A COMPARATIVE ANALYSIS OF MACHINE LEARNING AND INDEX-BASED APPROACH TO MANGROVE EXTENT MAPPING

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ABSTRACT: Mangroves are vital coastal ecosystems, playing a crucial role in ecological services and biodiversity support. However, these areas have experienced a decline in recent decades due to anthropogenic influences. Timely and accurate mapping of mangrove forests is essential for effective conservation and management. Remote sensing methods, including the Mangrove Vegetation Index (MVI), have been widely used for this purpose. However, MVI's reliance on varying threshold values for different sites can lead to inconsistencies and misclassifications in larger regions. To address this issue, this study proposes machine learning techniques for mangrove detection, utilizing MVI as an input, and aims to eliminate the need for site-specific threshold determination. The approach combines Sentinel-2 bands, MVI, and the Normalized Difference Vegetation Index (NDVI) as inputs in supervised classification methods such as Classification and Regression Trees (CART), Naïve Bayes (NB), Random Forest (RF), and Support Vector Machine (SVM). A comparative analysis of the results was conducted to assess the accuracy of the predictions against those obtained solely using the MVI. The results reveal significant improvement in mangrove prediction accuracy, particularly when the combination of Sentinel-2 bands and MVI is classified using SVM. These findings underscore the efficacy of machine learning (ML) techniques in enhancing mangrove mapping accuracy. Overall, this study demonstrates the potential of employing ML approaches to address the challenges encountered in index-based mangrove mapping. By incorporating additional inputs and utilizing advanced classification methods, the study contributes to improving the accuracy and efficiency of mangrove extent mapping. Effective mapping is crucial in supporting conservation and management initiatives aimed at preserving these invaluable coastal ecosystems.

1. INTRODUCTION

The Philippines' mangrove ecosystems are crucial for the country's ecological richness and cultural heritage. These ecosystems serve as sanctuaries for various marine and terrestrial species, including economically important fish and crustaceans. Additionally, mangroves act as natural barriers against typhoons and rising sea levels. However, human activities such as deforestation, land conversion, and aquaculture expansion have led to the decline of mangrove forests in the Philippines. This degradation poses a significant threat to the ecological integrity of these ecosystems and the livelihoods of communities dependent on them (Goldberg et al., 2020).

Effective conservation and management of mangrove ecosystems necessitate accurate and timely information on their extent and condition. Remote sensing techniques have emerged as indispensable tools for monitoring and mapping mangroves over large areas (Kuenzer et al., 2011). Among these techniques, the Mangrove Vegetation Index (MVI) has gained considerable attention as an index-based approach for mangrove extent mapping (Baloloy et al., 2020). The MVI, calculated from satellite imagery, uses a threshold value to distinguish mangrove vegetation from other land cover types based on spectral reflectance properties. While MVI has proven effective in many cases, its reliance on site-specific threshold values presents a challenge (Neri et al., 2021). These thresholds can vary significantly across different regions due to factors such as environmental conditions, sensor characteristics, and image acquisition dates, leading to inconsistencies and misclassifications.

To address this challenge, this research paper explores the integration of machine learning techniques into the process of mangrove mapping. Machine learning offers the potential to eliminate the need for site-specific threshold determination and enhance mapping accuracy by utilizing a combination of spectral bands, including the MVI, and other vegetation indices such as the Normalized Difference Vegetation Index (NDVI). The study employs a range of supervised classification methods, namely Classification and Regression Trees (CART), Random Forest (RF), Naïve Bayes (NB), and Support Vector Machine (SVM) for mangrove classification. A comparative analysis of the results assesses the accuracy of predictions against those obtained using the traditional MVI-based approach.

2. STUDY AREA AND DATA

2.1 Study area

Located between Mainland Luzon and Palawan, Mindoro Island is renowned for its ecological diversity and critical coastal ecosystems. The island's geographic positioning along the Verde Island Passage, often dubbed the "Center of the Center of Marine Biodiversity," (Carpenter & Springer, 2005) highlights its significance in terms of marine and terrestrial biodiversity. This makes it a vital region for conservation efforts, necessitating accurate and up-to-date mangrove extent mapping.

This study is set on the mangrove areas along the northern coast of Oriental Mindoro, which encompasses the municipalities of Puerto Galera, San Teodoro, Baco, Calapan, and Naujan (Figure 1). These municipalities were chosen as most of the mangroves in the northern Oriental Mindoro can be found here (Alcanices, 2017). With Calapan being the Capital of the province and Puerto Galera a busy tourist destination, these areas face increasing pressures from urbanization and tourism, making accurate and real-time mapping of natural resources essential for conservation and sustainable development planning.

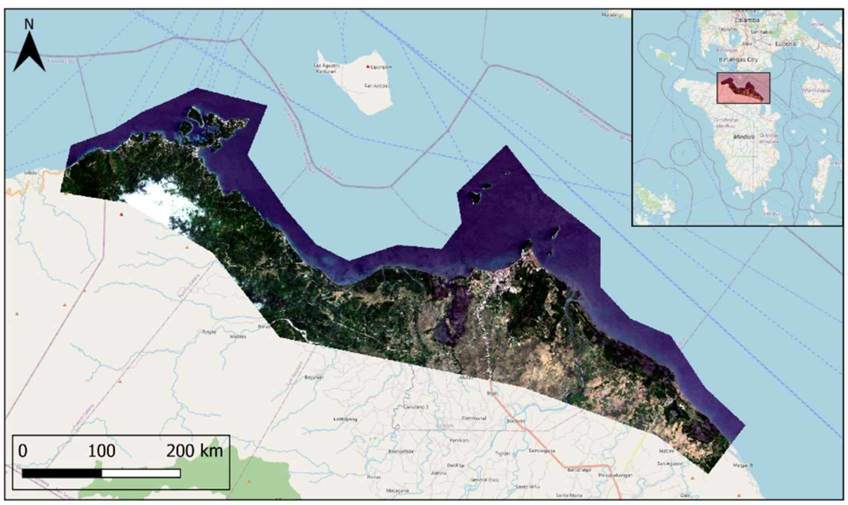

Figure 1. Mosaic Sentinel-2 image (2020-2023) covering the coastal areas of Puerto Galera, San Teodoro, Baco, Calapan, and Naujan.

2.2 Image dataset

The Copernicus Sentinel-2 mission is a constellation of two sun-synchronous polar-orbiting satellites, Sentinel-2A and Sentinel-2B. With a revisit time of 5 days, Sentinel-2 is widely used for land and maritime monitoring, as well as emergency management. Its Multispectral Instrument (MSI) samples 13 spectral bands encompassing visible, near-infrared, and shortwave infrared regions and is available in different levels of pre-processing. This study utilizes Sentinel-2 Level-2A images which are atmospherically corrected Surface Reflectance (SR) products.

2.3 Data Access and Processing

The Sentinel-2 Level-2A images are accessed via Google Earth Engine (GEE). GEE's publicly accessible data catalog comprises a diverse array of Earth science raster datasets that can be seamlessly imported into the script environment. All data processing pertinent to this research is exclusively executed within the GEE environment.

3. METHODS

The general methodology is shown in the flowchart in Figure 2.

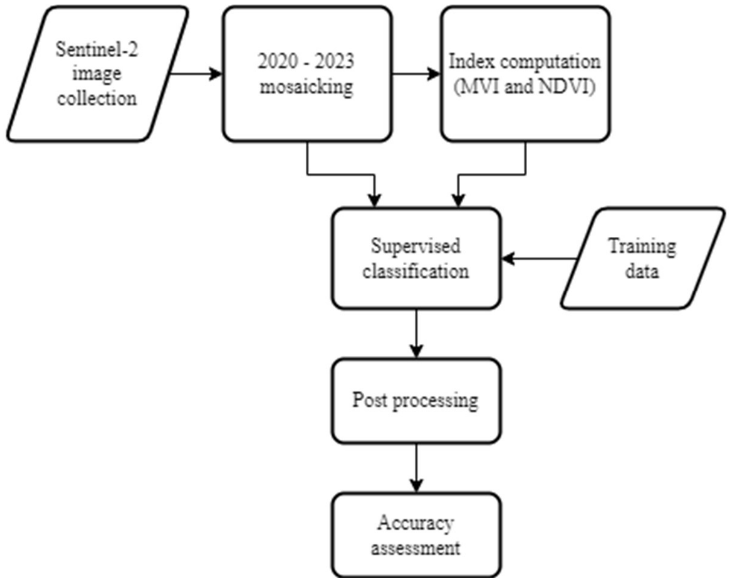

Figure 2. Workflow used to predict mangroves. The mosaicked Sentinel-2 image, NDVI, and MVI bands are used as inputs to supervised classifying methods.

3.1 Image collection and mosaicking

The Sentinel-2 Level-2A imagery for the study site was accessed via GEE and filtered for the period from January 2020 to July 2023. Inclusion in the image collection was limited to images with less than 10% cloud cover. For the creation of the mosaic, the median value of each pixel was computed from the image collection. This calculation procedure, relying on pixel-wise medians, was utilized to create a mosaic that reduces cloud presence, resulting in an almost unobstructed and seamless representation of the study site. This ensures the fidelity and utility of the resultant composite image.

3.2 Index computation

From the mosaic Sentinel-2 Level-2A image, the Normalized Difference Vegetation Index (NDVI) and the Mangrove Vegetation Index (MVI) were computed. These indices are fundamental inputs for the subsequent supervised classification algorithms.

The Normalized Difference Vegetation Index (NDVI) is a widely used vegetation index that provides information about the health and density of vegetation cover (Balzarolo et al., 2016). It is calculated using the reflectance of near-infrared (NIR) and red light wavelengths captured by remote sensing instruments, such as satellites. NDVI values range from -1 to 1, with higher values indicating denser and healthier vegetation cover. The formula for NDVI is expressed as follows:

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (0)$$

Where NIR represents the reflectance in the near-infrared band (Band 8) and Red represents the reflectance in the red band (Band 4).

MVI is a specialized index designed for mangrove extent mapping. The MVI formula is as follows:

$$MVI = \frac{NIR - Green}{SWIR1 - Green} \quad (1)$$

Where NIR is the reflectance in the near-infrared band (Band 8), Green is the reflectance in the green band (Band 3), and SWIR1 is the reflectance in the short-wave infrared band (Band 11). MVI values are used to differentiate mangrove areas from non-mangrove land cover. The specific threshold values applied to MVI can differ depending on the study area.

3.2.1 Mangroves detected using MVI: To identify the presence of mangroves, the Mangrove Vegetation Index (MVI) was used with a threshold range of 4.5 to 16.5. Notably, elevation data was purposely excluded from the mangrove masking process to determine if the index wrongly identifies inland vegetation as mangroves.

3.3 Training data creation

In this study, the generation of training data encompassed six distinct classes: water, mangroves, bare soil, built-up structures, inland vegetation, and clouds (Figure 3).

Training points for the mangrove class were delineated based on a historical mangrove shapefile sourced from the 2020 Philippine Mangrove Extent Layer produced by the Blue Carbon Project. To ensure precision, subjective manual visual assessments were conducted, considering textural characteristics and proximity to the coastline to ensure the accurate representation of mangrove areas. For the remaining training classes, visual identification was relatively straightforward, allowing for the careful selection of pixels representing these classes. 130 points were identified for each class, with a total of 780 points.

This training dataset has been partitioned into two distinct subsets. 60% of the dataset is designated for the training phase. Meanwhile, the remaining 40% of the dataset has been reserved for the testing phase, where the model's performance and accuracy are rigorously assessed against unseen data. This division strategy ensures a robust evaluation of our models' generalization capabilities, guaranteeing their effectiveness in making accurate classification predictions beyond the training dataset.

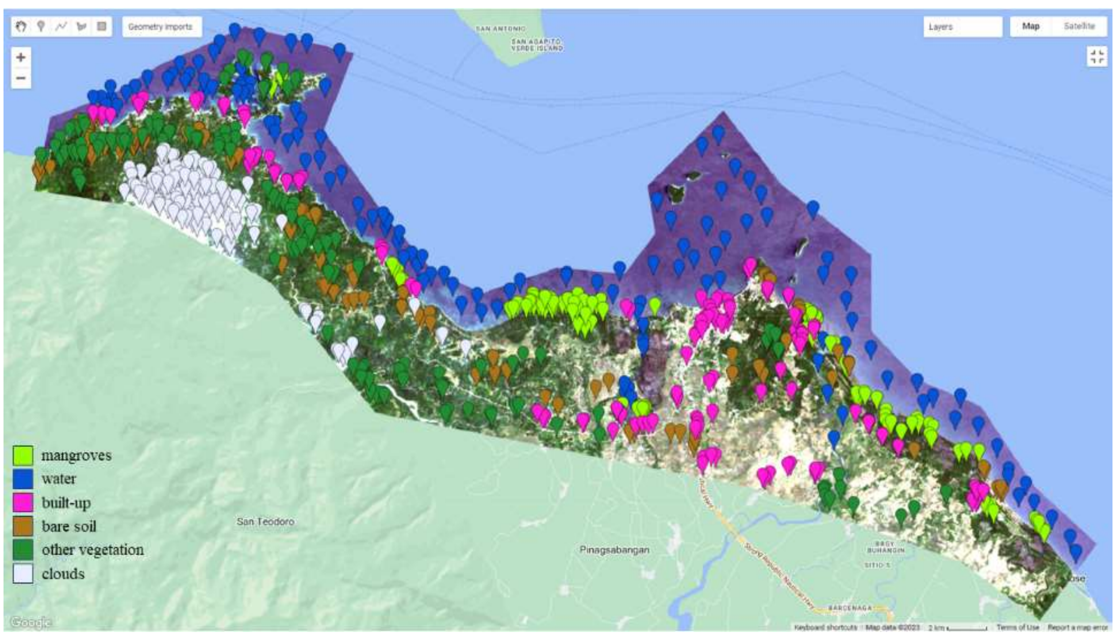

Figure 3. Data points used to train and test the supervised classification models. 130 points were created for each class, totalling to 780 points.

3.4 Layer stacking

Four distinct sets of stacked layers (Table 1) were prepared as an input to the image classification methods.

Table 1. Input feature sets

Stack	Layers
1	Sentinel-2 bands 2, 3, 4, 5, 6, 7, 8, and 11
2	Sentinel-2 bands 2, 3, 4, 5, 6, 7, 8, and 11 NDVI
3	Sentinel-2 bands 2, 3, 4, 5, 6, 7, 8, and 11 MVI
4	Sentinel-2 bands 2, 3, 4, 5, 6, 7, 8, and 11 MVI NDVI

3.5 Classification Algorithms

In this study, four different classification algorithms were applied to four different data layers, which are described in Table 2.

Table 2. Supervised classification models used in this study

Classification and Regression Trees (CART)	The CART model constructs prediction models by recursively partitioning the data space and fitting simple prediction models within each partition. It is represented graphically as a decision tree and can handle both classification and regression tasks. The CART model offers advantages in terms of interpretability, handling complex relationships, and computational efficiency.
Random Forest (RF)	The Random Forest classification model is an ensemble learning method that combines multiple decision trees to make predictions or classify data points. It is a powerful and widely used algorithm known for its accuracy and robustness in various domains.
Support Vector Machine (SVM)	Support-vector networks are a learning algorithm for pattern recognition that were introduced by Cortes and Vapnik published in Machine Learning in 1995. The algorithm is inspired by the human learning principles of structural risk minimization. Support-vector networks are considered to be a universal learning machine and are capable of solving any pattern recognition problem. They are particularly well-suited for large-scale applications.
Naïve Bayes (NB)	The Naive Bayes model is a classification algorithm based on Bayes' theorem and assumes that the features are conditionally independent given the class label. It is a simple and efficient algorithm that has been widely used in various applications, including text classification, spam filtering, and sentiment analysis.

3.6 Accuracy assessment

A confusion matrix was used to evaluate the accuracy of our classification models for each dataset in detecting mangroves. Misclassified and undetected mangrove areas were also analyzed by comparing the predicted mangroves with the 2020 Philippine Mangrove Extent Layer.

4. RESULTS

In this section, the analysis of the classification results obtained through various combinations of input data and classification algorithms is presented. Overall accuracy is computed for all six classes, while the Producer's and Consumer's Accuracy is computed for the mangrove class only. The summary of accuracy metrics is detailed in Table 3.

In addition to evaluating accuracy metrics, an assessment of misclassified and undetected mangrove areas is conducted. This analysis involves a comparison between the predicted mangrove extent generated by the classification algorithms and the 2020 Philippine Mangrove Extent Layer, as provided by the Blue Carbon Project. Misclassified mangroves pertain to areas identified by the classification algorithm but not included in the 2020 Mangrove Layer. Conversely, undetected mangroves are those found within the 2020 Mangrove Layer but undistinguished by the classification algorithm. The results of which are detailed in Table 4.

The analysis of the results was done for the whole study area. However, for better visualization of the findings, the resulting classified mangrove areas have been zoomed in, focusing on the municipalities of San Teodoro, Baco, and Calapan (Figure 4). This close-up view is essential and is used in the succeeding subchapters as it allows for a more granular view, which would be challenging to discern in the zoomed-out image.

Table 3. Summary of Classification Model Accuracy Metrics

Layer	Classification model	Overall accuracy	Producer's accuracy (for mangroves)	Consumer's accuracy (for mangroves)
S2 bands only	CART	92.83%	95.45%	91.30%
	NB	82.55%	95.45%	93.33%
	RF	96.57%	97.73%	95.56%
	SVM	95.33%	95.45%	97.67%
S2 bands and NDVI	CART	95.28%	87.23%	93.18%
	NB	85.53%	93.62%	95.65%
	RF	95.60%	93.62%	89.80%
	SVM	94.34%	95.74%	93.75%
S2 bands and MVI	CART	94.00%	92.68%	95.00%
	NB	81.33%	97.56%	97.56%
	RF	96.00%	92.68%	95.00%
	SVM	96.67%	100.00%	100.00%
S2 bands, MVI, and NDVI	CART	92.86%	92.16%	90.38%
	NB	81.49%	92.16%	90.38%
	RF	93.18%	90.20%	92.00%
	SVM	94.16%	94.12%	92.31%

Table 4. Summary of Misclassified and Undetected Mangrove Areas by Classification Models and MVI

Layer	Classification model	Misclassified mangrove area (km^2)	Undetected mangrove area (km^2)	Total area in km^2 (misclassified + undetected)
S2 bands only	CART	11.5	8.2	19.7
	NB	20.4	8.5	28.9
	RF	10.6	7.8	18.4
	SVM	8.1	8.3	16.5
S2 bands and NDVI	CART	15.3	7.8	23.2
	NB	22.1	8.8	30.9
	RF	11.1	7.7	18.9
	SVM	12.7	7.1	19.8
S2 bands and MVI	CART	9.0	9.2	18.2
	NB	21.4	8.3	29.7
	RF	7.7	8.9	16.6
	SVM	7.8	8.7	16.5
S2 bands, MVI, and NDVI	CART	10.9	8.3	19.2
	NB	22.2	8.4	30.6
	RF	10.3	7.9	18.2
	SVM	10.7	7.4	18.2
Index		**Misclassified mangrove area (km^2)**	**Undetected mangrove area (km^2)**	**Total area in km^2 (misclassified + undetected)**
MVI		22.3	10.2	32.5

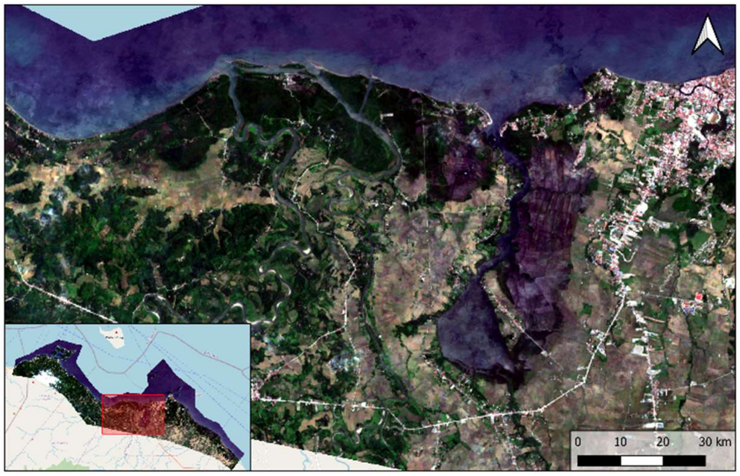

Figure 4. Close-up view of the coastal areas of the municipalities of San Teodoro, Baco, and Calapan

4.1 Sentinel-2 Bands Only:

In the case of Sentinel-2 bands only, the RF algorithm yielded the highest Overall Accuracy (96.57%), indicating strong performance in classifying land cover. Furthermore, RF exhibited excellent Producer's Accuracy (97.73%) and Consumer's Accuracy (95.56%) for mangroves. SVM also demonstrated notable accuracy, achieving an Overall Accuracy of 95.33%, a high Producer's Accuracy for mangroves (95.45%), and the least misclassified and undetected mangrove area (16.5 km^2). The comparison of the four classification algorithms is visualized in Figure 5.

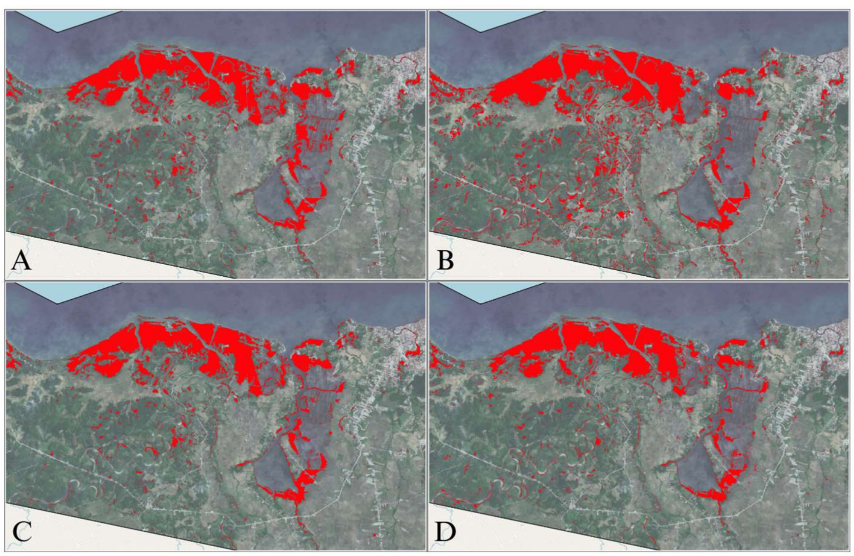

Figure 5. Mangroves detected using Sentinel-2 bands as input to CART (A), NB (B), RF (C), and SVM (D).

4.2 Sentinel-2 Bands and NDVI:

Incorporating the Normalized Difference Vegetation Index (NDVI) alongside Sentinel-2 bands led to good classification results as well. SVM remained a robust performer with an Overall Accuracy of 94.34% and high Producer's and Consumer's Accuracy for mangroves. CART and RF also exhibited notable accuracy, with Overall Accuracies of 95.28% and 95.60%, respectively. RF yielded the least misclassified and undetected mangrove areas at 18.9 km^2. The comparison of the four classification algorithms is visualized in Figure 6.

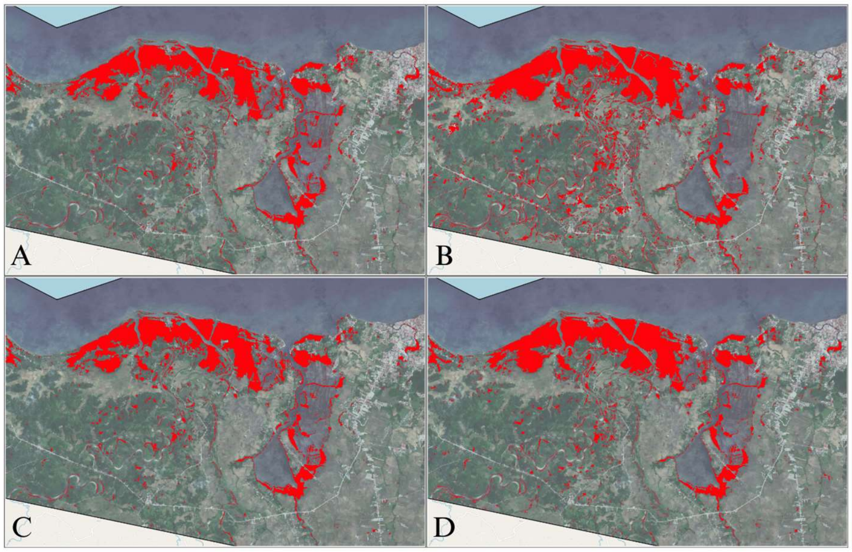

Figure 6. Mangroves detected using Sentinel-2 bands and NDVI as input to CART (A), NB (B), RF (C), and SVM (D).

4.3 Sentinel-2 Bands and MVI:

Integrating the Mangrove Vegetation Index (MVI) into the Sentinel-2 bands enhanced classification performance. SVM stood out as the top performer, achieving an impressive Overall Accuracy of 96.67% and perfect accuracy in detecting mangroves. It also yielded the least misclassified and undetected mangrove areas at 16.5 km^2. CART and RF also exhibited strong performance, with Overall Accuracies of 94.00% and 96.00%, respectively. The addition of MVI refined the models' ability to identify mangrove areas accurately. The comparison of the four classification algorithms is visualized in Figure 7.

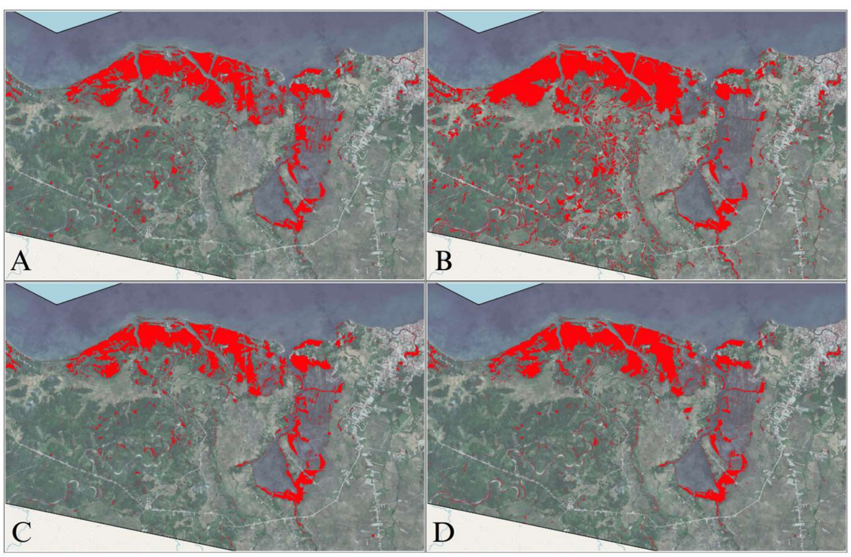

Figure 7. Mangroves detected using Sentinel-2 bands and MVI as input to CART (A), NB (B), RF (C), and SVM (D).

4.4 Sentinel-2 Bands, MVI, and NDVI:

The combination of Sentinel-2 bands, MVI, and NDVI yielded acceptable results, however, it did not surpass the performance achieved when they are separately integrated into the Sentinel-2 bands. Nevertheless, for this layer stack, SVM excelled once again, achieving an Overall Accuracy of 94.16% and demonstrating strong accuracy in detecting mangroves. CART and RF maintained their competitive performance, with Overall Accuracies of 92.86% and 93.18%, respectively. SVM and RF yielded the least misclassified and undetected mangroves at both 18.2 km^2**.** The comparison of the four classification algorithms is visualized in Figure 8.

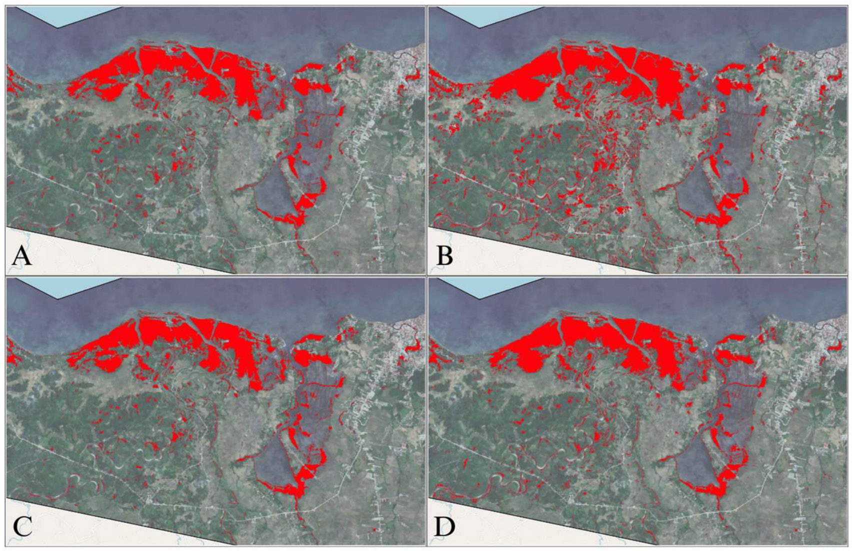

Figure 8. Mangroves detected using Sentinel-2 bands, MVI, and NDVI as input to CART (A), NB (B), RF (C), and SVM (D).

4.5 Mangroves detected using MVI and a threshold of 4.5 to 16.5:

Mangroves were identified using MVI with a threshold range of 4.5 to 16.5 (Figure 9), determined as the minimum and maximum values for mangroves (Baloloy et al., 2020). It is noteworthy that this threshold range may not yet represent the optimal value for this specific study area. Additionally, a 50-meter elevation mask was not applied during this detection process. When comparing the results to the 2020 Philippine Mangrove Extent Layer, as provided by the Blue Carbon Project, this methodology yielded 22.3 km^2 of misclassified mangrove areas and failed to detect 10.2 km^2 of existing mangroves. This combined to a total of 32.5 km^2.

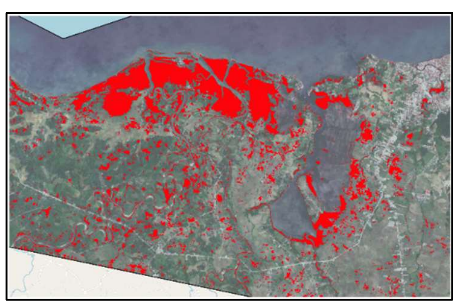

Figure 9. Mangroves detected using MVI with a threshold of 4.5 to 16.5.

The 16.5.lts underscore that when MVI is employed as a standalone classifier for mangrove areas, its effective application necessitates more than simply adopting the minimum and maximum values. Instead, it is advisable to exercise meticulous discretion in the selection of threshold values for MVI-based classification.

Overall, the results indicate that augmenting Sentinel-2 bands with vegetation indices such as MVI and NDVI could enhance the accuracy of mangrove detection. SVM consistently outperformed other algorithms across all datasets, highlighting its suitability for the task of mangrove extent mapping. It exhibited its optimal performance when applied to the stack comprising Sentinel-2 bands and MVI, yielding the highest accuracy and one of the lowest misclassified and undetected mangrove areas. This approach of integrating MVI into classification algorithms illustrates the potential to alleviate the burden associated with determining an optimal threshold in the MVI method.

5. DISCUSSION

The use of the MVI for mapping mangrove extent has a dual narrative. On one hand, challenges are associated with the threshold-dependent nature of MVI when used as a standalone classifier. The selection of an optimal threshold plays a pivotal role in the accuracy of mangrove detection. Deviations from this threshold can lead to considerable misclassifications, underscoring the sensitivity of MVI to threshold settings. This inherent limitation of index-based classification has been well-documented in previous studies and continues to be a prominent concern. In practice, it demands careful consideration and iterative threshold calibration to ensure accurate results.

However, this study proposes an alternative approach. When MVI is integrated as an input to classification models alongside Sentinel-2 bands, enhanced accuracy can be achieved. This transition from index-based classification to machine learning methodologies effectively mitigates the threshold dependency associated with MVI. Our results demonstrate that this approach improves the reliability and accuracy of mangrove classification. Notably, SVM algorithm emerged as a powerful tool within this context, consistently outperforming other methods.

The findings of this research carry implications for the broader field of remote sensing-based mangrove mapping. They emphasize the importance of reconciling the strengths of index-based approaches with the capabilities of machine learning techniques to address the challenges encountered in this field of study. The integration of MVI within classification models not only enhances accuracy but also offers a more robust and adaptive framework for mangrove extent mapping.

Further enhancements to classification models hold promise for refining the methodology. Fine-tuning model parameters or incorporating additional environmental variables could yield even greater accuracy. Additionally, the comparative analysis conducted in this study provides valuable insights into the suitability of different classification models for mangrove mapping, with SVM demonstrating its effectiveness.

6. CONCLUSIONS

This study underscores the intricacies and opportunities inherent in mangrove extent mapping. The threshold dependency of MVI, while a known limitation, can be effectively circumvented through the integration of MVI within classification models. This research contributes to the evolving field of remote sensing and ecological conservation by offering an avenue to enhance the precision of mangrove mapping. Ultimately, the findings support and inform conservation efforts aimed at preserving these vital coastal ecosystems.

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