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https://doi.org/10.19184/geosi.v9i3.4263 **Research Article**

Advanced Machine Learning Techniques for Tidal Marsh Classification: A Random Forest Approach using Sentinel-2A

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ABSTRACT

Tidal marshes play a vital role in coastal ecosystems, functioning in climate change mitigation, water filtration, and protection from coastal erosion. However, mapping and monitoring of these ecosystems is often hampered by difficult accessibility and dynamic environmental conditions. This study aims to improve tidal marsh classification accuracy by applying a Random Forest (RF) algorithm supported by Sentinel-2A satellite imagery. This image provides various spectral parameters and vegetation indices, including B1, GNDVI, BSI, and NDWI. Three RF models with varying parameters were tested to determine their effectiveness in tidal marsh classification. The model with 26 parameters (Model 3) performed best, with the lowest RMSE value of 0.22, the highest AUC of 0.87, and the highest overall accuracy of 95%. These results show that combining critical spectral parameters in the RF model can significantly improve the classification accuracy and biomass estimation in tidal marshes. This study also confirmed the effectiveness of Random Forest in addressing the challenges of high-accuracy mapping and monitoring. These findings provide a solid foundation for tidal marsh ecosystem conservation and management applications and support the application of machine learning in coastal ecosystem mapping for better and more accurate results.

Keywords: Sentinel 2A; Tidal Marsh; Machine Learning; Random Forest; Classification

INTRODUCTION

Tidal marshes are crucial in maintaining ecosystem balance, providing significant ecological benefits. As one of the most efficient ecosystems in carbon sequestration, tidal marshes can absorb carbon dioxide from the atmosphere and store it in biomass and soil, directly aiding climate change mitigation (Hilmi et al., 2021; Mcleod et al., 2011). In addition, tidal marshes serve as natural filters that strip water of pollutants, sediments, and excessive nutrients, thereby maintaining water quality and supporting aquatic life (Mitsch et al., 2015). Vegetation in tidal marshes also protects the shoreline from erosion by stabilizing the soil and reducing the impact of tidal currents and ocean waves (Barbier et al., 2011). These ecosystems also provide rich habitats for various species, supporting biodiversity and fisheries productivity (Alongi et al., 2016). Therefore, the conservation and restoration of tidal marshes is crucial in the face of climate change and environmental degradation.

Tidal marshes are vital ecosystems essential in maintaining environmental balance, especially in coastal areas such as Lampung Province. Tidal marshes can sequester carbon, critical in mitigating global climate change. In addition, this ecosystem also functions in flood control, water filtration, and protection against coastal erosion. Tidal marshes are also important habitats for various species of flora and fauna, making them a center of biodiversity in coastal Lampung. These ecological benefits play a direct role in maintaining the welfare of local communities who depend on these ecosystems for livelihoods such as fisheries and agriculture and untapped ecotourism potential.

In Lampung, tidal marshes exhibit unique characteristics shaped by the region's specific tidal patterns, vegetation composition, and climatic conditions. The interplay of seasonal rainfall and tidal cycles significantly affects sedimentation, nutrient flow, and vegetation growth, making the ecosystem highly dynamic. In certain areas, mangroves, salt marshes, and mudflats form a complex mosaic, providing crucial habitats for various aquatic species and supporting fisheries that local communities rely on.

However, mapping and monitoring of tidal marshes in Lampung faces various challenges. Hard-to-reach geographical conditions and tidal variability make access and monitoring difficult. In addition, seasonal changes in land conditions also make accurate mapping difficult. Additional threats come from ecosystem degradation caused by land conversion for agriculture or plantations, urbanization, and climate change impacts that worsen the stability of these ecosystems. Mapping and monitoring tidal marshes face various challenges related to accessibility and dynamic environmental conditions. Tidal marshes are often located in hard-to-reach areas, and unstable terrain conditions make conventional mapping difficult and expensive (Kuenzer et al., 2011). In addition, seasonal and climatic changes can affect land conditions, making consistent mapping challenging (Mahdavi et al., 2018). The need for accurate and up-to-date data also adds to the difficulty of effectively monitoring these ecosystems. Therefore, innovative and more accurate approaches are urgently needed to ensure proper mapping and management of tidal marshes.

Remote sensing, mainly using satellite imagery such as Sentinel-2A, has opened up new opportunities for mapping and monitoring tidal marsh ecosystems. This technology enables data collection with high spatial and temporal resolution, covering large areas with significant detail (Drusch et al., 2012). The multispectral imagery produced by Sentinel-2A enables the identification and mapping different vegetation types and land conditions in tidal marshes (Gascon et al., 2017). Sentinel-2 has the advantage of ample area coverage and high revision frequency with medium spatial resolution. Sentinel-2's advantages lie in its free data and broad spectral coverage, with 13 bands useful for various applications such as vegetation, water, and soil monitoring. Sentinel-2 is ideal for large-scale and periodic analysis. At the same time, PlanetScope and WorldView are more suitable for studies that require very high spatial resolution and detailed analysis at the local or small object scale. Remote sensing also allows real-time monitoring of ecosystem changes, which is crucial for conservation efforts (Kuenzer et al., 2011). As such, it provides a solution to the limitations of traditional mapping methods and supports more effective conservation efforts.

Machine learning algorithms, especially Random Forest (RF), have proven effective in improving the accuracy of satellite image classification and mapping. RF can handle complex and balanced datasets (Breiman, 2001), making it particularly useful in wetland mapping, including tidal marsh. The algorithm can process various features from satellite imagery to produce more accurate classifications and address noise in the data, which supports better ecosystem management (Belgiu & Csillik, 2018). Previous research have shown the potential of using RF and Sentinel-2A imagery in ecosystem mapping. This research has successfully applied RF for highly accurate vegetation classification and land condition identification (Rodriguez-Galiano et al., 2012). In addition, Sentinel-2A offers high-resolution multispectral data that is very useful in ecosystem analysis (Immitzer et al., 2016). However, there is still a need for further research focusing on mapping tidal marsh, which is the main objective of this study.

Given the importance of tidal marshes in climate change mitigation and biodiversity conservation, the need for more accurate and efficient mapping methods is increasingly urgent. Conventional methods are often unable to capture the complexity of these ecosystems with sufficient accuracy (Kuenzer et al., 2011). Although several studies have shown the great potential of using machine learning algorithms such as Random Forest in ecosystem mapping, especially using Sentinel-2A satellite imagery, some gaps still need to be fully addressed. One of the main gaps is the need for more research focusing on tidal marsh ecosystems in some coastal regions, such as Lampung Province, which has its ecological uniqueness. Most existing research focuses more on terrestrial ecosystems or other coastal areas, so approaches specific to the Lampung region still need to be expanded.

This research offers novelty by focusing specifically on tidal marsh ecosystems in Lampung Province, which have yet to be extensively studied despite their ecological and socio-economic importance. While previous studies have predominantly explored tidal marsh mapping in other regions or have generalized their methodologies, this study emphasizes Lampung's unique environmental and tidal characteristics. Additionally, this research combines the Random Forest algorithm with Sentinel-2A imagery, a combination that has yet to be explicitly applied to tidal marshes in Lampung. Integrating high-resolution multispectral data with advanced machine learning techniques is expected to overcome existing challenges in mapping dynamic tidal environments, providing more accurate and up-to-date data. Therefore, this study contributes significantly to regional-specific research on tidal marshes in Lampung and the broader field of machine learning applications in ecosystem mapping. In addition, while the Random Forest algorithm has proven effective in satellite image classification, previous studies have yet to fully explore its potential in dealing with the dynamic complexity of tidal marshes affected by seasonal changes and varying environmental conditions. Another gap is the limitation of conventional methods in monitoring these ecosystems in real-time and accurately, especially in areas that are difficult to access. Therefore, this research seeks to address these gaps by developing a more accurate mapping model using the Random Forest algorithm and Sentinel-2A imagery, which is expected to provide more detailed and relevant mapping results to support the conservation of tidal marsh ecosystems in Lampung.

Therefore, this study aims to develop a more accurate classification model for tidal marsh classification using the Random Forest algorithm with the support of Sentinel-2A imagery. With this model, a more detailed and precise mapping of tidal marshes is expected, which can be used as a basis for decision-making related to the conservation and management of this ecosystem (Rodriguez-Galiano et al., 2012). This research is expected to contribute significantly to developing machine learning-based ecosystem mapping methodologies, particularly in tidal marsh conservation.

METHODS

Research Design

The research was conducted in Lampung Province with an astronomical location of 105024”63’E – 105049”52’E and 5036”39’S – 5037”10’S located on the East and South Coast of Lampung Province. The selection of research sites should consider ecosystem diversity, data availability, local support, and relevance to environmental policy. This location was chosen because Lampung Province has the second longest coastline in Sumatra. This length of coastline provides a large and diverse area for studying coastal ecosystems and their interactions with the marine environment (Figure 1).

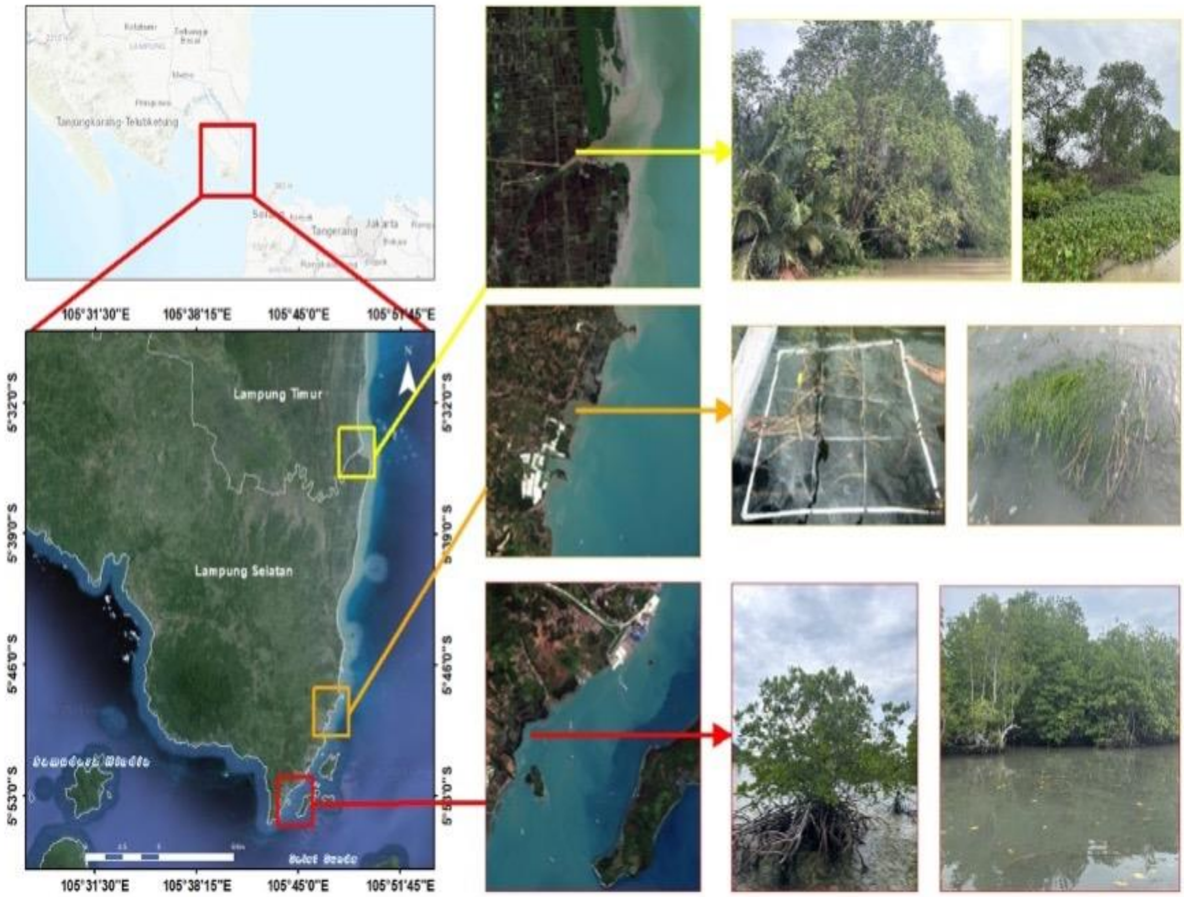

Figure 1. Study Area

The image pre-processing stage begins with radiometric correction to reduce the effects of atmosphere, sensor, and uneven illumination so that the digital value at each pixel accurately represents the reflection of objects on the Earth's surface. This involves atmospheric correction to reduce light scattering and absorption and sensor correction to address variations in sensor sensitivity. Next, geometric correction is performed to correct spatial distortions caused by sensor movement, topography, or viewing angle, using Ground Control Points (GCPs) to make the geographical position of each pixel more accurate. After that, the image was cropped according to the specific research area using geographical coordinates in the Lampung Limur and South Lampung regions, focusing on particular ecosystems such as mangroves and tidal swamps. The final stage was the removal of clouds and cloud shadows, which are often the central interference in optical remote sensing, with cloud masking techniques, such as using the Sen2Cor algorithm, to ensure that cloud-covered areas do not affect the analysis results. Data processing is done using ArcGIS Pro 3.3, which uses a machine learning-based classification process.

Machine learning (ML) provides computers with the capability to learn from data and experiences similarly to how the human brain operates. The primary objective of ML is to develop models that can self-train to enhance their understanding, recognize intricate patterns, and solve new problems based on historical data (Çelik, 2018). ML enables computers to conduct advanced analyses autonomously by continuously learning and adapting to the complexity of problems and the evolving need for flexibility (Alzubi et al., 2018; Breiman, 2001). The research flow is described in Figure 2.

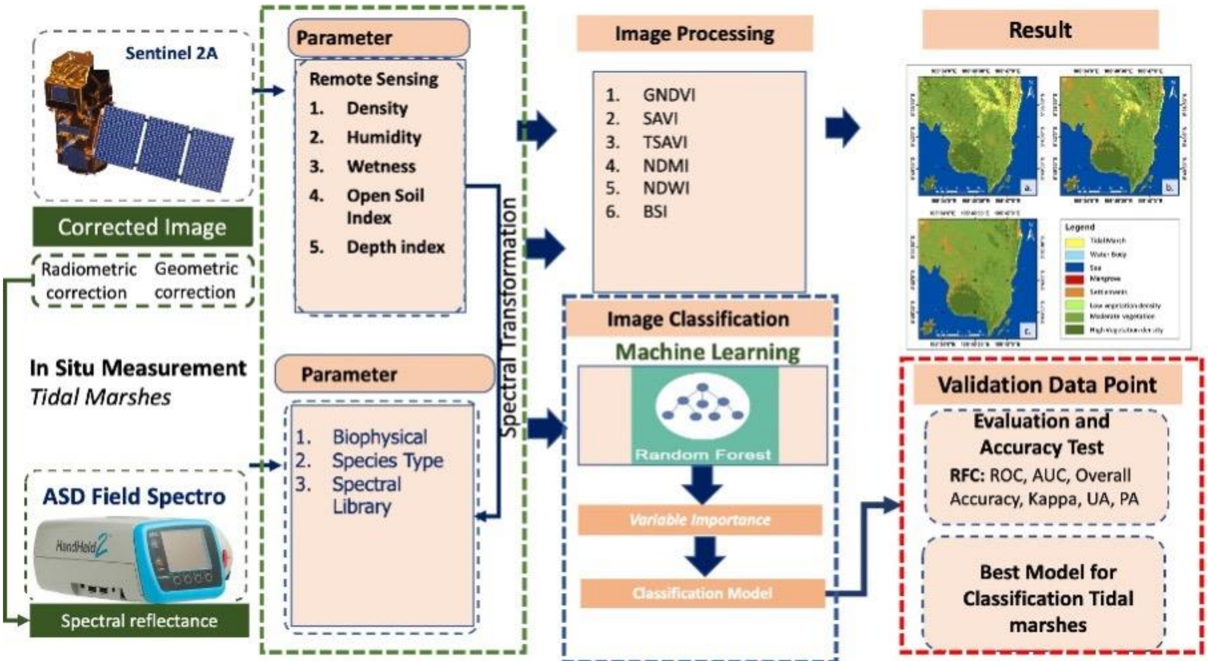

Figure 2. Classification workflow using RF classifier

The greater the impact, the more influential the variable. Determining variable importance uses the absolute value of the regression coefficient, where the more significant the coefficient value, the more outstanding the contribution of the variable to the biomass estimate for each one-unit change in the variable. In this study, determining variable importance does not only use one model using a specific data set in each method (Behera et al., 2021; Bhatnagar et al., 2020). The final prediction in the RF classifier method is made by voting with predictions from many decision trees. For classification tasks, the majority vote is considered as the final prediction. Improving processing effectiveness in classification is critical to understanding how each variable affects the outcome. The variable importance level, permutation importance (PI) value, or mean decrease accuracy (MDA) value determines the variable's contribution to the classification result. The more critical a variable is, the greater its permutation value. The importance of a variable increases as the accuracy decreases (Rodriguez-Galiano et al., 2012).

$$\text{Variable Importance} = \text{OOB permutation} - \text{OOBbas} \tag{1}$$

OOB permutation measures variable importance by permuting variable values on data not used in tree building. Out-of-bag basic (OOBbas) is a measure of variable importance without permutation. Counting instances of a variable in a group of decision trees is a simple method to determine the relevance of a variable—the importance of a variable increases with its influence. When determining a variable's relative relevance, the regression coefficient's absolute value is used; the higher the coefficient value, the more significant the contribution of the variable in question to the biomass estimate for each unit change in that variable. The method used in sampling was purposive random sampling (Elmahdy et al., 2020). Samples taken in purposive random sampling are based on considerations of built-up land development to consider the samples taken to represent the study area. The sample points obtained were used for training areas and accuracy tests. Sample selection was done by considering local knowledge and field checks.

The calculation of training data was done using the following formula by Tridawati et al. (2020):

$$\text{n} = \frac{N}{1+\text{N} \times (e)^2} \tag{2}$$

The variables are defined as follows: n represents the number of samples, N denotes the number of populations, and *e* is the margin of error (percentage of allowance for the accuracy of sampling errors that are still acceptable). Determining the number of testing points in this study refers to the approach by Fitzpatrick-Lins (1981) in Tridawati et al. (2020) commonly used to test the accuracy of remote sensing data classification results. The following is a formula for obtaining the minimum amount of testing data in the classification process:

$$N = \frac{Z^2(\mathrm{p})(\mathrm{q})}{E^2} \quad (3)$$

p represents the anticipated accuracy percentage, while qqq is calculated as 100−p100 - p100−p. The symbol EEE denotes the permissible margin of error, and ZZZ is equal to 2, derived from a standard deviation of 1.96 at a 95% confidence level. The ratio of the data in modeling is 70% Training Data and 30% Testing Data, with a total number of samples of 200 sample points and testing data of 60 sample points.

Before classifying species using the RF classifier algorithm, parameters related to identifying species are extracted to obtain accurate classification results. Parameter testing is done by analyzing the correlation between the parameters used.

1. Calculating OOB permutation where each variable permuted the values of that variable in OOB data and recalculated the model error (OOB permutation).
2. Calculating the variable importance value

The more significant the difference between OOB permutation and OOBbas, the more influential the variable is. The RF classifier algorithm model is based on several parameters and is categorized into three classification models. The distribution of sample points is presented in Figure 3.

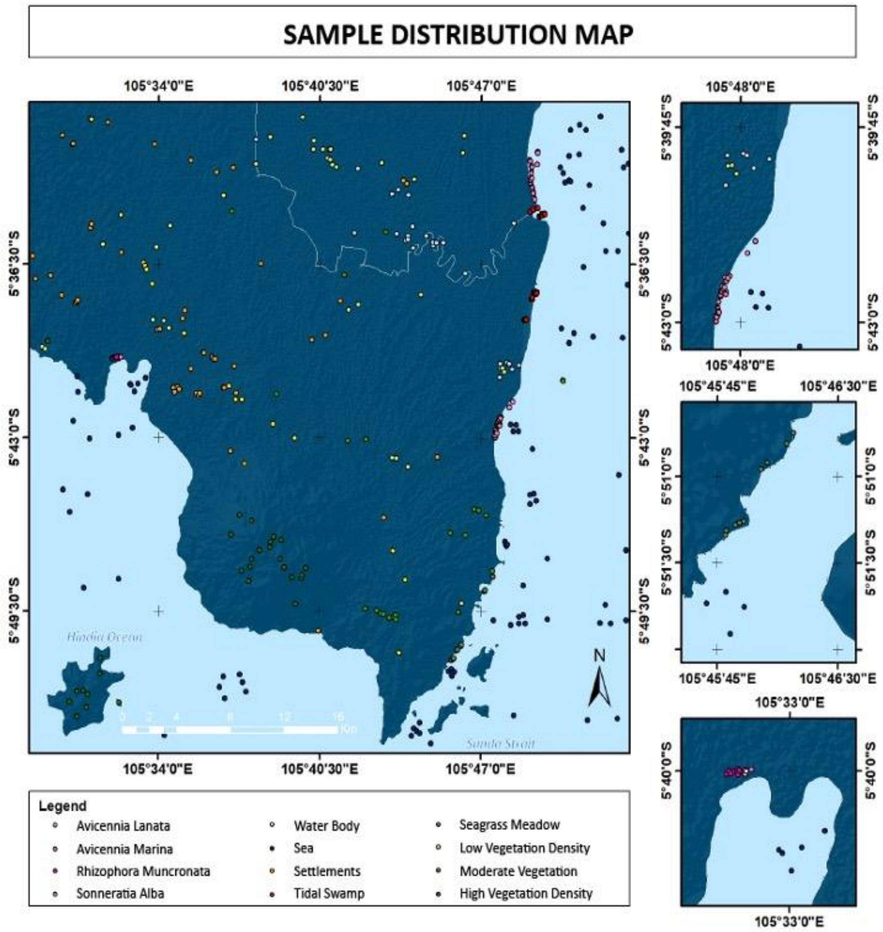

Figure 3. Classification workflow using RF classifier

Model 1 used 15 parameters, including various vegetation indices and bands from Sentinel 2A, such as GNDVI, NDWI, SAVI, band 7 to band 9, NDMI, BSI, and TSAVI. Model 2 expanded the number of parameters to 20 by adding band 4 from Sentinel 2A and four additional bands from the Spectroradiometer (band 1 to band 4). Model 3, the most comprehensive, uses 26 parameters by adding more bands from the Spectroradiometer (band 5 to band 9). These parameters include various indices used to measure vegetation health, moisture, and the presence of bare soil, as well as multiple wavelengths from the electromagnetic spectrum used by Sentinel 2A and the Spectroradiometer. The use of 3 scenario models using a combination of the number of parameters according to Table 1 is based on the permutation importance (PI) value analysis results. This determines the critical parameters that allow us to focus on them in model training, which can improve model performance and efficiency. The RF classifier classification model for mangrove, tidal marsh, and seagrass is presented in Table 1.

Table 1. Classification model using RF classifier

Model	**Number of parameters**	**Layer (parameter)**
Model 1	15	GNDVI, NDWI, SAVI, B 7 (Sentinel), B8 (Sentinel), B 8A (Sentinel), B 6 (Sentinel), B 9 (Sentinel), NDMI, BSI, B 5 (Sentinel), B 2 (Sentinel), B 1 (Sentinel), B 3 (Sentinel), TSAVI
Model 2	20	GNDVI, NDWI, SAVI, B 7 (Sentinel), B8 (Sentinel), B 8A (Sentinel), B 6 (Sentinel), B 9 (Sentinel), NDMI, BSI, B 5 (Sentinel), B 2 (Sentinel), B 1 (Sentinel), B 3 (Sentinel), NDMI, BSI, B 5 (Sen), B 2 (Sen), B1 (Spectro), B2 (Spectro), B3 (Spectro), B4 (Spectro), B5 (Spectro), B6 (Spectro), B7 (Spectro), B8 (Spectro), B8A (Spectro), B9 (Spectro)
Model 3	26	GNDVI, NDWI, SAVI, B 7 (Sentinel), B8 (Sentinel), B 8A (Sentinel), B 6 (Sentinel), B 9 (Sentinel), NDMI, BSI, B 5 (Sentinel), B 2 (Sentinel), B 1 (Sentinel), B 3 (Sentinel), NDMI, BSI, B 5 (Sen), B 2 (Sen), B 1 (Sen), B 3 (Sen), TSAVI, B4 (Sen), B1 (Spectro), B2 (Spectro), B3 (Spectro), B4 (Spectro), B5 (Spectro), B6 (Spectro), B7 (Spectro), B8 (Spectro), B8A (Spectro), B9 (Spectro)

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Performance Evaluation of Classification Models

Area Under the Curve (AUC) and Receiver Operating Characteristic (ROC) are commonly used performance evaluation metrics in ML, especially binary classification. They are often used to evaluate how much a classification model can distinguish between two classes. The ROC curve is a graphical representation that illustrates a model's performance across different decision thresholds by depicting the relationship between the True Positive Rate (TPR), also known as Sensitivity, and the False Positive Rate (FPR) (Forouzannia & Chamani, 2022; Kubben et al., 2019). The AUC serves as a quantitative metric to evaluate how well the model can differentiate between positive and negative classes. A high AUC value reflects a high level of sensitivity and a low level of specificity, indicating good performance (Forouzannia & Chamani, 2022; O'Connell et al., 2017). The equation that can be used for the calculation is:

$$TPR=TP+FNTP \qquad (4)$$
$$FPR=FP+TNFP \qquad (5)$$

The AUC, or Area Under the Curve, quantifies the area beneath the ROC curve. AUC values range from 0 to 1, with an AUC of 0.5 suggesting that the model's performance is equivalent to random guessing, while an AUC of 1 indicates that the model perfectly distinguishes between positive and negative classes. In contrast, AUC values close to 1 indicate that the model is excellent in classification (Kubben et al., 2019). Obtain the positive prediction probability of the model for each example in the test data. Then, various thresholds are determined to classify the probabilities into positive or negative classes. Perform TPR and FPR calculations for each decision threshold. The Area Under the Curve (AUC) is determined by measuring the area beneath the ROC curve, which can be calculated using various numerical methods or by summing the areas of small trapezoids under the curve (Kubben et al., 2019). The AUC is derived from the model's specificity and sensitivity, which reflect the model's success in classifying suitable or unsuitable habitats. AUC values greater than 0.9 are considered excellent, values between 0.8 and 0.9 are very good, values from 0.7 to 0.8 are satisfactory, and values below 0.7 indicate poor discriminatory ability (Muhamad et al., 2021).

Accuracy Test of Classification Results

The semi-empirical approach uses field parameter data measured from a specific tool and estimated using a particular method, so it is an indirect measurement in the field. This approach requires the selection of representative sample locations and an even distribution of sample values for modeling purposes and accuracy testing of modeling results (Kamal et al., 2020). Thematic information from image classification results needs to be assessed for its information content's accuracy, therefore, an accuracy test is necessary to assess whether the data is suitable for use (Talukdar et al., 2020).

The method used to assess accuracy is the confusion matrix test. The confusion matrix is often used to measure accuracy in data mining concepts or decision support systems. Overall classification accuracy is obtained by dividing the number of correctly classified sample points (i.e., the sum of all diagonal cells in the matrix) by the total number of sample points (Danoedoro & Murti, 2021). The samples used for instructions and the samples used for the accuracy test are not the same but are taken in different places to make them more acceptable (Karang et al., 2024). The statistical equation for the confusion matrix test is presented as follows:

$$\text{Kappa statistic} = \frac{\mathrm{N\sigma i{=}1nXii{-}\Sigma i{=}1nXi{+}(X{+}i)}}{\mathrm{N2{-}\Sigma i{=}1nXi{+}(X{+}i)}}\ x\ 100\% \qquad (6)$$

$$Overall\ Accuracy = \frac{\sum_{i=1}^{n} \mathrm{Xii}}{N}\ x\ 100\% \qquad (7)$$

$$User\ Accuracy = \frac{\mathrm{Xii}}{X+i}\ x\ 100\% \qquad (8)$$

$$Producer\ Accuracy = \frac{\mathrm{Xii}}{X+i}\ x\ 100\% \qquad (9)$$

N represent the total number of pixels used for observation. Xii denotes the diagonal value of the contingency matrix at row and column. X+i is the total number of pixels in column, and Xi+ is the total number of pixels in row i.

RESULTS AND DISCUSSION

Variable Importance Analysis of Tidal Marsh Classification Models

The variable importance analysis illustrates various parameters' contributions in the tidal marsh's three classification models. In Model M1, several variables showed a high level of importance. Variable B1 (0.87) has the highest importance, followed by GNDVI (0.82) and BSI (0.80). This shows that specific spectral parameters such as B1, GNDVI, and BSI highly influence this classification model. In the M2 model, the variables GNDVI (0.74) and BSI (0.70) remain prominent, showing the consistent importance of these two variables in the various models. In addition, variables such as NDWI (0.60) and TSAVI (0.44) also show values of meaningful importance in this model. In the M3 model, NDWI has the highest importance (0.86), showing the significant influence of this parameter in the classification. In addition, the variables GNDVI (0.67) and BSI (0.68) also remain essential in this model, consistent with the results from models M1 and M2. Some additional variables, such as SPB1 to SPB9, have lower importance values, indicating that they are less influential in the classification process than the main spectral variables. This analysis shows that spectral variables such as B1, GNDVI, BSI, and NDWI are essential in tidal marsh classification. The PI values of the tidal marsh classification model are described in Table 4.

Table 2. PI value of tidal marsh classification model

No	Parameter	Model 1	Model 2	Model 3
1	B1	0.87	0.63	0.48
2	B2	0.64	0.69	0.41
3	B3	0,52	0.51	0.51
4	B4	-	0.51	0.73
5	B5	0.69	0.60	0.56
6	B6	0.56	0.63	0.57
7	B7	0,59	0.55	0.58
8	B8	0.57	0.56	0.51
9	B8A	0.66	0.49	0.50
10	B9	0.56	0.57	0.57
11	GNDVI	0.82	0.74	0.67
12	SAVI	0.62	0.55	0.42
13	TSAVI	0.77	0.44	0.51
14	NDWI	0.73	0.60	0.86
15	NDMI	0.60	0.50	0.58
16	BSI	0.80	0.70	0.68
17	SPB1	-	0.19	0.11
18	SPB2	-	0.16	0.10
19	SPB3	-	0.20	0.06
20	SPB4	-	0.16	0.11
21	SPB5	-	-	0.07
22	SPB6	-	-	0.07
23	SPB7	-	-	0.09
24	SPB8	-	-	0.09
25	SPB8A	-	-	0.11
26	SPB9	-	-	0.05

The variable importance of the tidal marsh classification model is presented visually in Figure 4.

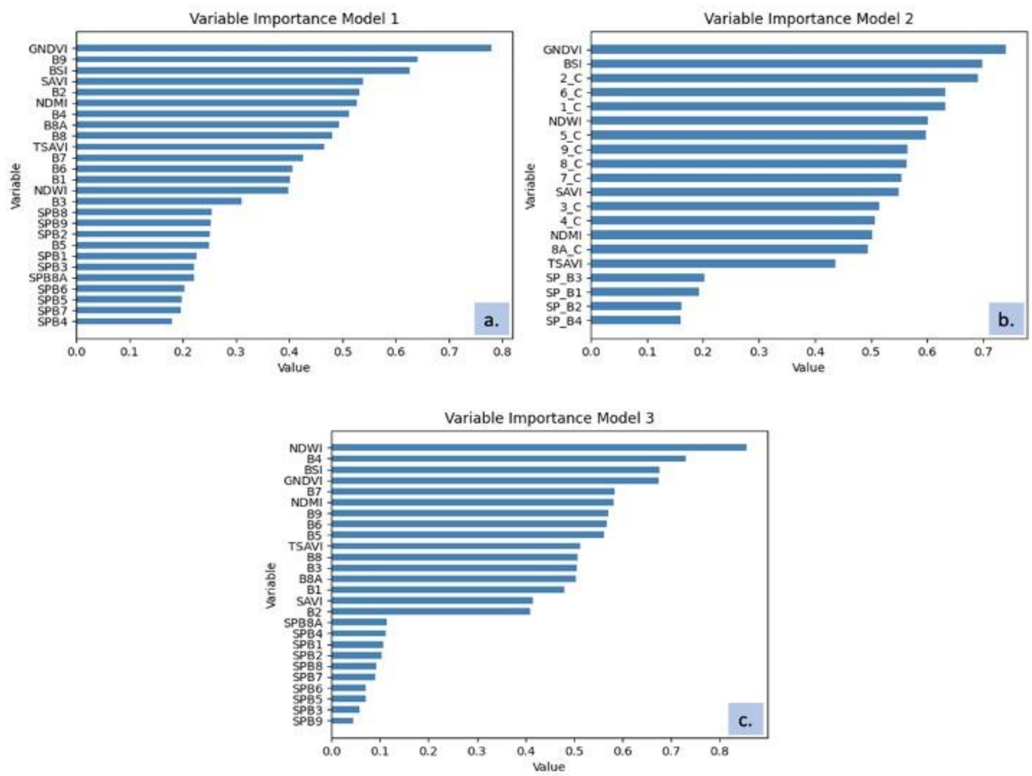

Figure 4. Variable importance of tidal marsh classification model (a) model 1; (b) model 2; (c) model 3

The consistent importance of these variables in the various models suggests that they are vital factors influencing classification results, while SPB variables have a lesser contribution. They are mapping the distribution of salt marsh species Zhang et al. (2021) by integrating optical (Sentinel-2) and SAR (Sentinel-1) images using spectral features, NDWI, VI, red edge index, and Backscattering. Combining temporal spectral features with spatial-temporal features from SAR data enhances the ability to distinguish between objects. Compared to optical or SAR data alone, integrating both data types increases the kappa coefficient by 0.10-0.19 and improves overall classification accuracy by 6.04-11.61%. The most significant variables in this improvement are the MASVI and NDVI indices.

Tidal Marsh Classification

Based on the classification results of tidal marsh ecosystems analyzed using the RF classifier algorithm with several parameters, it shows that the level of detail of tidal marsh object information is better. This classification uses a decision tree (number of trees) of 100 with data division into 70% for training and 30% for testing. Tidal marsh classification based on O'Connell et al. (2017) explained that NDWI is suitable for identifying pre-tidal conditions because it follows phenological parameters like NDVI. The findings in this study show that the variables with the highest importance values are GNDVI and NDWI. GNDVI and NDWI, with their sensitivity to vegetation and moisture variations, are critical in detecting and classifying the various components in this environment. This makes them of high importance in tidal marsh research and mapping.

In addition, Zhu et al. (2020) classified *Kandelia candle* and *Sonneratia apetala* species. Meanwhile, the findings of this study can classify low-density vegetation, medium-density vegetation, high-density vegetation, mangrove species *A. lanata, A. marina, R. mucronata, S. alba,* tidal marsh, ponds, sea, water bodies, and settlements which also obtained relatively high accuracy results. This is due to the parameters used, one of which is in situ spectral measurements. Thus, based on the results of this study and previous research, the RF algorithm is efficient enough to classify mangroves.

The east coast region has many mangrove plants in Merak Belantung Village. It has mangroves that grow lushly. Mangroves also grow in good condition around the Tarahan PLTU area, but the population is small. Furthermore, the classification of tidal marshes carried out is on the part of the land connected to the sea, adjacent to the estuary; this area is strongly influenced by saltwater/sea tides with characteristics of fine sandy beaches and waves directly reaching the shoreline. The results showed that unvegetated mud flats are immersed in this estuary area at low tide and will appear at high tide. This area usually has a higher topography, with some/all of it still inundated by the tide. The species in the swamp are dominated by A. marina and S. alba mangrove species. The tidal marsh in the study area is located at the mouth of the Way Sekampung River in Kuala Jaya Village, which has a large area with a thick, muddy bottom.

Based on Thomas et al. (2019) the RF algorithm can represent multiple spectral classes, which helps combine heterogeneous pixels of many species into one class. This approach to observing coastal wetlands can be easily applied in any coastal region worldwide. The results of the tidal marsh ecosystem classification are presented visually in Figure 5.

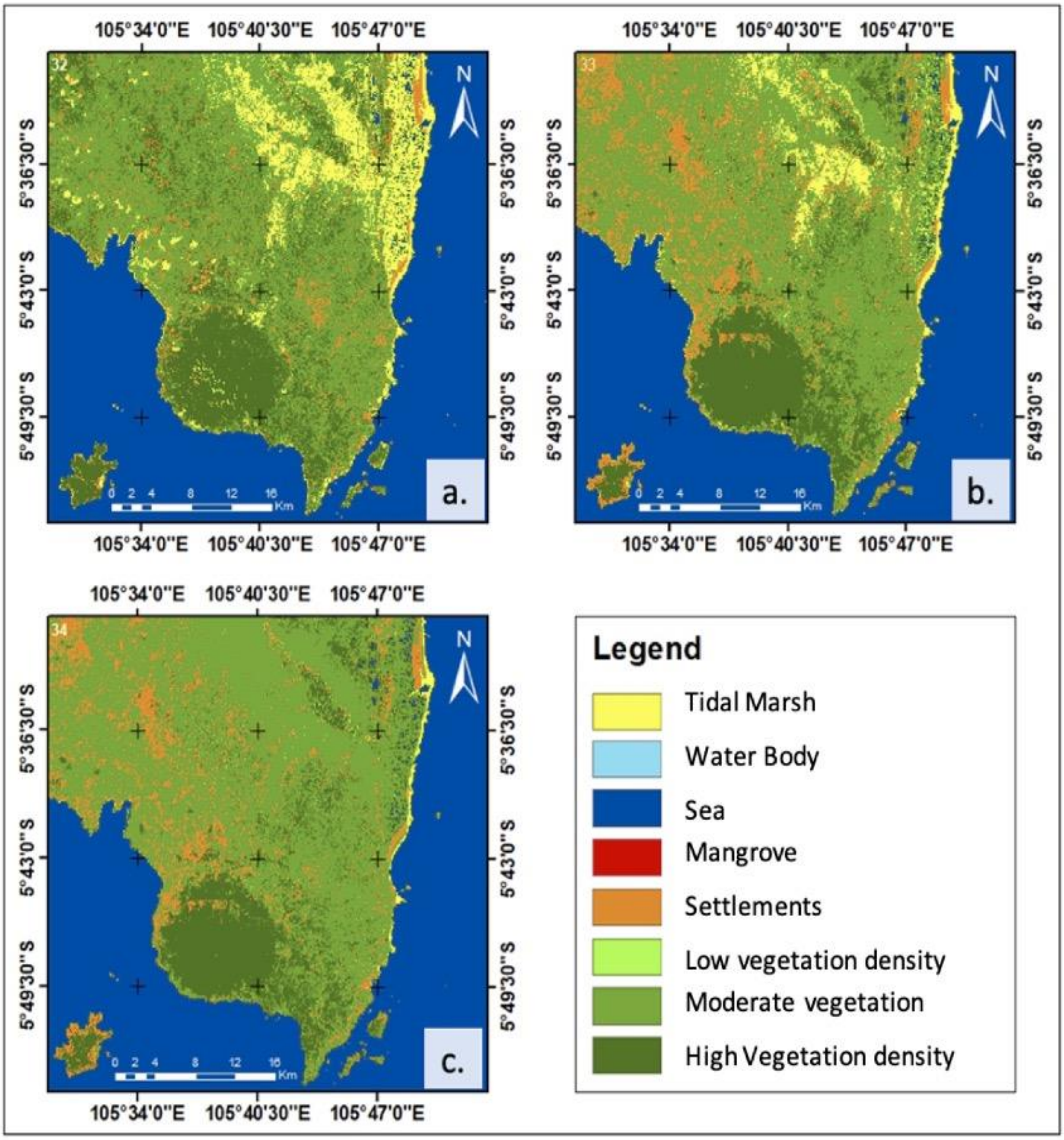

Figure 5. Tidal marsh ecosystem classification results (a) model 1, (b) model 2, (c) model 3

Comparison with the results of Forouzannia dan Chamani. (2022) explained that most of the suitable habitats for A. marina are scattered along the banks of the tributaries entering into the estuary, while the suitable habitats for R. mucronata are mostly scattered on the bottom of the main tributaries in the part of the estuary that leads to the sea. The results showed that R. mucronata tended to form mangrove line structures along the tributaries entering the estuary. At the same time, R. apiculata preferred the seaward side of the existing mangrove patches and was threatened by sea level rise. Rahmawati et al. (2022) classified mangroves with species of *S. alba, R. stylosa, R. mucronata, A. marina, Bruguiera gymnorrhiza,* and several other species.

For the classification evaluation using RF, the analysis approach includes determining the model's goodness based on RMSE. The data were divided into two parts: training data and testing data. The evaluation results showed that the model with parameters using index transformation gave the lowest RMSE, so this model was selected as the best model for biomass estimation. The RMSE values of tidal marsh estimation models are described in Table 3.

Table 3. The RMSE values of tidal marsh estimation models

Tidal Marshes	
Model	**RMSE**
Model 1	0.78
Model 2	0.24
Model 3	0.22

Table 3 shows the RMSE analysis on the three modeling models for tidal marsh classification, which shows variations in the level of prediction accuracy. Model 3, with an RMSE value of 0.22, shows as the model with the best accuracy, followed by Model 2 (0.24) and Model 1 (0.78). The decrease in RMSE value from Model 1 to Model 3 reflects the improved performance of the model in predicting mangrove biomass. The lower RMSE value indicates that Model 3 can classify more accurately than Model 1 and Model 2.

Performance Evaluation of Tidal Marsh Classification Models

Furthermore, the RMSE analysis of the three modeling models for tidal marsh shows the accuracy of water level prediction in tidal variations. Model 3 showed the best performance with a low RMSE value of 0.22, significantly better than Model 1 (0.78) and Model 2 (0.24). The decrease in RMSE values from Model 1 to Model 3 reflects the substantial improvement in the model's ability to predict the biomass of objects in the tidal marsh. The first model had an AUC of 0.66, indicating moderate performance distinguishing between positive and negative classes on the ROC curve. The second model showed a higher AUC of 0.85, indicating a better ability to separate the interest classes. Meanwhile, the third model had the highest AUC of 0.87, indicating excellent performance and a high ability to distinguish between positive and negative classes on the ROC curve. The AUC values of mangrove classification models in tidal marshes are presented in Table 4.

Table 4. AUC value of mangrove classification model in tidal marshes

Model	**AUC Value**
Model 1	0.66
Model 2	0.85
Model 3	0.87

This shows that the higher the AUC value, the better the ability of the model to separate between positive and negative samples. Therefore, the third model has the most optimal performance among the three models, while the second model also shows good performance. The ROC curve of tidal marsh biomass is presented in the figure 5.

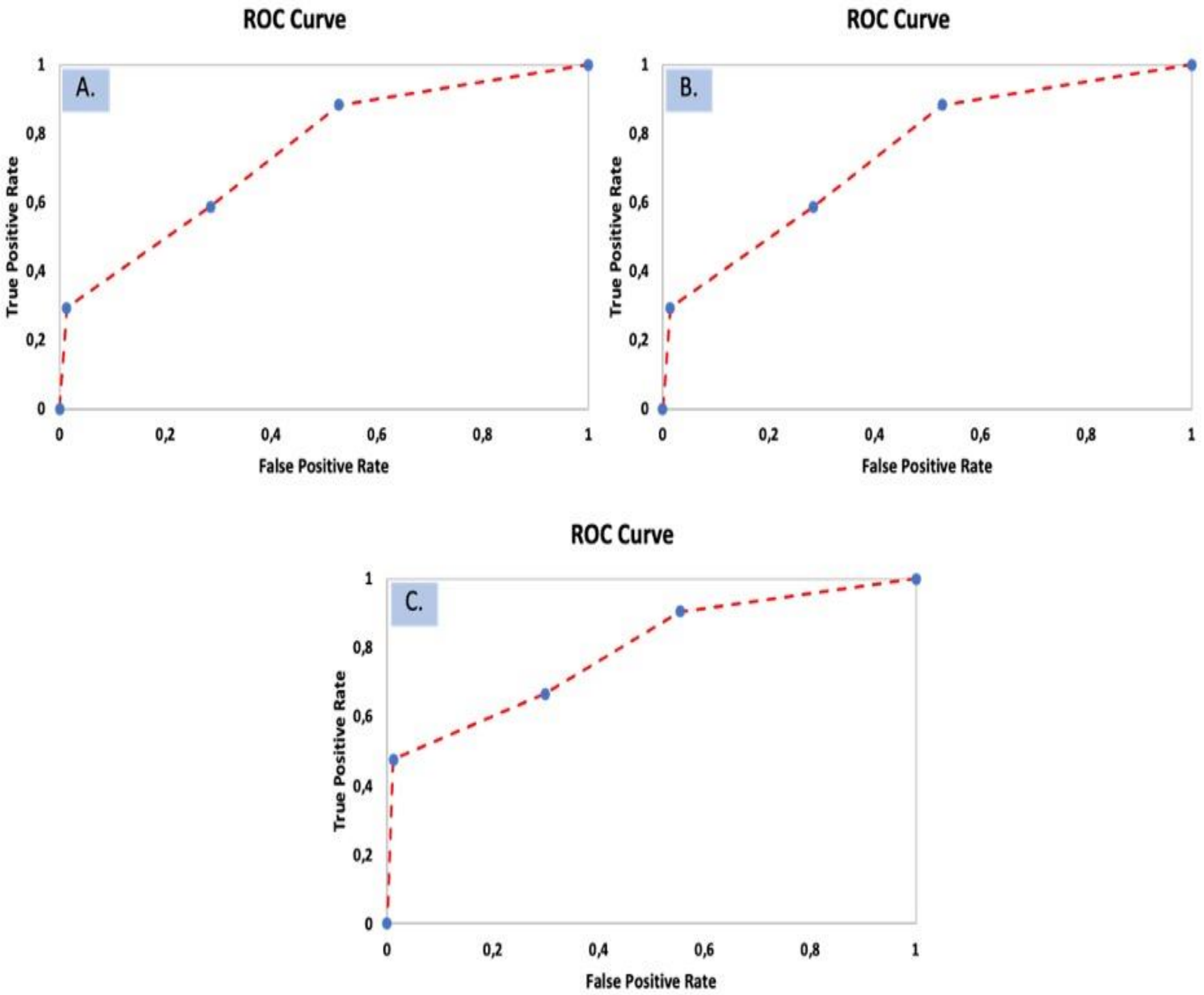

Figure 6. ROC curve of tidal marsh biomass (a) model 1, (b) model 2, (c) model *3*

Based on O'Connell et al. (2017) obtained AUC values using the tidal marsh inundation index (TMII) and NDWI of 0.91 and 0.81, respectively, while the findings in this study show that the highest AUC value is 0.87. This analysis explains that the model that maximizes the AUC has a high accuracy overall. The highest accuracy for each model will be obtained by the decision limit that creates the specificity and sensitivity points in the upper left corner of the ROC curve.

Accuracy Test

The accuracy test results of each classification based on the most critical variables, as shown in the table above, show a difference in accuracy. Model 1 has a lower OA of 94.2 with kappa, PA, and UA values of 0.918, 77.04%, and 80.96%, respectively. Increased accuracy in model 2 with OA, kappa, PA, and UA are 94.3%, 0.92, 78.49%, and 87.42%, respectively. Meanwhile, model 3 has 95%, 0.92, 80.51%, and 89.60%. Model 1 has an OA value of 94.6% and kappa of 0.92, PA 79%, UA 83.4%, model 2 with an OA value of 94.9% and kappa of 0.92, PA 78%, UA 81%, and model 3 has an OA value of 95% and kappa 0.92, PA 81, UA 89.6%. The classification model accuracy test is presented in Table 5.

Table 5. The classification model accuracy test

Class	Model 1				Model 2				Model 3			
	PA	UA	OA (%)	Kappa	PA	UA	OA (%)	Kappa	PA	UA	OA (%)	Kappa
Tidal marsh	100	100	**94.60**	**0.92**	100	100	**94.90**	**0.92**	100	100	**95.0**	**0.92**
settlements	99.6	95			99.10	99			100	99		
Pond	20	31			10	12			16.30	100		
High density vegetation	99.7	100			97.30	100			96.70	100		
Moderate density vegetation	99	100			99	100			99	100		
Low density vegetation	99	100			87	99			86	99		
Sea	36	29			38	31			38	30		
Seagrass	98	95			97	94			100	95		
A. lanata	100	100			100	100			100	100		
A. marina	100	96			100	96			100	96		
R. mucronata	14	100			19	100			31	100		
S. alba	91	99.5			98.00	96.80			98.00	99.70		

The accuracy test results indicate that Model 3, which includes 26 parameters—B1, B2, B3, B4, B5, B6, B7, B8, B8A, B9, B11 (Sentinel), GNDVI, SAVI, TSAVI, (B1, B2, B3, B4, B5, B6, B7, B8, B8A, B9 (Spectro), NDWI, NDMI—achieves the highest overall accuracy (OA). In contrast, Model 1, which uses 15 parameters—B1, B2, B3, B4, B5, B6, B7, B8, B8A, B9, B11 (Sentinel), GNDVI, SAVI, TSAVI, (B1, B2, B3, B4, B5, B6, B7, B8, B8A, B9 (Spectro)—shows the lowest OA value. Unlike other studies, the highest accuracy for mangrove species distribution mapping was achieved using spectral information divergence (SID) classification at Levels 1, 2, and 3, with overall accuracies of 49.72%, 22.60%, and 15.20%, respectively. The most accurate mangrove species mapping (Level 4) was obtained using spectral feature fitting (SFF) classification, with an overall accuracy of 5.08%. The low accuracy is attributed to the high species heterogeneity in the field, which causes pixel mixing and limited access to precise accuracy points (Rahmandhana et al., 2022). Meanwhile, the location of the research conducted has a high level of homogeneity, which also significantly affects the accuracy of the mapping.

The findings from this study highlight the effectiveness of the Random Forest (RF) algorithm in classifying tidal marsh ecosystems using Sentinel-2A imagery, achieving a high level of accuracy in mapping the spatial distribution of these ecosystems. This result aligns with previous research, underscoring the value of RF in ecosystem mapping. However, it is essential to position these results within the broader context of remote sensing and machine learning applications in ecological studies. By comparing the performance of RF with other machine learning models used in similar research, such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Xtreme Gradient Boosting, this discussion aims to emphasize both the strengths and limitations of the RF algorithm for tidal marsh classification. Additionally, this study explores how incorporating other advanced techniques, including temporal data integration and hybrid approaches, could further enhance the accuracy and robustness of tidal marsh mapping and monitoring efforts.

Research by Kang et al. (2023) has successfully mapped swamp species with acceptable accuracy using RF and SVM algorithms. Moreover, integrating temporal and spectral features from Sentinel 2A with spatial-temporal features from SAR data significantly enhances the capability to differentiate swamp ecosystems. The combination of optical and SAR data, or using either type of data alone, resulted in an increase in the kappa coefficient and overall classification accuracy by 0.10-0.19 and 6.04-11.61% (Zhang et al., 2021). OA generated using Sentinel 2 images with five vegetation indices and three bands Modified Chlorophyll Absorption in Reflectance Index (MCARI), inverted red-edge chlorophyll index (IRECI), NDVI, Pigment-specific simple ratio of chlorophyll a (PSSRa), MERIS terrestrial chlorophyll index (MTCI), B4, B5, B6) obtained an OA of 74% and Kappa of 0. 61 indicating that ML models with several suitable parameters allow for optimal mapping and classification of mangroves (Behera et al., 2021). At the same time, Rahmawati et al. (2022) obtained an OA of 76.83%, with a Kappa value of 0.71 with the parameters of vegetation index, building index, and wetness index.

Upadhyay et al. (2020) obtained seagrass classification results using RF with an accuracy value of 97.16 and a Kappa value of 0.94, while the results of this study show lower accuracy results of around 95%. However, this accuracy value is still classified as accurate because the average PA and UA values are above 90%. In contrast to the research of Karang et al. (2024) the level of accuracy obtained was 65%. Still, this study used UAVs to classify seagrass beds at the species level. At the same time, Sentinel 2A imagery could only distinguish seagrass and non-seagrass beds. Ginting et al. (2024) using RF obtained R2 between 0.49-0.64 and 0.50-0.58, with RMSE ranging from 18.50%-21.41% and 19.36%-20.72%. According to (Bakirman & Gumusay, 2020) Seagrass mapping obtained a classification accuracy and kappa coefficient of 94% and 0.89 for RF, 71% and 0.61 for RVM. Uhrin & Townsend (2016) found that the LSU classification method successfully differentiated between seagrass and bare substrate, producing seagrass maps with overall thematic accuracy surpassing the 85% target, ranging from 86.3% to 99.0%. Similarly, the seagrass classification model in this study achieved accuracy levels above 90%. The accuracy test results, including R^2, RMSE, and the spatial distribution of seagrass, indicate that the RF model delivers superior mapping outcomes, particularly in regions with a high percentage of seagrass cover.

Research by Hu et al. (2021) used artificial neural networks (ANN), namely MultiBoost artificial neural network (MBANN) and rotation artificial neural network (RANN), showed that these two methods significantly improved the performance of wetland cover classification compared to single artificial neural network (ANN), VGG11, and Random Forest (RF) methods. In addition Govil et al. (2022) mapped wetlands using Xtreme Gradient Boosting has the best performance on cross-site datasets with 83.20% accuracy and an Area Under Curve (AUC) score of 0.89. Based on previous research, when looking at the accuracy obtained, it is possible to use methods other than random forest; other methods, such as ANN, MBANN, and Xtreme Gradient Boosting, can be used to map tidal marshes.

CONCLUSION

This study successfully analyzed tidal marsh classification using three Random Forest (RF)-based modeling models with various spectral parameters and vegetation indices, identifying essential variables such as B1, GNDVI, BSI, and NDWI that contribute significantly to classification accuracy. Model 3, which integrated 26 parameters, performed best with the lowest RMSE value (0.22) and highest AUC (0.87), reflecting excellent accuracy in mangrove biomass classification. The model also achieved an % overall accuracy of 95%, with consistently high kappa values and user and producer accuracy. These findings suggest that proper selection and combination of spectral parameters in RF models can improve classification accuracy and biomass estimation, which aligns with previous studies highlighting the effectiveness of RF. This study underscores the importance of critical spectral parameters in improving the performance of classification models and provides a solid foundation for applications in tidal marsh ecosystem management and conservation.

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DECLARATIONS

Conflict of Interest

We declare no conflict of interest, financial or otherwise.

Ethical Approval

On behalf of all authors, the corresponding author states that the paper satisfies Ethical Standards conditions, no human participants, or animals are involved in the research.

Informed Consent

On behalf of all authors, the corresponding author states that no human participants are involved in the research and, therefore, informed consent is not required by them.

DATA AVAILABILITY

Data used to support the findings of this study are available from the corresponding author upon request.

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