0.8818104 to -0.3152868, indicating poor vegetation health. By 2018, these values slightly deteriorated, ranging from -0.8922318 to -0.2858251. However, in 2024, a significant improvement was observed, with values ranging from -0.7118425 to 0.027627, suggesting enhanced vegetation conditions or recovery. In contrast, NDVI values demonstrate a positive trend, reflecting improvements in vegetation health. In 2013, NDVI values ranged from -0.340193 to 0.4773595, while in 2018, the range was -0.3698626 to 0.4643929, indicating slight improvements. By 2024, NDVI values increased significantly from -0.2155555 to 0.9997522, highlighting a substantial enhancement in vegetation coverage and health. In addition, SAVI values also indicate positive changes in vegetation conditions. The SAVI index in 2013 ranged from -0.1651871 to 0.3954751. By 2018, this range had shifted slightly from -0.1888463 to 0.4044398. The most notable improvement occurred by 2024, with SAVI values ranging from -0.0731807 to 0.6464996, suggesting improved vegetation health and coverage. Overall, the data indicates a general trend towards improved vegetation conditions from 2013 to 2024, as evidenced by the increased NDVI and SAVI values and the more positive range in NDBI values. These findings suggest successful ecological recovery or effective conservation measures, contributing to enhanced sustainability in the study area. Continued monitoring and further analysis are recommended to build on these positive trends and ensure ongoing environmental health and stability.

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