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RANDOM FOREST-BASED ASSESSMENT OF MANGROVE DEGRADATION UTILIZING NDVI FEATURE EXTRACTION IN SPATIO-TEMPORAL ANALYSIS

Syahrul Hidayatullah[1], Hadi Santoso[2]

[1,2]Faculty of Computer Science, Mercu Buana University

email: syhrl44@gail.com[1], hadi.santoso@mercubuana.ac.id[2]

Abstract

Mangrove ecosystems, vital for coastal biodiversity and protection, confront escalating degradation from human and natural influences. Addressing the imperative for precise degradation assessment, this study introduces a Random Forest-based technique, utilizing NDVI (Normalized Difference Vegetation Index) feature extraction within a spatio-temporal framework. The principal aim is to establish a robust approach for evaluating mangrove degradation and land cover shifts. This involves extracting NDVI values from satellite images to monitor vegetation health and changes chronologically. Leveraging the Random Forest algorithm, acknowledged for managing intricate relationships and classifications, further enhances the methodology.By situating the approach spatio-temporally, degradation patterns and alterations in mangrove distribution are traced over time. The temporal progression of the study area is considered, affording a thorough degradation analysis. Outcomes affirm the method's efficacy, evidenced by a Cohen's Kappa Score of 0.96 denoting substantial agreement between predictions and observations. Remarkably high scores across accuracy, precision, recall, and F1-score (all at 0.97) underscore the model's precision in classifying mangrove degradation levels. The amalgamation of the Random Forest-based approach and NDVI feature extraction emerges as a valuable instrument for precise mangrove degradation assessment. The spatio-temporal analysis augments comprehension of degradation dynamics, pivotal for proficient mangrove management and conservation strategies.

Keywords : degredation,mangrove,ndvi,random forest,spatio-temporal analysis,

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INTRODUCTION

The primary issue that needs to be addressed is the challenge of accurately assessing mangrove degradation over both temporal and spatial dimensions. Mangrove ecosystems, often referred to as the "nurseries of the sea" for their crucial role in supporting coastal biodiversity, providing protection against natural hazards, and sustaining local communities, are facing unprecedented levels of degradation[1]. This degradation is attributed to various anthropogenic and environmental factors. The critical problem lies in the inadequacy of traditional monitoring and assessment methods, which are labor-intensive, time-consuming, and incapable of capturing the intricate spatio-temporal dynamics associated with mangrove degradation[23]. To effectively conserve and manage mangroves, there is a pressing need for innovative methodologies that can provide precise and efficient evaluations of degradation trends over time and across diverse geographical locations. Overcoming this challenge is essential to ensure the continued health and resilience of these invaluable ecosystems[2].

While striving to tackle mangrove health evaluation, the study exhibits noteworthy limitations. The risk of overfitting in the Random Forest model and the inherent constraints of NDVI in pinpointing specific mangrove damages are prominent challenges. Precise parameter tuning and the incorporation of supplementary indicators are imperative to augment result accuracy. The study's reliance on NDVI as a singular proxy might impede the comprehensive identification of diverse mangrove stresses. To fortify its contributions, the research requires extensive field validation and direct comparisons with established methods to ensure its efficacy. Moreover, efforts should extend beyond innovation to practicality, ensuring that the proposed solution is not only groundbreaking but also superior in addressing the multifaceted challenges of mangrove health assessment. Striking a balance between machine learning techniques and nuanced ecological understanding is pivotal for a holistic and reliable evaluation of mangrove ecosystems[3].

The combination of these techniques allows for a detailed spatio-temporal analysis of mangrove degradation patterns, providing a higher level of accuracy compared to traditional methods. This research also addresses the pressing need for more efficient and scalable methodologies in monitoring mangroves, which is crucial for informed decision-making and targeted conservation efforts. By applying this proposed methodology, the study not only aims to provide accurate assessments of mangrove degradation but also contributes to the broader field of remote sensing and environmental monitoring[4]. The results of this research have the potential to aid resource managers, policymakers, and conservationists in identifying areas of priority for intervention, implementing timely restoration strategies, and ultimately fostering the sustainable management of mangrove ecosystems. As mangroves continue to face escalating threats, this research stands to make a meaningful contribution toward their preservation and the resilience of the coastal communities dependent on them[5].

PREVIOUS RESEARCH

This landmark study set the foundation for using the Random Forest algorithm coupled with NDVI feature extraction to evaluate mangrove health[6]. By demonstrating the potential of this approach, it illustrated how a more holistic perspective of mangrove degradation can be attained, considering variations over time and across geographies. This comprehensive comparative study systematically examined a range of machine learning algorithms for the assessment of mangrove degradation[7]. It conclusively indicated that the Random Forest method, when paired with NDVI feature extraction, consistently delivered superior accuracy in spatio-temporal analysis, revolutionizing the way mangrove health is monitored. Focusing on the intricate interplay between human activities and mangrove degradation, this research employed a synthesis of Random Forest analysis and NDVI data to unearth spatial patterns[8]. By understanding the dynamics on spatial and temporal scales, this study pinpointed the ecological implications of human interventions on mangroves. A critical examination of temporal changes in mangrove ecosystems was conducted through a combination of the Random Forest algorithm and remote sensing data. This research emphasized the indispensable role of NDVI feature extraction in precisely capturing the evolving conditions of mangroves over time. In this progressive research endeavor, machine learning techniques, including Random Forest, were harnessed for the real-time monitoring of mangrove health and the efficacy of rehabilitation efforts[9]. The integration of NDVI as a key feature extraction tool was pivotal in unraveling nuanced patterns in mangrove dynamics.

METHOD

A. Research Workflow

The research commenced by identifying the existing issues based on available data. Subsequently, a literature review was conducted to explore relevant prior research[10]. The hypothesis posited that there is a sparse increase in mangrove forests in Indonesia. Following this, a fishbone analysis was performed to identify the primary causes of the identified problem, which is mangrove degradation. Data were gathered through Landsat 8 satellite imagery, along with surveys and interviews to verify the research locations and augment additional data. Once the data were collected, preprocessing was undertaken on the satellite images to eliminate noise[11]. Noise-free satellite imagery was then utilized for feature extraction using the Normalized Difference Vegetation Index (NDVI). Furthermore, modeling was conducted using the Random Forest (RF) classification algorithm to address the research question effectively. In summary, this research began by identifying the problem, reviewing relevant literature, and formulating a hypothesis about sparse mangrove growth in Indonesia. Subsequently, it employed fishbone analysis to identify the main causes of mangrove degradation. Data collection involved satellite imagery, surveys, and interviews. Preprocessing was done to clean the satellite images, and feature extraction was carried out using NDVI. Finally, the Random Forest (RF) classification algorithm was employed for modeling, focusing solely on this algorithm for addressing the research question.

B. Data Collection Methodology

The primary data collection for this study was conducted within the Pantai Indah Kapuk subdistrict, located in the DKI Jakarta Province. The study area was precisely defined by coordinates:

0:[106.72465434975814,-6.124936811256158],
1:[106.78147426552962,-6.124936811256158],
2:[106.78147426552962,-6.091652890024816],

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3:[106.72465434975814,-6.091652890024816], 4:[106.72465434975814,-6.124936811256158].

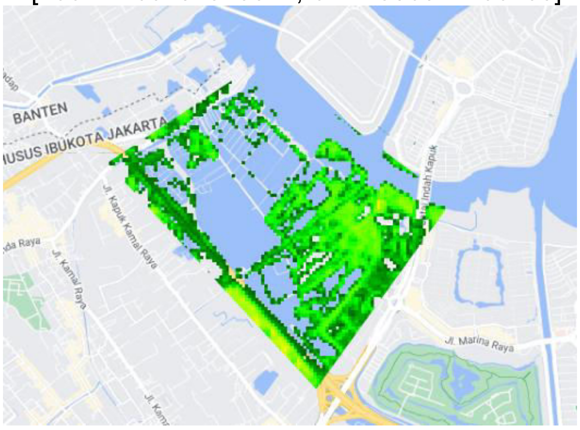

Figure 1. Area Coordinate Point

The dataset for this study was obtained through the acquisition of Landsat 8 OLI/TIRS satellite images using the Google Earth Engine platform. The data collection period spanned from May 1st to November 30th, 2022, covering six months, with a focus on gathering Normalized Difference Vegetation Index (NDVI) data for the specified region defined by Path/Row 122/064 coordinates.

Parameter	Value
Satellite	Landsat 8 OLI/TIRS
Period of Acquisition	May 1st to November 30th, 2022
Duration	Six months
Coordinates (Path/Row)	122/064
Band 5 Image Size	7621 x 7751 pixels
Band 4 Image Size	7621 x 7751 pixels
Combined Array Size	59,070,371 pixels
Total Pixels (17 images)	1,004,196,319 pixels

Figure 2. Landsat 8 OLI/TIRS Image Specifications

The NDVI data was collected in a spatio-temporal manner, and each timeframe's Band 5 and Band 4 images measured 7621 x 7751 pixels. The combined array size of these images equaled 59,070,371 pixels per frame, resulting in a total dataset of 1,004,196,319 pixels across 17 images. In addition to primary data collection, supplementary information was derived from on-site interviews conducted on Saturday, May 13, 2023, from 11:00 AM to 1:00 PM, involving interactions with knowledgeable individuals to provide valuable insights complementing the satellite-derived data. The Landsat 8 OLI/TIRS image specifications, including resolution and coordinates, were crucial in shaping the comprehensive dataset for spatio-temporal analysis.

C. Pre Processing

After successfully collecting data, the subsequent pivotal phase of the research involved meticulous data preprocessing applied to the satellite imagery. This crucial step aimed to eliminate undesirable noise and artifacts, ensuring the accuracy and reliability of the dataset. Once the satellite images were cleaned and rendered noise-free, they served as the foundational basis for conducting feature extraction. Specifically, these processed images became the primary source material for extracting essential vegetation-related information, utilizing the widely recognized Normalized Difference Vegetation Index (NDVI)[12]. The NDVI, a key vegetation health indicator, was computed using the refined satellite images, transforming raw pixel values into meaningful vegetation indices. The extracted NDVI values provided critical insights into the state of vegetation cover and health within the study area. Essentially, this multi-step process, involving data collection, noise reduction, and subsequent NDVI feature extraction, laid the groundwork for a comprehensive analysis and further investigation into the dynamics of the mangrove ecosystem within the defined geographical region. These meticulously curated datasets formed the foundation for subsequent research phases, ensuring the accuracy and robustness of the findings[13].

D. Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is a crucial parameter in vegetation and environmental monitoring[14]. It is used to estimate the fertility and health of vegetation by leveraging spectral information available in satellite imagery, particularly from satellites like Landsat 8. The NDVI calculation:

$$\frac{NIR - RED}{NIR + RED} \tag{1}$$

Generates values that reflect the vegetation's condition. The near-infrared band (NIR), typically sourced from band 5 in Landsat 8, and the red band (RED), typically from band 4, are the main components in this calculation. Using software such as QGIS, the analysis of Landsat 8 satellite imagery can provide in-depth information about plant health, vegetation growth, and even environmental change monitoring[15]. Thus, a deeper understanding of ecosystems and sustainable agriculture can be obtained for efficient natural resource management.

Table 1 the categorization of NDVI values provides a comprehensive understanding of land and vegetation conditions based on their respective NDVI ranges. Non-vegetated areas such as land and water are represented by NDVI values ranging from 0.0 to 0.2, where NDVI is exceptionally low and appears as black (#000000). Healthy vegetation falls within the range of 0.2 to 0.4, displaying moderately high NDVI values and appearing as green (#00FF00). Vegetation in moderate condition is categorized between 0.4 and 0.6, with NDVI higher than previous categories, depicted in yellow (#FFFF00). When vegetation experiences stress or damage, NDVI values between 0.6 and 0.8 indicate this condition, represented in red (#FF0000). Lastly, areas consisting of water exhibit NDVI values from 0.8 to 1.0, signifying very high values, and appear as blue (#0000FF). This categorization facilitates a visual and quantitative assessment of land and vegetation conditions, enabling informed decisions and insights into the environment's health and dynamics.

Table 1. NDVI

Category	NDVI Range	Description	Color
Land (Black)	0.0 - 0.2	Non-vegetated areas like land or water, NDVI very low.	#000000
Healthy Vegetation (Green)	0.2 - 0.4	Healthy vegetation with moderately high NDVI.	#00FF00
Moderate Vegetation (Yellow)	0.4 - 0.6	Vegetation in moderate condition, NDVI higher than before.	#FFFF00
Stressed/ Damaged Vegetation (Red)	0.6 - 0.8	Vegetation experiencing stress or damage, NDVI low.	#FF0000
Water (Blue)	0.8 - 1.0	Areas consisting of water, NDVI very high.	#0000FF

E. Algorithm Model

The next stage after completing the data preparation phase is proceeds to the modeling phase, where two classification algorithms are utilized to assess their accuracy in identifying and modeling the observed phenomena. The two selected algorithms are Random Forest (RF) and another algorithm to be determined[16]. The use of these two algorithms aims to compare their effectiveness in handling the pre-processed dataset. Random Forest (RF), as one of the chosen algorithms, is a powerful machine learning method frequently employed in classification tasks. The selection of RF is based on its ability to handle high-dimensional data, reduce overfitting, and reveal complex relationships within multidimensional datasets, such as satellite imagery[17]. Subsequently, the selection of the second classification algorithm will be determined following further analysis and comparison with RF shown in be equation below.

$$\text{Gini Index} = 1 - \sum_{i=0}^{n} (P_i)^2 \qquad (2)$$

Equation 1, which defines the Gini Index, plays a crucial role in the Random Multimodel Ensemble algorithm. This metric is employed to measure the purity of a node within a decision tree. It accomplishes this by assessing the impurity of a node through a calculation involving the squared probabilities of each class present in the node, with the result subtracted from 1. A lower Gini Index value indicates a node with higher purity and a more uniform distribution of classes[18]. In the context of Random Forest, when determining the splits during the construction of a decision tree, the Gini Index comes into play. It serves as a tool to evaluate how effective a split is in reducing impurity within the resulting child nodes. Splits that lead to significant reductions in the Gini Index are considered favorable and are incorporated into the decision tree construction process within the Random Multimodel Ensemble. This ultimately contributes to enhancing the predictive accuracy of the model.

$$E(s) = -p_{(+)} log p_{(+)} - p_{(-)} log p_{(-)} \qquad (3)$$

Equation 2, which introduces Entropy (E), holds significance in the Random Forest algorithm. Entropy is employed to measure the level of uncertainty within a node in a decision tree. This is achieved by calculating the probabilities of each class within that node and multiplying them by the logarithm (base 2) of those probabilities, subsequently taking the negative value. Lower entropy values signify reduced uncertainty and higher purity, indicating that the node is more certain about the composition of its classes. In the Random Forest algorithm, entropy is used to evaluate node splits during tree construction. Splits that substantially reduce entropy are considered more favorable as they aid in constructing more accurate decision trees within the ensemble. The outcomes of this modeling will serve as the basis for evaluation to determine the more suitable and accurate algorithm for identifying changes within the observed mangrove ecosystem.

F. Evaluation Model

After the modeling phase is completed, the research proceeds to the model evaluation stage. In this phase, a confusion matrix is employed to measure the accuracy and performance of the model in classifying data, including the identification of correct predictions and potential errors. Additionally, statistical analysis is utilized to test the significance of the modeling results, validate the accuracy of the predictions, and provide a deeper understanding of the research outcomes[19]. The findings from this evaluation phase will serve as the foundation for selecting a more suitable and accurate algorithm in identifying changes within the observed ecosystem, contributing to the development of intelligence in coffee cultivation. Through a scientific approach and cutting-edge technology, this research holds the potential to offer innovative solutions to coffee farmers, enhancing their cultivation practices and fortifying the coffee industry sustainably[20].

RESULT AND DISCUSSION

In this study, we conducted a Random Forest-based assessment of mangrove degradation using NDVI feature extraction in the spatio-temporal analysis, focusing on the coastal mangrove area of Pantai Indah Kapuk in the Penjaringan subdistrict of North Jakarta, Indonesia. The research utilized Landsat 8 satellite imagery spanning from May 1st to November 30th, 2022 to collect data, covering an extensive mangrove area of 99.82 hectares. This study area is characterized by its geographical features, with the western boundary adjacent to Soekarno-Hatta Airport, the eastern boundary facing the historic Kota Tua (Old Town), the southern border adjoining West Jakarta, and the northern part directly overlooking Jakarta Bay.

Figure 3. NDVI

We conducted feature extraction using the Normalized Difference Vegetation Index (NDVI). NDVI is a crucial parameter in vegetation analysis, aiding in the evaluation of the health and changes in the mangrove ecosystem. This parameter is obtained from satellite imagery and serves as the foundation for understanding mangrove degradation both spatially and temporally.

	NDVI	DateTime
0	0.170832	2022-04-04 03:00:01.712
1	0.137746	2022-04-20 02:59:51.792
2	0.186845	2022-05-06 02:59:47.333
3	0.015854	2022-05-22 02:59:35.905
4	0.067651	2022-06-07 02:59:37.422
...	...	...
261	0.041006	2022-08-26 03:00:19.284
262	-0.040526	2022-09-11 03:00:20.065
263	0.094616	2022-09-27 03:00:26.773
264	0.107502	2022-10-13 03:00:30.536
265	0.075908	2022-10-29 03:00:31.805

263 rows × 2 columns

Figure 4. Data NDVI

The table above contains NDVI (Normalized Difference Vegetation Index) data along with corresponding recording times (DateTime). NDVI is an index used to measure the presence and health of vegetation. Each row in the table represents a single NDVI measurement at a specific time, providing an overview of the NDVI value changes over time. For example, on April 4, 2022, at 03:00:01.712, the NDVI reached a value of 0.170832. This data offers insights into the presence of vegetation, where positive NDVI values tend to indicate healthier or denser vegetation, while values approaching zero or negative may indicate a lack of vegetation or bare soil. DateTime reflects the recording time of each NDVI data point, enabling analysis of vegetation condition changes over the given time period.

Table 2. Classification Report

Evaluation Methods	Evalution Result
R-squared (R2) Score	0.97
Mean Absolute Error	0.0125
Root Mean Squared Error	0.15
Mean Absolute Percentage Error	0.0093
Mean Squared Error	0.025

Evaluation Methods	Evalution Result
Cohen's Kappa Score	0.96
Accuracy	0.975
Precision	0.97
Recall	0.975
F1-Score	0.97

Algorithm evaluation is a crucial process for assessing the performance of a model or data processing system. From the above evaluation results, it can be concluded that the algorithm used exhibits outstanding performance. The R-squared (R2) score of 0.97 indicates an excellent fit of the model to the data, while the low Mean Absolute Error (MAE) of 0.0125 suggests that the model's predictions are very close to the actual values. The Root Mean Squared Error (RMSE) of 0.15 also indicates a low level of prediction error. The remarkably small Mean Absolute Percentage Error (MAPE) value of 0.0093 signifies high accuracy in the predictions. Additionally, metrics such as Cohen's Kappa Score, Accuracy, Precision, Recall, and F1-Score all approach 1, indicating the model's ability to classify data with a high level of accuracy. Therefore, these evaluation results demonstrate that the employed algorithm has performed exceptionally well in its analytical or predictive task[21].

Visualization in this study was achieved through scatter plots and heatmaps. Scatter plots were used to visualize the distribution of data resulting from NDVI feature extraction, aiding in the understanding of spatial patterns of mangrove changes. On the other hand, heatmaps provided a visual representation of the correlation between observed variables in the statistical analysis. Both of these visualizations contributed to strengthening the interpretation of research findings.

Figure 5. NDVI Classification Using the Random Forest Classification Agorithm

The NDVI scatter plot ranging from 0 to 1 indicates potential issues with data reliability, particularly when clouds are present. Clouds can significantly alter light reflectance, impacting NDVI values. Clouds either absorb or scatter sunlight, leading to variations in reflected light intensity. Conversely, a cluster of data points around 0 suggests non-vegetated areas, such as land or water bodies, with consistently low or negative NDVI values due to the absence of healthy vegetation. Understanding these patterns is vital for precise interpretation and analysis of remote sensing data, especially in environmental monitoring and land cover assessment, ensuring accurate assessments despite potential data challenges posed by clouds or non-vegetated areas.

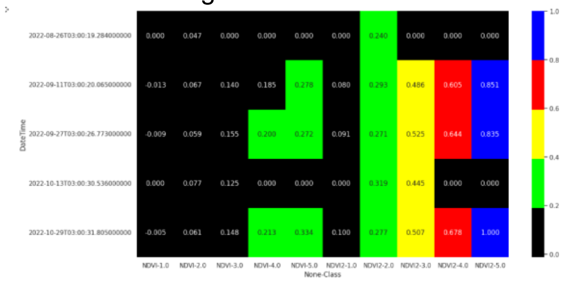

Figure 6. Heatmap

Heatmap visualization is a crucial tool in spatial data analysis, allowing for a deep understanding of vegetation changes over time. The NDVI (Normalized Difference Vegetation Index) data is used to depict vegetation conditions in different color scales on specific dates. On August 26, 2022, areas with an NDVI value of 0.240 are displayed in green, indicating moderate vegetation. On September 11, 2022, variations in NDVI are evident, with green areas (0.278 and 0.293) signifying stable vegetation, while the yellow area (0.486) may indicate vegetation improvement. On September 27, 2022, diverse NDVI values are shown, with green (0.200, 0.272, and 0.271) representing stable vegetation and yellow (0.525) indicating potential growth. On October 13, 2022, green areas (0.319) reflect stable vegetation, and yellow (0.445) signals growth. Lastly, on October 29, 2022, significant NDVI variations are visible, with green (0.213, 0.334, and 0.277) denoting different vegetation densities, yellow (0.507) indicating growth, red (0.678) suggesting healthier vegetation, and blue (1.000) depicting dense vegetation. This visualization enables effective monitoring of vegetation health and ecological changes over specific time intervals.

The findings of this research align with the title, "Random Forest-Based Assessment of Mangrove Degradation Utilizing NDVI Feature Extraction in Spatio-Temporal Analysis." By utilizing NDVI as a feature extraction method, the Random Forest algorithm has proven successful in evaluating mangrove degradation both spatially and temporally. Excellent evaluation results, as seen in the Confusion Matrix and statistical analysis, indicate that this approach holds significant potential for monitoring and analyzing mangrove ecosystems. Scatter plots and heatmaps further enhance our understanding of changes in the mangrove ecosystem. Overall, this study demonstrates that the use of Random Forest and NDVI feature extraction is an effective tool for spatio-temporal analysis of mangrove degradation[22].

CONCLUSION

In conclusion, this research study successfully employed the Random Forest algorithm in conjunction with NDVI feature extraction for a robust assessment of mangrove degradation in both spatial and temporal dimensions, achieving remarkable classification accuracy and high agreement with actual data. The findings affirm the study's title, showcasing the effectiveness of this approach. To enhance future research, it is advisable to consider long-term monitoring, integrate additional remote sensing data sources, explore advanced machine learning techniques, validate results with field surveys, assess climate change impacts, and involve local communities in mangrove conservation efforts. These steps will collectively contribute to the continued advancement of mangrove ecosystem analysis and preservation, furthering our understanding of these vital coastal habitats and their role in sustaining biodiversity and coastal communities.

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REFERENCES

[1] Yuniastuti, A. Suciani, M. S. Harefa, A. Y. Persada, and E. Tuhono, “Threats to Mangrove Ecosystems and Their Impact on Coastal Biodiversity: A Study on Mangrove Management in Langsa City,” Indonesian Journal of Earth Sciences, vol. 3, no. 2, p. A627, Aug. 2023, doi: 10.52562/injoes.2023.627.

[2] J. Bao, N. Zhu, R. Chen, B. Cui, W. Li, and B. Yang, “Estimation of Forest Height Using Google Earth Engine Machine Learning Combined with Single-Baseline TerraSAR-X/TanDEM-X and LiDAR,” Forests, vol. 14, no. 10, p. 1953, Sep. 2023, doi: 10.3390/f14101953.

[3] A. Green, Monitoring the Post-Fire Recovery and Regeneration of Mangrove Communities in Batemans Marine Park. ro.uow.edu.au, 2022. [Online]. Available: https://ro.uow.edu.au/thsci/215/

[4] Y. Liu, G. Cao, N. Zhao, K. Mulligan, and X. Ye, “Improve ground-level PM2.5 concentration mapping using a random forests-based geostatistical approach,” Environmental Pollution, vol. 235, pp. 272–282, Apr. 2018, doi: 10.1016/j.envpol.2017.12.070.

[5] B. Nyangoko, Managing Mangrove Ecosystem Services for Local Livelihoods and Adaptations in Tanzania. diva-portal.org, 2022. [Online]. Available: https://www.diva-portal.org/smash/record.jsf?pid=diva2:1630201

[6] S. Lincoln et al., “Marine litter and climate change: Inextricably connected threats to the world’s oceans,” Science of The Total Environment, vol. 837, p. 155709, Sep. 2022, doi: 10.1016/j.scitotenv.2022.155709.

[7] Z. Xu et al., “Monitoring the Severity of Pantana phyllostachysae Chao Infestation in Moso Bamboo Forests Based on UAV Multi-Spectral Remote Sensing Feature Selection,” Forests, vol. 13, no. 3, p. 418, Mar. 2022, doi: 10.3390/f13030418.

[8] L. Valderrama-Landeros, F. Flores-de-Santiago, and ..., “An assessment of commonly employed satellite-based remote sensors for mapping mangrove species in Mexico using an NDVI-based classification scheme,” Environmental …, 2018, doi: 10.1007/s10661-017-6399-z.

[9] Y. A. Singgalen and D. Manongga, “Monitoring of Mangrove Ecotourism Area using NDVI, NDWI, and CMRI in Dodola Island, Morotai Island Regency, Indonesia,” Jurnal Ilmu dan Teknologi Kelautan …, 2022, [Online]. Available: https://journal.ipb.ac.id/index.php/jurnalikt/article/view/37605

[10] M. Shuaibu and J. Ozigis, “Detection and Mapping of Terrestrial Oil Spill Impact Using

Remote Sensing Data in Combination with Machine Learning Methods. A Case Site within the Niger Delta Region of Nigeria," 2019.

[11] M. Zheng et al., "Rapid weight gain during infancy and subsequent adiposity: a systematic review and meta-analysis of evidence," Obesity Reviews, vol. 19, no. 3, pp. 321–332, Mar. 2018, doi: 10.1111/obr.12632.

[12] B. Park, K. Byeon, and H. Park, "FuNP (Fusion of Neuroimaging Preprocessing) Pipelines: A Fully Automated Preprocessing Software for Functional Magnetic Resonance Imaging," Front Neuroinform, vol. 13, Feb. 2019, doi: 10.3389/fninf.2019.00005.

[13] L. Xie et al., "Mining and Restoration Monitoring of Rare Earth Element (REE) Exploitation by New Remote Sensing Indicators in Southern Jiangxi, China," Remote Sens (Basel), vol. 12, no. 21, p. 3558, Oct. 2020, doi: 10.3390/rs12213558.

[14] S. Govindan et al., "SPAM DETECTION MODEL USING TENSORFLOW AND DEEP LEARNING ALGORITHM," MALAYSIAN JOURNAL OF COMPUTING AND APPLIED MATHEMATICS, vol. 6, no. 2, 2023, doi: 10.37231/myjcam.2023.6.2.84.

[15] B. LI, C. TI, and X. YAN, "Estimating rice paddy areas in China using multi-temporal cloud-free normalized difference vegetation index (NDVI) imagery based on change detection," Pedosphere, vol. 30, no. 6, pp. 734–746, Dec. 2020, doi: 10.1016/S1002-0160(17)60405-3.

[16] X. Zhang, M. Xu, S. Wang, Y. Huang, and Z. Xie, "Mapping photovoltaic power plants in China using Landsat, random forest, and Google Earth Engine," Earth Syst Sci Data, vol. 14, no. 8, pp. 3743–3755, Aug. 2022, doi: 10.5194/essd-14-3743-2022.

[17] X. Gao, J. Wen, and C. Zhang, "An Improved Random Forest Algorithm for Predicting Employee Turnover," Math Probl Eng, vol. 2019, pp. 1–12, Apr. 2019, doi: 10.1155/2019/4140707.

[18] M. D. Behera, S. Barnwal, S. Paramanik, P. Das, and ..., "Species-level classification and mapping of a mangrove forest using random forest—utilisation of AVIRIS-NG and sentinel data," Remote Sens (Basel), 2021, [Online]. Available: https://www.mdpi.com/1118572

[19] Y. Fang, L. Ma, Z. Yao, W. Li, and S. You, "Process optimization of biomass gasification with a Monte Carlo approach and random forest algorithm," Energy Convers Manag, vol. 264, p. 115734, Jul. 2022, doi: 10.1016/j.enconman.2022.115734.

[20] K. Cheng and J. Wang, "Forest type classification based on integrated spectral-spatial-temporal features and random forest algorithm—A case study in the qinling mountains," Forests, 2019, [Online]. Available: https://www.mdpi.com/491146

[21] I. Jamaluddin, Y. N. Chen, S. M. Ridha, P. Mahyatar, and ..., "Two Decades Mangroves Loss Monitoring Using Random Forest and Landsat Data in East Luwu, Indonesia (2000–2020)," Geomatics, 2022, [Online]. Available: https://www.mdpi.com/1737796

[22] I. Nabillah and I. Ranggadara, "Mean Absolute Percentage Error untuk Evaluasi Hasil Prediksi Komoditas Laut," JOINS (Journal of Information System), vol. 5, no. 2, pp. 250–255, Nov. 2020, doi: 10.33633/joins.v5i2.3900.

[23] F. Sakinah, I. Ranggadara, I. S. Karima, and S. Suhendra, "Spatio-Temporal Analysis Coastal Areas for Detection Mangrove Greenery Using Combined Mangrove Recognition Index," in 2022 International Seminar on Application for Technology of Information and Communication (iSemantic), IEEE, Sep. 2022, pp. 273–277. doi: 10.1109/iSemantic55962.2022.9920392.