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Integrating Remote Sensing and Spatial Data for Ecological Sustainability through Spatio-temporal Analysis

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Abstract−This research underscores the pivotal role of integrating spatial data and remote sensing technologies within a spatio-temporal analysis framework for regional development planning. Analyzing NDVI, NDBI, and SAVI values from 2013, 2018, and 2024 provided significant insights into vegetation health, urbanization, and soil conditions on Kumo Island. The NDVI values exhibited changes from a minimum of -0.0549, a mid-value of 0.1782, and a maximum of 0.4690 in 2013 to a minimum of 0.2456, a mid-value of 0.8296, and a maximum of 0.9416 in 2024. Similarly, the NDBI values shifted from a minimum of -0.8734, a mid-value of -0.5779, and a maximum of 0.0009 in 2013 to a minimum of -0.6561, a mid-value of -0.4304, and a maximum of 0.0247 in 2024. The SAVI values showed notable changes from a minimum of -0.0365, a mid-value of 0.1245, and a maximum of 0.3814 in 2013 to a minimum of 0.1138, a mid-value of 0.4953, and a maximum of 0.6160 in 2024. These findings highlight the importance of ecological sustainability in decision-making processes, demonstrating how advanced spatial analysis within a spatio-temporal framework can effectively monitor and manage land use changes. The urgency of this research lies in addressing rapid environmental changes and escalating human activities, necessitating timely and accurate monitoring techniques. The study reveals the utility of the NDVI, NDBI, and SAVI indices in assessing vegetation health, urbanization, and soil conditions, which are instrumental in identifying trends and informing sustainable development strategies. The research advocates for the continued use of remote sensing and spatial data to ensure balanced and informed regional development, emphasizing the necessity of sustainable practices to preserve ecological integrity while supporting socio-economic growth. Integrating remote sensing into the decision-making process enhances the accuracy and reliability of spatial data, leading to more effective and responsible regional development.

Keywords: Spatio-Temporal Analysis; Remote Sensing; NDVI; NDBI; SAVI

1. INTRODUCTION

Monitoring the sustainability of tourist areas presents significant challenges, particularly in optimizing oversight and land use permits for residential settlements and developing tourism-related economic infrastructure. Adequate supervision requires balancing preserving ecological integrity and accommodating necessary urban expansion [1], [2]. Achieving this balance often involves complex decision-making processes considering diverse stakeholder interests and environmental impacts [3], [4]. A robust framework that integrates advanced monitoring technologies and participatory governance enhances the efficiency and effectiveness of these efforts. Addressing these challenges is crucial for ensuring the long-term viability of tourism destinations.

Utilizing Landsat 8/9 OLI satellite imagery raster data significantly enhances land use monitoring processes in archipelagic regions by enabling the identification of changes in vegetation indices, which serve as indicators of ecological sustainability [5], [6]. This technology facilitates precise tracking of vegetative cover variations, providing critical insights into environmental health and land management practices [7], [8]. Integrating such remote sensing data in ecological monitoring supports informed decision-making, promoting sustainable development. Employing advanced satellite imagery, therefore, proves indispensable in maintaining the delicate balance between development and ecological preservation in island ecosystems.

The sustainability of the tourism industry is intrinsically linked to the maintenance of ecological balance, particularly on small islands. Practical environmental monitoring activities are crucial in optimizing oversight to ensure ecological sustainability [9]–[11]. Such activities involve systematic observation and data collection, enabling the identification of potential threats and the implementation of timely interventions [12]–[15]. Continuous and rigorous monitoring is essential to protect these fragile ecosystems, supporting long-term tourism viability. Therefore, integrating advanced monitoring techniques is imperative for safeguarding the environmental foundations upon which the tourism industry relies.

This study aims to process Landsat 8/9 OLI raster data to identify landscape changes on Kumo Island in North Halmahera Regency using NDVI, NDBI, and SAVI Performance models. These indices facilitate detailed analysis of vegetation cover, built-up areas, and soil adjustments, respectively [16]–[22]. Integrating these models provides a comprehensive understanding of the island's ecological and infrastructural dynamics [23]–[29]. Such an analytical approach is essential for informing sustainable land management strategies and environmental conservation efforts. Consequently, this research contributes significantly to effectively monitoring and preserving Kumo Island's landscape.

The urgency of this research lies in its potential to address critical gaps in sustainable land management and ecological conservation. Rapid environmental changes and escalating human activities necessitate timely and accurate monitoring techniques. By utilizing advanced remote sensing models such as NDVI, NDBI, and SAVI Performance, this study offers a robust framework for detecting and analyzing landscape transformations [30]. This approach enhances the understanding of ecological and infrastructural dynamics and informs strategic planning and policy-making. Therefore, the outcomes of this research are pivotal in fostering sustainable development and environmental stewardship.

This research's theoretical and practical implications are profound, offering valuable insights into sustainable land management and ecological monitoring. Theoretically, the study advances the understanding of remote sensing models such as NDVI, NDBI, and SAVI Performance in detecting landscape changes. This contribution enriches the existing body of knowledge and provides a foundation for future research in the environmental monitoring [31]–[33]. Practically, the research offers actionable data and methodologies that policymakers and land managers can employ to implement effective conservation strategies. Consequently, the findings have significant potential to influence academic discourse and real-world environmental practices, promoting a more sustainable approach to land use and ecological preservation.

Limitations of this study on NDVI, NDBI, and SAVI models in specific areas, such as Kumo Island in North Halmahera Regency, highlight both the potential and challenges of using remote sensing for ecological monitoring. Comparable studies have demonstrated the efficacy of these indices in assessing vegetation health, urban expansion, and soil conditions [31], [34]–[37]. However, limitations arise due to factors such as the spatial and temporal resolution of the satellite imagery and the specificity of environmental conditions unique to each region [32], [38]–[40]. These constraints can affect the precision and generalizability of the findings. Despite these challenges, applying NDVI, NDBI, and SAVI models remains a valuable approach for monitoring and managing land use changes, underscoring the need for continuous refinement and adaptation of remote sensing methodologies.

2. RESEARCH METHODOLOGY

2.1 Gap Analysis

Conducting a gap analysis in this research is essential for evaluating the advancements in remote sensing studies that utilize similar models or perspectives, thereby identifying gaps within remote sensing in tourism areas. This analysis facilitates a comprehensive understanding of existing methodologies and their applicability to different environmental contexts. By scrutinizing these gaps, the research can reveal potential areas for innovation and improvement in monitoring and managing tourism-related ecological impacts. Such an evaluative approach enhances the robustness of current remote sensing practices and guides future research directions. Addressing these gaps is crucial for developing and refining remote sensing applications in sustainable tourism management.

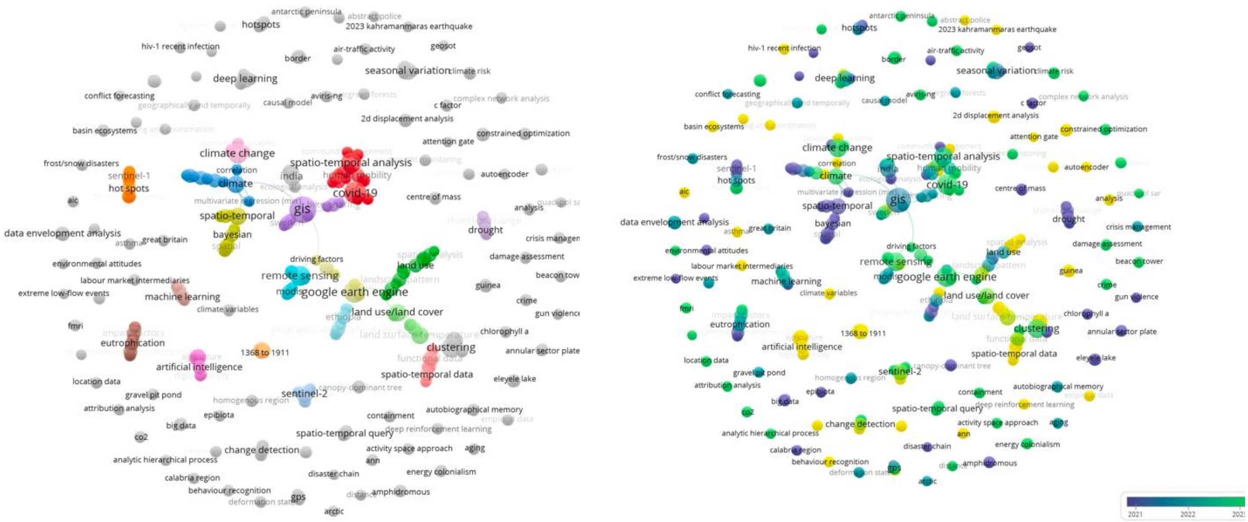

Figure 1. Network and Overlay Visualization of Spatio-temporal Analysis

Figure 1 shows the gap analysis using Vosviewer. Based on the identification of gaps, a study on spatio-temporal analysis is essential. This approach enables a comprehensive understanding of the dynamic changes in land use, vegetation health, and urbanization over time [41]–[43]. Addressing these gaps through spatio-temporal analysis can reveal critical trends and patterns that static analyses might overlook [44]–[46]. Therefore, incorporating this method is crucial for developing effective strategies in environmental management, urban planning, and sustainable development. Ultimately, a spatio-temporal analysis provides valuable insights that inform data-driven decision-making processes.

Considering these factors, the study titled "Evaluation of NDVI, NDBI, and SAVI Performance in Land Use Monitoring using Landsat 8 OLI" is conducted within the context of Kumo Island, North Halmahera Regency, North Maluku Province, Indonesia. This research aims to assess the effectiveness of these indices in monitoring land use changes and environmental conditions. The study uses Landsat 8 OLI data to identify trends and patterns in vegetation health, urbanization, and soil conditions over time. By evaluating the performance of NDVI, NDBI, and SAVI, the research provides critical insights that support sustainable land management and urban planning efforts in the region. Consequently, this evaluation is essential for informed decision-making and strategic environmental conservation.

2.2 Spatio Temporal Analysis

The methodology employed is spatio-temporal analysis, encompassing various systematic stages to ensure comprehensive results [47]. The data collection phase initially involves gathering relevant satellite imagery and ancillary data critical for subsequent analysis. The processing stage includes preprocessing steps such as atmospheric correction and geometric alignment, then identifying the region of interest to focus on specific areas pertinent to the study. Vegetation indices calculation, including NDVI, NDBI, and SAVI, is then conducted to quantify vegetation health, built-up areas, and soil adjustments. The core of the methodology, spatio-temporal analysis, examines changes over time and space, while statistical analysis provides quantitative insights into the observed patterns. Interpretation and reporting synthesize these findings into coherent narratives, complemented by visualization and mapping techniques to effectively illustrate spatial distributions and temporal trends. Validation ensures the accuracy and reliability of the results, forming a foundation for application in real-world scenarios and informed decision-making processes. This methodical approach facilitates a robust understanding of landscape dynamics, highlighting its indispensability in ecological and land management studies.

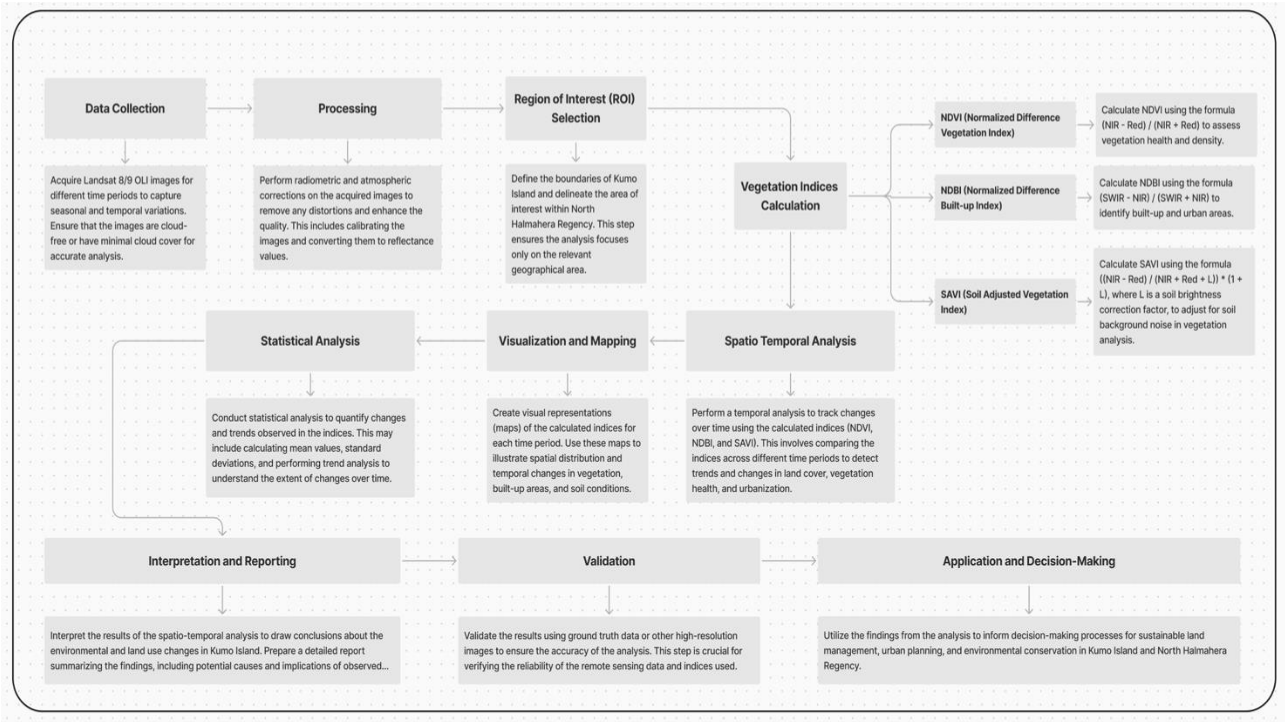

Figure 2. Spatio-temporal Analysis Framework

Figure 2 shows the spatio-temporal analysis framework. The spatio-temporal analysis approach proves highly pertinent for this study, focusing on the region of interest in Kumo Island, North Halmahera Regency. This method allows for the detailed examination of spatial and temporal variations, which is crucial for understanding the dynamic environmental and infrastructural changes in this fragile island ecosystem [48]. The precise monitoring of vegetation indices and land use patterns facilitates the identification of significant trends and potential issues impacting the region's sustainability. Employing this analytical framework underscores its value in offering actionable insights and ensuring informed decisions that support sustainable development and ecological preservation.

The consideration of employing spatio-temporal analysis using NDVI, NDBI, and SAVI models is closely tied to the necessity for spatial data concerning vegetation conditions, non-vegetated areas, and residential settlements. Such data provide critical insights into the ecological and infrastructural dynamics of Kumo Island, North Halmahera Regency. By accurately capturing the state of these variables, the analysis informs policy-making processes, ensuring that development initiatives align with sustainability goals. This method enhances decision-making by offering a comprehensive understanding of the interactions between natural and human-modified landscapes, ultimately supporting long-term environmental stewardship and sustainable growth.

2.2.1 Data Collection

Landsat 8/9 OLI raster data, sourced from the United States Geological Survey (USGS) via https://earthexplorer.usgs.gov/, provide critical geospatial information for the study area. These datasets obtained explicitly for coordinates lat 1.5074 and long 127.8937, offer high-resolution imagery essential for detailed environmental and infrastructural analysis. Utilizing such reliable and precise data enhances the accuracy of spatio-temporal studies, contributing significantly to the development and sustainability assessment of Kumo Island, North Halmahera Regency. This approach ensures informed decision-making, supporting the region's effective management and conservation strategies.

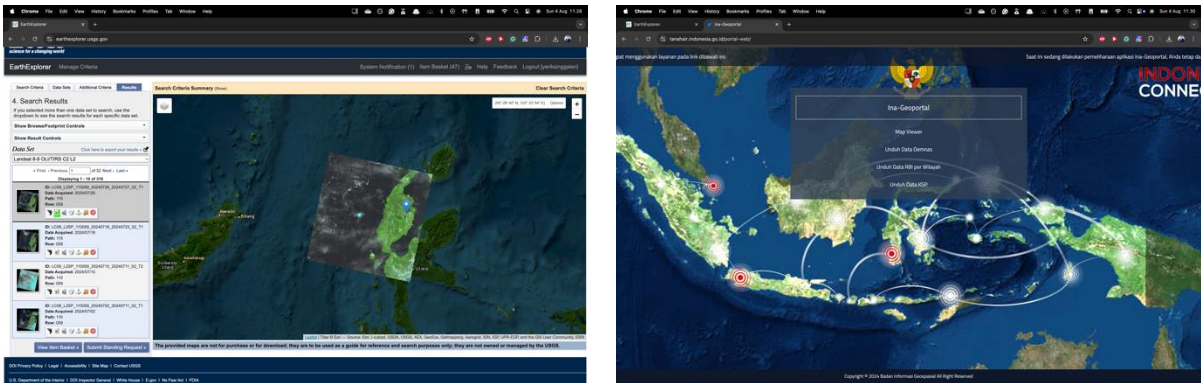

Figure 3. Raster and Vector Data Source

Figure 2 shows the raster data and vector data sources. Shapefile data for Kumo Island in North Halmahera Regency, sourced from Ina-Geoportal via https://tanahair.indonesia.go.id/, offers comprehensive information on the existing spatial conditions at the provincial, regency, and district levels. These data sets provide detailed insights into land use, vegetation cover, and infrastructural elements across different administrative divisions. The availability of such precise and up-to-date spatial data is crucial for conducting robust geographical analyses and supporting sustainable development initiatives. This resource significantly enhances the capacity for informed decision-making and effective regional planning and conservation efforts management.

The collected raster data includes datasets from 2013, 2018, and 2024, enabling the identification and analysis of temporal changes between 2013-2018 and 2018-2024. This temporal range allows for a comprehensive examination of landscape dynamics and environmental transformations over significant intervals. By analyzing these changes, insights can be gained into development patterns, degradation, and ecological shifts. Such a longitudinal approach is essential for understanding human activities and natural processes' long-term impacts, facilitating informed policy-making and sustainable management strategies.

2.2.2 Processing

The collected raster data underwent a rigorous cleaning process using QGIS, incorporating atmospheric, radiometric, and geometric corrections. These preprocessing steps are crucial for ensuring the accuracy and reliability of the satellite imagery, thereby enhancing the quality of subsequent analyses. Atmospheric correction removes distortions caused by atmospheric interference, while radiometric and geometric corrections adjust the data for sensor inconsistencies and spatial alignment. Employing such meticulous preprocessing techniques is essential for obtaining precise and valid results, ultimately supporting robust spatial analysis and informed decision-making.

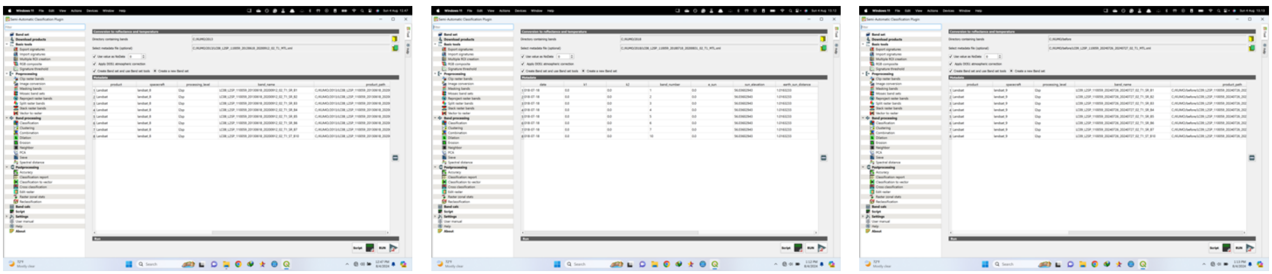

Figure 4. Atmospheric and Radiometric Correction

Atmospheric correction entails the removal of distortions induced by aerosols, water vapor, and other atmospheric constituents that impact satellite imagery. This process is pivotal for eliminating the atmospheric noise that skews the actual reflectance values of the Earth's surface. Ensuring the accuracy of these reflectance values is critical, as it forms the foundation for reliable remote sensing analysis. Through meticulous atmospheric correction, satellite data can more accurately reflect the actual conditions on the ground, thus enhancing the integrity and applicability of subsequent environmental assessments and geospatial analyses.

Radiometric correction involves adjusting pixel values for sensor noise and other radiometric distortions. This process is critical for ensuring the consistency and reliability of satellite data by normalizing reflectance values. The data becomes more accurate and dependable by eliminating these distortions, facilitating meaningful and precise analysis. Radiometric correction thus plays a fundamental role in preparing remote sensing data for in-depth environmental assessments and other scientific evaluations, ultimately enhancing the quality and applicability of the derived information.

Geometric correction aligns satellite imagery spatially, rectifying geometric distortions caused by the satellite's motion, the Earth's curvature, and topographic variations. This process ensures that raster data accurately corresponds to real-world coordinates, thereby maintaining spatial integrity. The alignment is crucial for reliable spatial analysis and precise mapping, as it allows for accurate overlay and comparison of different geospatial datasets. Consequently, geometric correction is a foundational step in remote sensing, facilitating the production of high-quality, geographically accurate maps and analyses essential for informed decision-making and effective spatial planning.

2.2.3 Region of Interest

This study's region of interest is Kumo Island, located in North Halmahera Regency, North Maluku Province, Indonesia. This area was selected due to its unique environmental characteristics and the pressing need for sustainable development strategies. Focusing on Kumo Island allows a detailed examination of ecological and infrastructural dynamics within a localized context. This targeted approach enhances the analysis's precision and provides valuable insights into the broader implications for regional planning. Thus, the study's findings are expected to significantly contribute to the sustainable management of similar island ecosystems in the region.

Figure 5. Region of Interest (Roi)

Figure 5 shows the coordinates of Kumo Island. The coordinates for Kumo Island are 61.256440 (latitude) and 22.357220 (longitude). These precise geospatial references are essential for conducting detailed and accurate spatial analyses. Such exact coordinates facilitate the alignment of satellite imagery and GIS data, ensuring that all spatial information accurately represents the physical location of Kumo Island. Utilizing these coordinates enhances the validity of environmental and infrastructural assessments, thereby supporting more effective planning and decision-making. Consequently, these precise locational details are fundamental for the integrity and reliability of geospatial studies involving Kumo Island.

Based on the region of interest, the area of Kumo Island can be precisely calculated according to the required models during the vegetation indices calculation stage. This focus allows for detailed analysis of vegetation health, land cover changes, and environmental conditions using indices such as NDVI, NDBI, and SAVI. Implementing these models provides critical insights into the ecological status and trends within the island's landscape. Thus, accurate calculation and application of these vegetation indices are vital for informed environmental monitoring and sustainable land management strategies.

2.2.4 Vegetation Indices Calculation: NDVI, NDBI, SAVI

During the vegetation indices calculation stage, raster data from 2013, 2018, and 2024 are computed using the NDVI, NDBI, and SAVI models. This process facilitates assessing vegetation health, land cover changes, and soil conditions over the specified periods. Employing these indices ensures a comprehensive understanding of the environmental dynamics and anthropogenic impacts on Kumo Island. Consequently, the calculated indices serve as a robust foundation for subsequent spatial analyses and informed decision-making in environmental management.

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) for Landsat 8 is calculated using the formula (B5 - B4) / (B5 + B4). This index utilizes the near-infrared (Band 5) and red (Band 4) wavelengths to measure vegetation health and density. By comparing the reflectance values in these bands, NDVI effectively highlights healthy, dense vegetation versus sparse or stressed vegetation areas. This ratio-based calculation provides a standardized method to assess and monitor vegetation dynamics over time. Therefore, NDVI is a crucial tool in remote sensing for environmental monitoring and ecological research.

The Normalized Difference Built-up Index (NDBI) for Landsat 8 is computed using the formula (B6 - B5) / (B6 + B5). This index leverages the shortwave infrared (Band 6) and near-infrared (Band 5) wavelengths to differentiate built-up areas from natural vegetation. By contrasting these spectral bands, NDBI effectively highlights urban and developed regions, making it a valuable tool for monitoring urbanization and land-use changes. The utilization of NDBI enhances the accuracy of spatial analysis in detecting anthropogenic impacts on the landscape. Thus, NDBI is a critical indicator in urban planning and environmental management studies.

The Soil-Adjusted Vegetation Index (SAVI) is calculated using the formula ((B5 - B4) / (B5 + B4 + 0.5)) * 1.5. This index incorporates a correction factor for soil brightness, which can influence vegetation reflectance measurements. By adjusting for soil effects, SAVI provides a more accurate assessment of vegetation health, especially in areas with sparse vegetation cover. Including the 0.5 constant and the multiplication factor of 1.5 enhances the index's sensitivity to vegetation variations, making it a robust tool for remote sensing applications. Consequently, SAVI is essential for precise vegetation analysis in diverse environmental conditions.

2.2.5 Spatio-temporal Analysis

Performing a temporal analysis to track changes over time using the calculated indices (NDVI, NDBI, and SAVI) from 2013, 2018, and 2024 is essential for detecting trends and changes in land cover, vegetation health, and urbanization. This longitudinal study enables the identification of patterns and shifts in the ecological and urban landscape, providing valuable insights into the impact of natural and anthropogenic factors. These indices can be observed by analyzing significant trends over multiple years, informing sustainable land management and urban planning decisions. This temporal analysis is critical for understanding and managing environmental and developmental changes.

Table 2. Spatio-temporal Analysis of NDBI, NDVI, and SAVI (2013, 2018, and 2024)

Model	Year	Min	Mid	Max
NDBI	2013	-0.87336683273314997	-0.57791237840576493	0.00086643534993369
NDBI	2018	-0.867453873157501	-0.57744201278639196	0.00086056931860867
NDBI	2024	-0.65607023239135698	-0.43035712424448902	0.0246747327544702
NDVI	2013	-0.0549353733658791	0.178161481188403	0.46901224390233998
NDVI	2018	-0.0944312512874603	0.16125981107590701	0.42468346605106899
NDVI	2024	0.24563761055469499	0.82956136025133598	0.94162753443554004
SAVI	2013	-0.0365268476307392	0.124497346713075	0.38138903820488101
SAVI	2018	-0.0680616721510887	0.11603026526669701	0.357123146609714
SAVI	2024	0.11382171511650099	0.49526625455371898	0.61603042533788699

Table 2 shows the spatio-temporal analysis of NDBI 2013, NDBI 2018, and NDBI 2024 in the Region of Interest (ROI) Kumo Island, North Halmahera Regency. The NDBI values for 2013, 2018, and 2024 demonstrate notable changes in the urbanization patterns on Kumo Island. In 2013, the NDBI ranged from a minimum of -0.8734 to a maximum of 0.0009, with a mid-value of -0.5779. By 2018, the range slightly adjusted, with values from -0.8675 to 0.0009 and a mid-point of -0.5774, indicating a consistent built-up area. However, in 2024, a significant shift is observed, with the NDBI ranging from -0.6561 to 0.0247 and a mid-value of -0.4304, suggesting increased urban development. These variations reflect the ongoing urbanization and land cover changes, emphasizing the importance of continuous monitoring for sustainable urban planning.

The NDVI values for 2013, 2018, and 2024 exhibit significant changes in vegetation health on Kumo Island. In 2013, the NDVI ranged from -0.0549 to 0.4690, with a mid-value of 0.1782, indicating moderate vegetation health. By 2018, the NDVI range shifted slightly from -0.0944 to 0.4247, with a mid-point of 0.1613, suggesting a slight decline in vegetation quality. However, in 2024, the NDVI values dramatically increased, ranging from 0.2456 to 0.9416, with a mid-value of 0.8296, reflecting significant improvement in vegetation health and density. These trends highlight the dynamic nature of vegetation cover and underscore the importance of continuous ecological monitoring to inform sustainable environmental management practices.

The SAVI values for 2013, 2018, and 2024 indicate notable shifts in soil-adjusted vegetation indices on Kumo Island. In 2013, the SAVI ranged from -0.0365 to 0.3814, with a mid-value of 0.1245, reflecting moderate vegetation density adjusted for soil brightness. By 2018, the SAVI values shifted from -0.0681 to 0.3571, with a mid-point of 0.1160, indicating a slight decrease in vegetation density. However, in 2024, the SAVI values significantly increased, ranging from 0.1138 to 0.6160, with a mid-value of 0.4953, demonstrating substantial improvement in vegetation cover and health. These trends underscore the importance of continuous monitoring and adaptive management strategies to sustain and enhance the region's ecological health.

2.2.6 Visualization and Mapping

The calculated raster data results based on the NDBI, NDVI, and SAVI models are visualized to facilitate comparative analysis that is aligned with the research objectives. This visualization allows for precisely representing different land cover types, vegetation health, and urbanization patterns. Comparing these visual outputs achieves a more comprehensive understanding of the spatial and temporal dynamics within the study area. The graphical representation of these indices enhances the clarity and accessibility of the data, making it a vital tool for practical analysis and decision-making. Therefore, visualizing these calculated models is essential for achieving the analytical goals.

The differences in NDVI, NDBI, and SAVI values are integrated with the calculated raster data from 2013, 2018, and 2024 to observe changes in vegetation, soil, and residential areas on Kumo Island, North Halmahera Regency, North

Maluku Province. This integration allows for a comprehensive analysis of land cover dynamics, highlighting significant trends and shifts in the ecological and urban landscape. Examining these temporal variations provides critical insights into the impacts of natural processes and human activities on the environment. Consequently, this analysis is instrumental in informing sustainable land management and urban planning strategies.

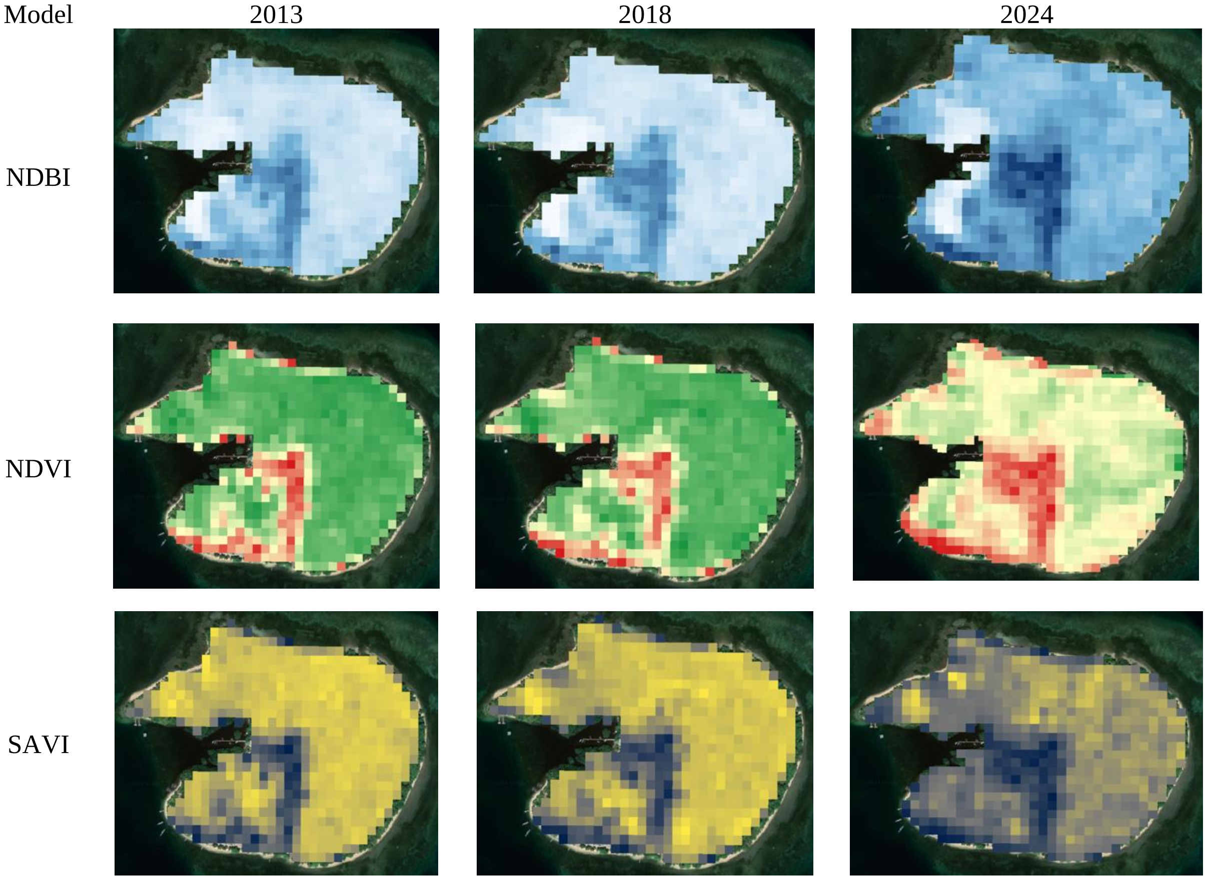

Figure 6. Spatio-temporal Analysis of NDBI, NDVI, and SAVI (2013, 2018, and 2024)

Figure 6 shows the visualization of NDBI, NDVI, and SAVI from 2013-2024. Visualization and mapping facilitate the comparative analysis of value and color changes based on the NDVI, NDBI, and SAVI models for Kumo Island, North Halmahera Regency, North Maluku Province. This approach allows for clearly identifying spatial and temporal variations in vegetation health, urbanization, and soil conditions. By visually comparing these indices, the analysis provides a detailed understanding of the environmental dynamics specific to Kumo Island. These visual representations' enhanced clarity and interpretability significantly aid in effective environmental monitoring and decision-making. Thus, visualization and mapping are crucial tools for achieving comprehensive analytical objectives.

2.2.7 Statistical Analysis

A statistical analysis will quantify the changes and trends observed in the indices, calculate mean values and standard deviations, and perform trend analysis over the specified years. The data sets for NDBI, NDVI, and SAVI from 2013, 2018, and 2024 are used for this purpose. For NDBI, the minimum values range from -0.8734 in 2013 to -0.6561 in 2024, the mid-values shift from -0.5779 to -0.4304, and the maximum values increase from 0.0009 to 0.0247. For NDVI, the minimum values range from -0.0549 in 2013 to 0.2456 in 2024, mid-values shift from 0.1782 to 0.8296, and maximum values increase from 0.4690 to 0.9416. Similarly, SAVI shows a shift in minimum values from -0.0365 in 2013 to 0.1138 in 2024, mid-values from 0.1245 to 0.4953, and maximum values from 0.3814 to 0.6160. These calculations and trend analyses highlight significant changes, providing critical insights into vegetation health, soil conditions, and urbanization trends. Understanding these trends is essential for informed decision-making and sustainable environmental management.

Visualization and mapping facilitate the comparative analysis of value and color changes, clearly representing spatial data. This process allows for practically identifying patterns and trends in various environmental indices, such as NDVI, NDBI, and SAVI. By using color-coded maps, differences in vegetation health, urbanization, and soil conditions become readily apparent, enabling more precise and informed analysis. Consequently, the enhanced visual clarity supports better decision-making and strategic planning in environmental management and urban development. Visualization thus plays a crucial role in interpreting complex data sets and communicating findings effectively.

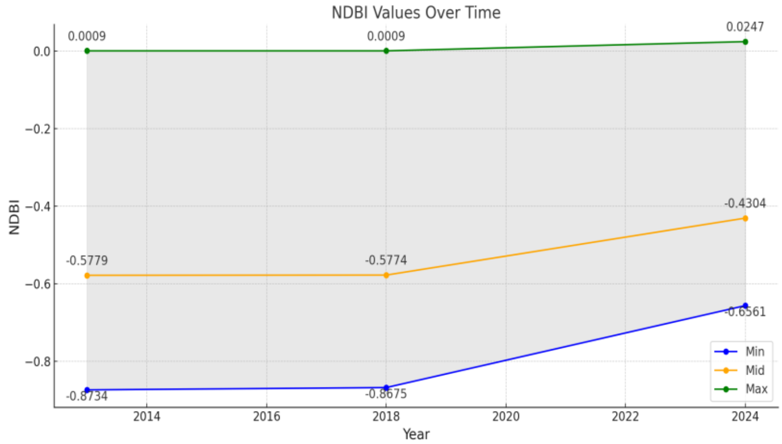

Figure 7. NDBI Values Over Time

Figure 7 shows the NDBI values over time. The NDBI values over time reveal significant changes in urbanization patterns. The minimum values increased from -0.8734 in 2013 to -0.8675 in 2018 and -0.6561 in 2024, reducing negative NDBI values. The mid values exhibit a similar trend, shifting from -0.5779 in 2013 to -0.5774 in 2018 and then to -0.4304 in 2024, suggesting gradual urban growth. The maximum values rise from 0.0009 in 2013 and 2018 to 0.0247 in 2024, reflecting an increase in built-up areas. These trends underscore the ongoing urban expansion and highlight the necessity for sustainable development planning to mitigate environmental impacts.

The minimum values increased from -0.8734 in 2013 to -0.8675 in 2018 and -0.6561 in 2024, indicating a reduction in negative NDBI values and a decrease in barren or undeveloped land. The mid values exhibit a similar trend, shifting from -0.5779 in 2013 to -0.5774 in 2018 and then to -0.4304 in 2024, suggesting gradual urban growth and an increase in developed areas. Furthermore, the maximum values rise from 0.0009 in 2013 and 2018 to 0.0247 in 2024, reflecting a noticeable increase in built-up areas. These trends underscore the ongoing urban development on Kumo Island, highlighting the need for sustainable planning and management to balance growth with ecological preservation.

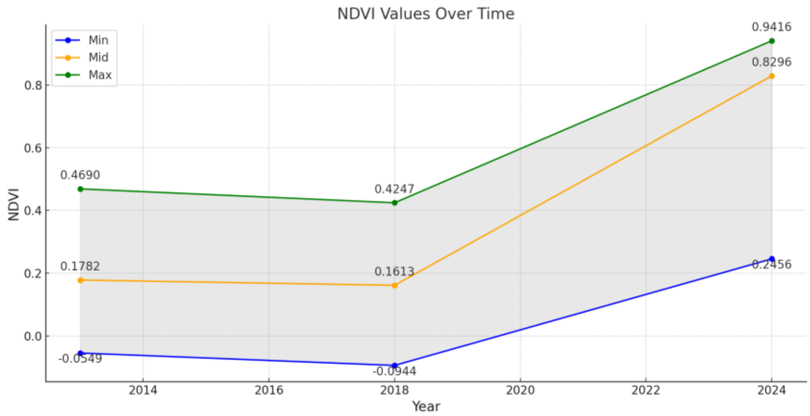

Figure 8. NDVI Values Over Time

Figure 8 shows the NDVI values over time. The NDVI values over time highlight significant fluctuations in vegetation health. The minimum values display a notable shift from -0.0549 in 2013 to -0.0944 in 2018 before rising to 0.2456 in 2024, indicating initial degradation followed by substantial recovery. The mid values reflect a similar pattern, decreasing from 0.1782 in 2013 to 0.1613 in 2018, then significantly increasing to 0.8296 in 2024, suggesting a dramatic improvement in vegetation density. The maximum values also show an upward trend, decreasing slightly from 0.4690 in 2013 to 0.4247 in 2018 and then rising sharply to 0.9416 in 2024. These trends underscore the dynamic nature of vegetation cover and emphasize the need for continuous ecological monitoring to support effective environmental management.

The minimum values display a notable shift from -0.0549 in 2013 to -0.0944 in 2018 before rising to 0.2456 in 2024, indicating initial degradation followed by substantial recovery. The mid values reflect a similar pattern, decreasing from 0.1782 in 2013 to 0.1613 in 2018, then significantly increasing to 0.8296 in 2024, suggesting a dramatic improvement in vegetation density. Additionally, the maximum values show an upward trend, decreasing slightly from 0.4690 in 2013 to 0.4247 in 2018 and then rising sharply to 0.9416 in 2024. These trends indicate a period of ecological stress followed by significant regrowth and highlight the importance of continuous monitoring and effective management strategies to ensure sustainable ecological recovery and resilience on Kumo Island.

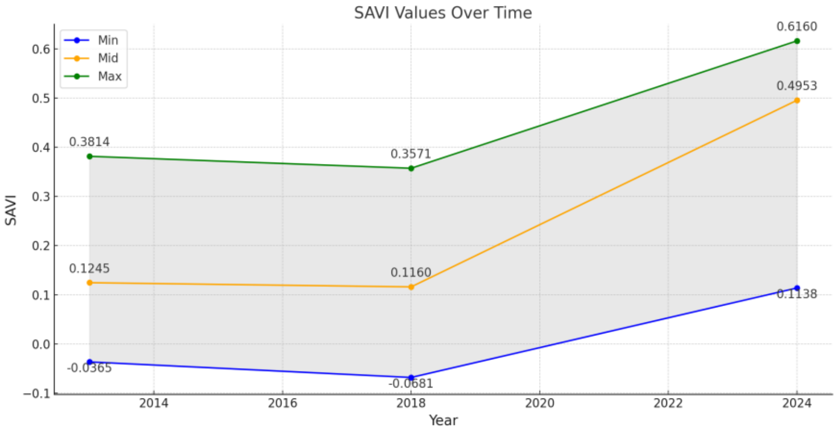

Figure 9. SAVI Values Over Time

Figure 9 shows the SAVI over time. The SAVI values over time reveal substantial changes in soil-adjusted vegetation conditions. The minimum values show a decline from -0.0365 in 2013 to -0.0681 in 2018, followed by a significant increase to 0.1138 in 2024, indicating initial soil and vegetation stress with subsequent recovery. The mid values reflect a slight decrease from 0.1245 in 2013 to 0.1160 in 2018, then rise sharply to 0.4953 in 2024, suggesting marked improvement in vegetation health. The maximum values illustrate a similar trend, decreasing from 0.3814 in 2013 to 0.3571 in 2018 and then increasing to 0.6160 in 2024. These trends highlight the dynamic interplay between soil and vegetation and underscore the importance of sustained monitoring for effective land management.

The minimum values show a decline from -0.0365 in 2013 to -0.0681 in 2018, followed by a significant increase to 0.1138 in 2024, indicating initial soil and vegetation stress with subsequent recovery. The mid values reflect a slight decrease from 0.1245 in 2013 to 0.1160 in 2018, then rise sharply to 0.4953 in 2024, suggesting marked improvement in vegetation health. Additionally, the maximum values illustrate a similar trend, decreasing from 0.3814 in 2013 to 0.3571 in 2018 and then increasing to 0.6160 in 2024. These patterns highlight the importance of sustained monitoring and adaptive management strategies to address environmental stresses and promote long-term ecological recovery on Kumo Island.

2.2.8 Interpretation and Reporting

Interpretation and reporting based on the data reveal significant trends and changes across various environmental indices from 2013 to 2024. The NDBI values indicate a decrease in negative values and an increase in maximum values, suggesting a gradual rise in urbanization over the years. Meanwhile, the NDVI values show an initial decline in vegetation health between 2013 and 2018, followed by a substantial improvement by 2024. Similarly, SAVI values reflect a consistent pattern of initial stress on vegetation and soil conditions, with marked recovery and growth by 2024. These findings highlight the dynamic interactions between urban development and environmental health, underscoring the importance of continuous monitoring and sustainable management practices to mitigate adverse impacts and promote ecological resilience.

Interpretation and reporting will be tailored to meet the data requirements for a comprehensive analysis of the existing vegetation and landscape conditions of Kumo Island, as well as residential settlements from 2013-2018 and 2018-2024. This approach ensures that the temporal changes in ecological and urban metrics are accurately captured, providing insights into environmental and infrastructural development dynamics. The study aims to identify significant trends and patterns that inform sustainable management practices by focusing on detailed data analysis. Consequently, this thorough interpretation and reporting process will support effective decision-making and strategic planning for the region's development.

2.2.9 Validation

The validation process, based on the processed data, is crucial for ensuring the accuracy and reliability of the analytical results. This involves cross-referencing the calculated indices with ground truth data to verify their correspondence with real-world conditions. By employing statistical techniques such as root mean square error (RMSE) and correlation coefficients, the validation aims to quantify the precision of the data. Such rigorous validation enhances the credibility of the findings and supports robust conclusions. Ultimately, this process ensures that the data-driven insights are dependable and can effectively inform environmental and urban planning decisions.

Validating the results using ground truth data or other high-resolution images is essential to ensure the accuracy of the analysis. This step involves comparing the remote sensing data and indices with actual on-the-ground measurements to verify their reliability. Ground truth validation helps identify and correct any discrepancies, thereby enhancing the precision of the remote sensing analysis. Consequently, incorporating ground truth data is a critical process that strengthens the credibility of the findings and supports informed decision-making based on accurate environmental assessments.

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 NDBI, NDVI, and SAVI indicate the model's accuracy over time. For NDBI, the RMSE values are 2019.1371 for the minimum, 2018.8668 for the mid, and 2018.3295 for the maximum, reflecting consistent error levels across different ranges. NDVI exhibits RMSE values of 2018.3060 for the minimum, 2017.9481 for the mid, and 2017.7261 for the maximum, suggesting slightly lower but consistent error rates. Similarly, SAVI shows RMSE values of 2018.3351 for the minimum, 2018.0927 for the mid, and 2017.8866 for the maximum, indicating a similar accuracy pattern. These RMSE values highlight the importance of precise calibration and validation to improve the reliability of environmental monitoring and analysis. Enhanced model accuracy is essential for effective decision-making and sustainable land management.

The correlation coefficients for NDBI, NDVI, and SAVI reveal significant insights into the relationships between these indices and temporal progression. The NDBI correlation coefficients are notably high, with values of 0.9016 for the minimum, 0.8923 for the mid, and 0.8909 for the maximum, indicating a strong positive relationship with time. Similarly, the NDVI correlation coefficients are also substantial, showing values of 0.8378 for the minimum, 0.8808 for the mid, and 0.8533 for the maximum. These values suggest a robust correlation between vegetation health and the years studied. The SAVI correlation coefficients, with values of 0.8056 for the minimum, 0.8820 for the mid, and 0.8493 for the maximum, further emphasize the strong association between soil-adjusted vegetation health and temporal changes. These high correlation coefficients underscore the importance of these indices in environmental monitoring, reflecting their reliability in tracking ecological and urban dynamics over time.

2.2.10 Application and Decision Making

Utilizing the findings from the analysis is imperative for informing decision-making processes related to sustainable land management, urban planning, and environmental conservation in Kumo Island and North Halmahera Regency. These insights provide a data-driven foundation for developing strategies that balance ecological preservation with urban development. By integrating remote sensing data into planning frameworks, stakeholders can make informed decisions that promote long-term sustainability and resilience. Consequently, applying these findings supports creating policies and initiatives that address the region's environmental and developmental needs.

Recommendations for decision-making processes for sustainable land management, urban planning, and environmental conservation in Kumo Island and North Halmahera Regency should be based on the calculated NDVI, NDBI, and SAVI data from 2013, 2018, and 2024. The analysis reveals significant trends in vegetation health, urbanization, and soil conditions, highlighting areas of improvement and concern. By integrating these insights into planning frameworks, stakeholders can develop strategies that promote ecological balance while accommodating urban growth. Implementing data-driven policies ensures that development efforts are environmentally sustainable and socio-economically beneficial. Consequently, leveraging this comprehensive data analysis is essential for informed and effective regional decision-making.

3. RESULT AND DISCUSSION

The discussion in this study is divided into two sections. First, it evaluates the performance of the NDVI, NDBI, and SAVI models in analyzing Kumo Island vegetation, soil, and built-up indices. This evaluation aims to determine the accuracy and reliability of these indices in capturing the land use characteristics of the area. Second, it analyzes landscape changes in the tourist destination, focusing on how these transformations impact the environment and local development. Understanding these changes is crucial for developing strategies that balance tourism growth with environmental sustainability. Consequently, these discussions provide comprehensive insights for effective land use planning and conservation efforts.

3.1 Performance Evaluation of NDVI, NDBI, and SAVI Models using Landsat 8/9 OLI from 2013-2024

Several key insights can be drawn based on evaluating NDVI, NDBI, and SAVI performance on Kumo Island in 2013. The NDBI values for 2013 range from -0.8734 to 0.0009, with a mid-value of -0.5779, indicating varying degrees of urbanization. The NDVI values span from -0.0549 to 0.4690, with a mid-value of 0.1782, reflecting the health and density of the vegetation. Similarly, the SAVI values range from -0.0365 to 0.3814, with a mid-value of 0.1245, highlighting the soil-adjusted vegetation index. These indices provide a comprehensive understanding of land cover and use, essential for informed decision-making in environmental management and urban planning. Therefore, the performance of these indices in 2013 underscores their utility in monitoring and analyzing landscape dynamics on Kumo Island.

NDBI 2013 NDVI 2013 SAVI 2013

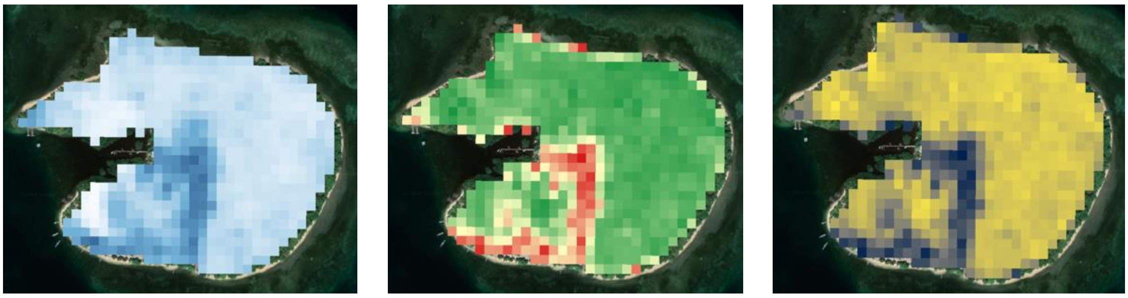

Figure 10. Result of the 2013 Raster Data Process

Figure 10 shows the result of the raster data process. The interpretation of the 2013 raster data processing for NDBI, NDVI, and SAVI provides significant insights into the land cover characteristics of Kumo Island. The NDBI analysis indicates a range of values highlighting urbanization levels, where lower values suggest minimal built-up areas. The NDVI data reflects varying vegetation health, with higher values denoting denser and healthier vegetation cover. The SAVI results adjust the vegetation index for soil brightness, presenting a nuanced view of vegetation health concerning soil conditions. These analyses collectively offer a comprehensive understanding of the island’s landscape in 2013, which is crucial for informing future land management and environmental conservation strategies. Consequently, these indices underscore their value in monitoring and assessing landscape dynamics over time.

Several key insights can be discerned when evaluating NDVI, NDBI, and SAVI performance on Kumo Island in 2018. The NDBI values in 2018 range from -0.8675 to 0.0009, with a mid-value of -0.5774, indicating the extent of urbanization and built-up areas. The NDVI values span from -0.0944 to 0.4247, with a mid-value of 0.1613, reflecting vegetation health and density changes. Similarly, the SAVI values range from -0.0681 to 0.3571, with a mid-value of 0.1160, highlighting the soil-adjusted vegetation index and its implications for soil and vegetation health. These indices collectively provide a comprehensive snapshot of land cover and use in 2018, which is essential for making informed environmental management and urban planning decisions. Therefore, the performance of these indices in 2018 underscores their utility in monitoring and analyzing landscape dynamics on Kumo Island.

NDBI 2018 NDVI 2018 SAVI 2018

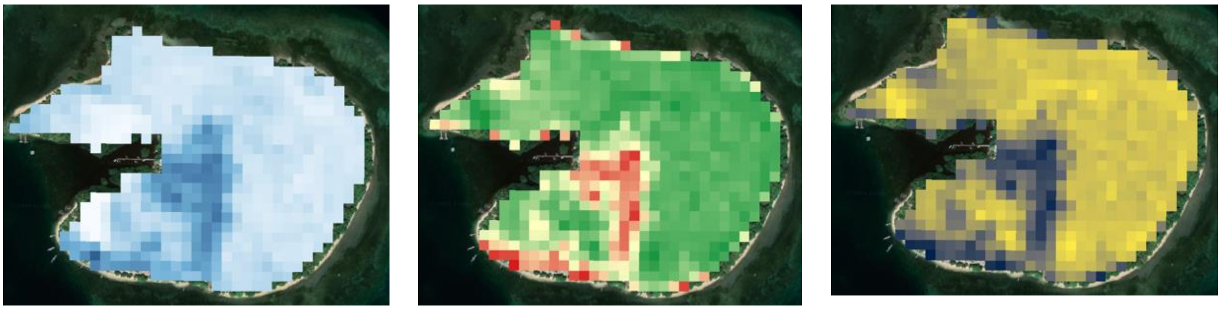

Figure 11. Result of the 2018 Raster Data Process

Figure 11 shows the result of the 2018 raster data process. In 2018, significant changes were observed in NDVI, NDBI, and SAVI values on Kumo Island. The NDVI values indicate variations in vegetation health, with some areas showing decreased vegetation density compared to previous years. The NDBI analysis reveals shifts in urbanization patterns, highlighting increased built-up areas. The SAVI values, adjusted for soil brightness, also reflect changes in vegetation health and soil conditions, indicating soil erosion or degradation areas. These changes underscore the dynamic nature of the island's landscape and the need for ongoing monitoring to inform sustainable land management and environmental conservation efforts. Consequently, understanding these variations is crucial for effective planning and mitigation strategies.

Several significant insights emerge in evaluating NDVI, NDBI, and SAVI performance on Kumo Island in 2024. The NDBI values 2024 range from -0.6561 to 0.0247, with a mid-value of -0.4304, indicating notable changes in urbanization and built-up areas. The NDVI values span from 0.2456 to 0.9416, with a mid-value of 0.8296, reflecting substantial improvements in vegetation health and density. Similarly, the SAVI values range from 0.1138 to 0.6160, with a mid-value of 0.4953, highlighting improvements in the soil-adjusted vegetation index. These indices collectively provide a detailed understanding of land cover and use in 2024, which is crucial for effective environmental management and urban planning. Therefore, the performance of these indices in 2024 underscores their continued utility in monitoring and analyzing landscape dynamics on Kumo Island.

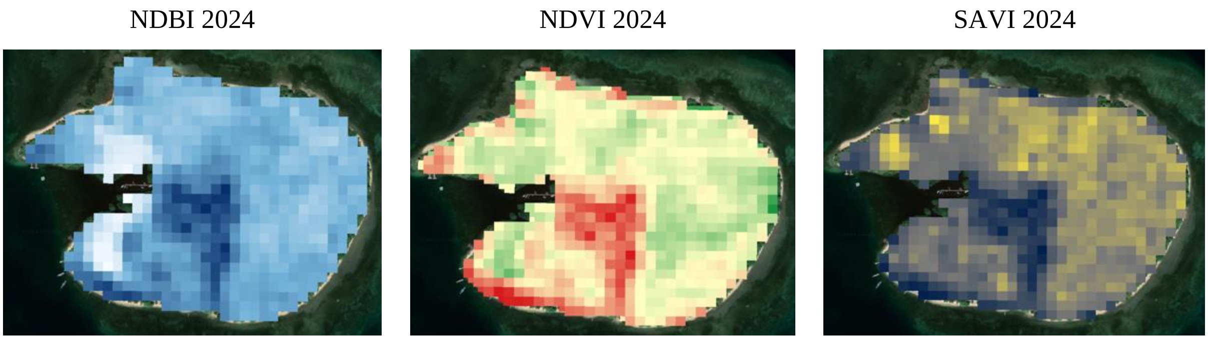

Figure 12. Result of the 2024 Raster Data Process

Figure 11 shows the result of the 2024 raster data process. In 2024, notable changes were observed in NDVI, NDBI, and SAVI values on Kumo Island. The NDVI values significantly increased, indicating substantial improvements in vegetation health and density across the island. Concurrently, the NDBI values showed a marked decrease in negative values, suggesting further urbanization and an increase in built-up areas. The SAVI values, which adjust for soil brightness, reflected enhanced vegetation health and soil conditions, pointing towards effective soil management practices. These transformations highlight the dynamic shifts in land use and environmental conditions, emphasizing the need for continuous monitoring and adaptive management strategies. Therefore, understanding these variations is crucial for developing sustainable land management and urban planning policies.

Based on the satellite image data processing results, decision-making for infrastructure development and land use on Kumo Island must prioritize sustainability. The analysis highlights significant changes in vegetation health, urbanization, and soil conditions, which are crucial factors to consider. Sustainable practices will ensure that development efforts do not compromise the island's ecological balance and long-term viability. Thus, incorporating sustainability into planning and policy frameworks is essential for the harmonious growth of Kumo Island, balancing development needs with environmental preservation. This approach will support resilient and sustainable land management strategies.

3.2 Discussion

Remote sensing is a crucial approach for spatial data processing to identify landscape changes related to vegetation, soil, buildings, and water bodies. This technique enables the comprehensive monitoring of environmental and infrastructural dynamics through the analysis of satellite imagery [49]. By capturing temporal and spatial variations, remote sensing provides valuable insights into the health and distribution of natural and man-made features [50]. Integrating this technology in landscape assessment is essential for informed environmental management and urban planning decision-making. Ultimately, remote sensing offers a reliable method for tracking and understanding complex landscape transformations.

Kumo Island in North Halmahera Regency is a popular domestic tourist destination, especially during weekends. Consequently, identifying and analyzing spatial data is crucial in informing infrastructure development policies on the island. Accurate spatial analysis aids in understanding the island's current landscape and predicting future changes, ensuring that development is both sustainable and beneficial for tourism. Effective infrastructure planning based on detailed spatial data will support the island's growth while preserving its natural and cultural attractions. Thus, integrating spatial analysis into policy-making is essential for the balanced development of Kumo Island.

The challenge of sustainability in tourist destination areas lies in balancing economic, socio-cultural, ecological, and other sectors. Development must ensure that economic growth does not compromise the destination's ecological integrity or cultural heritage [51]. Additionally, socio-cultural considerations must be integrated to maintain the community's identity and social cohesion [52]. Balancing these diverse aspects requires a holistic approach to planning and policy-making. Therefore, a sustainable development strategy that addresses these multifaceted challenges is crucial for the long-term viability of tourist destinations.

The findings of this study emphasize the critical importance of ecological sustainability in regional development decision-making. Ensuring that development projects do not compromise the ecological integrity of an area is essential for maintaining long-term environmental health. Integrating ecological considerations into planning helps balance human activities with the natural environment [53]. This approach not only preserves biodiversity but also enhances the resilience of ecosystems against environmental changes. Therefore, prioritizing ecological sustainability is vital for sustainable and responsible regional development.

Organizing areas for land use monitoring effectively manage environmental degradation issues resulting from tourism sector development. Implementing systematic monitoring practices allows for the early detection of ecological impacts and enforcing sustainable land use policies [54]. Additionally, continuous observation helps identify trends and patterns indicating potential degradation [55]. This proactive approach ensures that tourism development is balanced with environmental preservation. Consequently, effective land use monitoring is crucial for maintaining ecological integrity while supporting the growth of the tourism industry.

Future research recommendations emphasize the importance of spatial data-driven regional development decision-making through remote sensing. Utilizing high-resolution satellite imagery allows for precise monitoring and analysis of land use changes and environmental impacts. This approach facilitates data-driven planning, ensuring that developmental activities are sustainable and well-informed. Integrating remote sensing into the decision-making process enhances the accuracy and reliability of spatial data, leading to more effective and responsible regional development. Thus, advancing research in this field is essential for optimizing land use planning and environmental management strategies.

4. CONCLUSION

The conclusion of this research highlights the critical role of integrating spatial data and remote sensing technologies in regional development planning. Based on the analysis of NDVI, NDBI, and SAVI values from the years 2013, 2018, and 2024, significant insights into vegetation health, urbanization, and soil conditions on Kumo Island were obtained. The NDVI values showed changes from a minimum of -0.0549, a mid-value of 0.1782, and a maximum of 0.4690 in 2013 to a minimum of 0.2456, a mid-value of 0.8296, and a maximum of 0.9416 in 2024. Similarly, the NDBI values indicated a shift from a minimum of -0.8734, a mid-value of -0.5779, and a maximum of 0.0009 in 2013 to a minimum of -0.6561, a mid-value of -0.4304, and a maximum of 0.0247 in 2024. The SAVI values also demonstrated notable changes, with a minimum of -0.0365, a mid-value of 0.1245, and a maximum of 0.3814 in 2013, compared to a minimum of 0.1138, a mid-value of 0.4953, and a maximum of 0.6160 in 2024. These findings underscore the importance of ecological sustainability in decision-making processes, demonstrating how advanced spatial analysis can effectively monitor and manage land use changes. The performance of the NDVI, NDBI, and SAVI indices revealed their utility in assessing vegetation health, urbanization, and soil conditions. These indices are instrumental in identifying trends and informing sustainable development strategies. The research advocates for the continued use of remote sensing and spatial data to ensure balanced and informed regional development, emphasizing the necessity of sustainable practices to preserve ecological integrity while supporting socio-economic growth. Thus, integrating remote sensing into the decision-making process enhances the accuracy and reliability of spatial data, leading to more effective and responsible regional development.

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