Multi-sensor decision tree machine learning algorithm for identifying mangrove ecosystem

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Abstract. This paper compares the reliability of multi-spatial-resolution PlanetScope imagery in Tapanuli Tengah, Sentinel-2A imagery in Asahan Regency, and Landsat-8 imagery in Asahan Regency for detecting mangroves and their vegetation density using a decision tree machine learning (DT-ML) approach. Landsat 8 and Sentinel-2A were used to identify mangrove and non-mangrove classes, while high-resolution PlanetScope was specifically examined to detect mangrove density, i.e., dense, medium, and sparse. This study demonstrates that DT-ML achieves overall accuracies of 92.4% (Landsat 8), 93.0% (Sentinel-2A), 92.1% (PlanetScope Tapanuli Tengah Site), and 94.5% (PlanetScope Langkat Site). NDVI and substrate were found to be the most influential variables across all datasets, particularly in distinguishing mangrove from non-mangrove ecosystems, thereby reducing misclassification of non-mangrove classes. PlanetScope's high spatial resolution (3 m) delivers superior detail, enabling more accurate detection of canopy density. The Sentinel-2A Red Edge channel is crucial for distinguishing mangroves from other vegetation types. The Decision Tree algorithm has been successfully adapted to multi-resolution imagery, yielding a model with good interpretability and straightforward generalization. It is concluded that Decision Tree Machine Learning may provide higher accuracy and the ability to integrate spectral variables from satellite imagery with non-spectral socio-geo-biophysical variables.

1 Introduction

Over the past decade, mangroves in Southeast Asia, including Indonesia, have been lost at a massive scale, with nearly 80% of mangrove ecosystems converted to fishponds, agricultural land, industrial forest plantations, and plantations [1-4]. This trend is highly concerning if efforts are not made to prevent the decline of mangrove ecosystems. Prevention can be achieved by

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understanding the location, extent, spatial distribution, and current health of mangroves. Mangrove density is a key indicator for mangrove inventory and rehabilitation. Mangrove restoration in damaged (rare) mangrove areas significantly contributes to increasing mangrove carbon stocks. Conversely, mangrove deforestation contributes significantly to carbon emissions [5]. Therefore, one crucial step in controlling mangrove ecosystem conversion while maintaining a balance between the ecological and economic functions of mangroves for the environment and society is to develop rapid techniques for detecting mangrove presence and condition.

Currently, the availability of various types of digital spatial data, including cloud-stored continuous medium- and high-resolution remote sensing imagery, the ability of computers to process "big data," and the availability of machine learning-based algorithms have shifted the classification paradigm from parametric to nonparametric approaches. The non-parametric approach, specifically the decision tree machine learning approach, studied in this research, combines traditional approaches using ratio-type data derived from satellite data with non-ratio data such as interval, ordinal, and nominal (text) data derived from social, geographic, and biophysical aspects of each study location. Data on anthropogenic and biophysical factors, such as proximity to settlements, roads, rivers, and coastlines, as well as elevation and slope, are generally interval, nominal, or ordinal. The current decline in mangrove area, approximately 40%, is estimated to originate from anthropogenic influences [6]. In light of the availability of multi-sensor data at varying spatial resolutions and the development of machine-learning-based algorithms, the study objective is to compare the performance of machine-learning-based multi-sensor systems for detecting mangrove ecosystems and mangrove condition classes by integrating spectral and non-spectral variables.

2 Methods

2.1 Study sites

This research was conducted in three locations: Tapanuli Tengah Regency, Langkat Regency, and Asahan Regency, North Sumatra Province. The research location in Tapanuli Tengah Regency spans from 98º29’0” E to 98º53’30” E and from 1º28’0” N to 1º52’32” N. The location in Langkat Regency is located between coordinates 98º 0’ 0” E to 98º 40’ 0” N; and between 3º 40’ 0” N to 3º 20” 0’N, while the location in Asahan Regency is located at 2° 03’ 00”- 3° 10’00’ ’N and 99°1’00”-100°00”E (Figure 1).

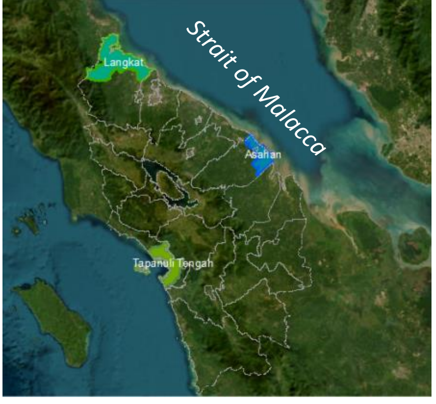

Fig. 1. Study sites: (a) Langkat, (b) Asahan and (c) Tapanuli Tengah

2.2 Primary and supporting data

The primary data used are PlanetScope imagery recorded in July 2024 for the Tapanuli Tengah and Langkat locations, and Sentinel-2A and Landsat-8 imagery, each recorded in 2024 for the Asahan location. Other supporting data include spatial data on substrate type and water salinity, digital elevation models (DEMs), river and road networks, settlement locations, and coastlines. In this study, due to the availability of "cloud-free" data in 2024, only the Asahan site used Landsat and Sentinel imagery, whereas the Tapanuli Tengah and Langkat sites used only PlanetScope imagery. We used this consideration because the atmospheric conditions in 2024 at these three locations were relatively similar, and they are study areas with a relatively uniform mangrove ecosystem, including the estuarine mangrove type group. To reduce variation in topographic (biophysical) influences across study sites, this study used index images derived from the original image channels with approximately the same wavelength range (blue, green, red, NIR, and MIR). Index images derived from ratio operations can reduce the influence of topographic variations. Consequently, the classification process relies more on the relative spectral responses of vegetation and land-cover types than on absolute reflectance values , which may vary between sites.

2.3 Preprocessing

The primary data used are PlanetScope imagery recorded in July 2024 for Tapanuli Tengah and Langkat, and Sentinel-2A and Landsat-8 images recorded in 2024 for the Asahan site. All data sets derived from satellite imagery are transformed into synthetic layers such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Green Atmospherically Resistant Index (GARI), Salinity Index (SI), Soil Adjusted Vegetation Index (SAVI), Green Normalized Difference Vegetation Index (GNDVI), Normalized Green-Red Vegetation Index (NRGI), Atmospherically Resistant Vegetation Index (ARVI), Vegetation Difference Vegetation Index (VDVI), Atmospherically Resistant Vegetation Index (ARVI), Combined Mangrove Recognition Index (CMRI). The applied non-spectral factors include substrate, water salinity, slope, elevation, proximity to settlements, proximity to coastlines, and proximity to rivers. Other supporting data are spatial data on substrate types, water salinity, digital elevation models (DEM), river networks, road networks, settlement locations, and coastlines. Various spectral indices have been widely used for mangrove detection [7].

In this study, to develop a decision tree model, we used approximately 300 training data samples per class at each study site. Thus, for all 11 classes, we collected approximately 3300 training data samples from the mangrove ecosystem. The size of each training area is 5 x 5 pixels, taken at a relatively homogeneous location that represents each class defined in this study. For ratio-type variables, statistics for each training data were calculated using the average method, while data with nominal types were calculated using the majority (highest frequency). The data sample for each study site was divided into two subsets using a stratified sampling approach, with 70% allocated to model development and 30% to model validation (accuracy assessment). The separation of the training data set for accuracy assessment was implemented to ensure that model performance was evaluated on data sets not used in model development. This process reduces the possible bias and overfitting. We noted that overfitting could be identified from the spatial patterns of the classification results, which typically follow the spatial patterns of the predictor variables, particularly non-spectral variables such as proximity to rivers, roads, the coastline, and other ancillary spatial variables used in the model. In this study, the resulting classification patterns did not show such artificial spatial conformity, indicating that the model generalization remained stable.

2.4 Class scheme

In the high-resolution PlanetScope imagery studied at the Tapanuli Tengah and Langkat research sites, this study built 12 classes, including three mangrove density classes. The class scheme includes Water bodies (BAIR/TBA), Ponds (TMBK/TBK), Open land (TTR/LT), Built-up areas (ATB/LTB), Shrubs (SBL), Rice fields (SWH), Mixed dryland agriculture (PLKC), Plantations (PKBN), Dryland forests (HLK), Sparse mangrove forests (HMJ), Dense mangrove forests (HMR), and Dense mangrove forests (HML). Meanwhile, for Sentinel-2A and Landsat-8 medium resolution images in the Asahan location, this study built 11 classes, namely Water bodies (BAIR), Fishponds (TBK), Settlements (PMK), Open land (ATB/LTB), Shrubs (SMK/SBL), Rice fields (SWH), Plantations (PKB/PKBN), Sparse mangrove forests (MGJ), Medium mangrove forests (MGS), Dense mangrove forests (MGR), Clouds and cloud shadows (AWN). The mangrove density classes are defined as follows: Sparse mangrove forests are mangrove forests that have a canopy cover percentage lower than 30%; Medium mangrove forests have a canopy cover percentage in the range of 39-70%; and Dense mangrove forests have a canopy cover percentage greater than 70%.

2.5 Decision tree machine learning

The Decision Tree Machine Learning (DT-ML) algorithm studied in this study was trained on a dataset that represented all classes. Seventy percent of the dataset was used to build the model. To determine the weight of each variable studied, this study used several entropy-based criteria, namely Information Gain (IG), Gini Index (GI), Gain Ratio (GR), and Brute Force (BF). To obtain the best DT-ML model, this study also tested various combinations of: entropy reduction criteria using IG, GI, and GR; model data retrieval methods from the dataset using stratified or automatic sampling; setting several maximum decision tree depth values; testing several minimum leaf values before splitting; testing several minimum leaf values in each class; implementing running (or not), applying pre-pruning (or not), and the number of pre-pruning alternatives.

2.6 Model validation

Each model generated at each location was tested for performance using several accuracy measures, including overall accuracy (OA), Kappa Coefficient (KA), User's accuracy (precision), and producer's accuracy (recall). OA is used to measure the model's overall performance, measured based on the total number of correctly classified pixels compared to the total number of validation pixels. Precision or user's accuracy is accuracy from the user's perspective, measuring the percentage of correctly classified samples in each class compared to the total number of samples categorized as a particular class on the map; conversely, recall or producer's accuracy is accuracy from the map maker's perspective, describing the percentage of correctly classified samples compared to the total number of pixels in that class used by the analyst for validation testing. This study also tested accuracy using a 5-fold cross-validation approach to measure the stability of the machine learning approach, which tends to overfit.

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3 Results and discussion

3.1 Variable weight

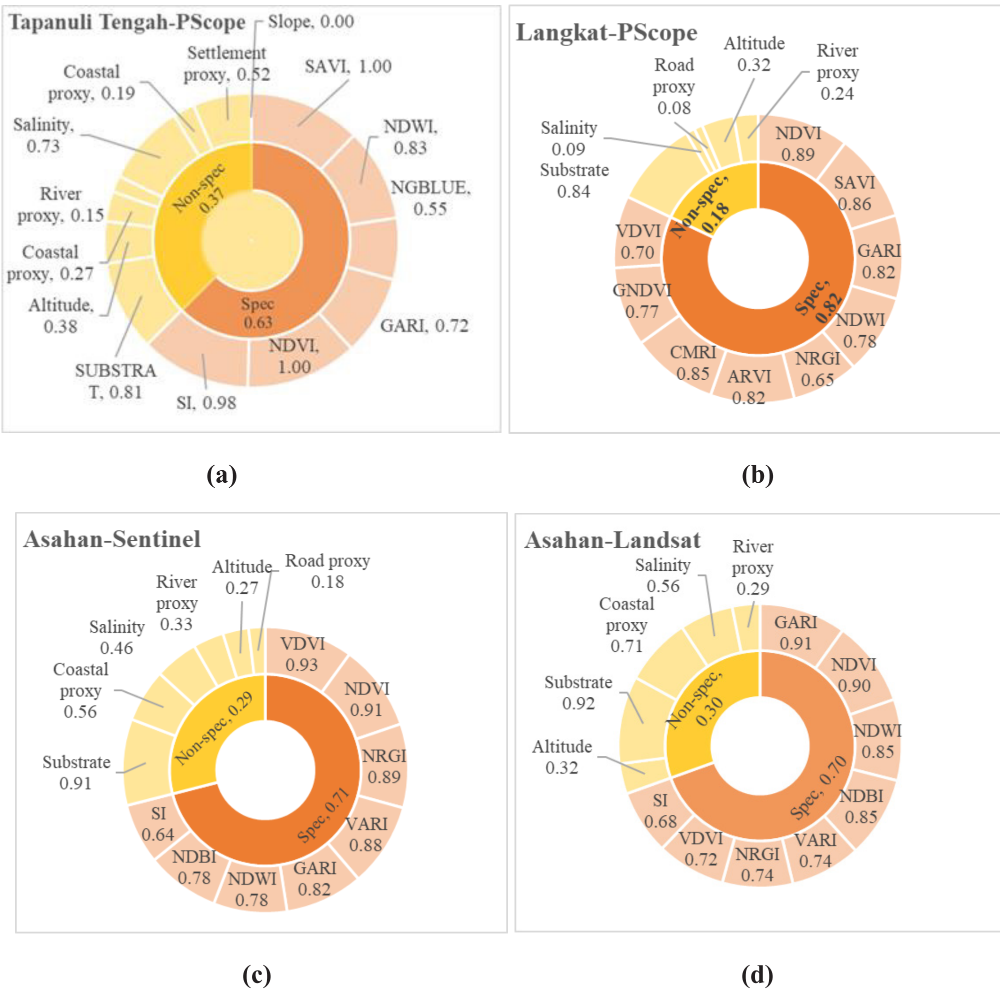


Fig. 2. The weight of each variable in the study site (a) Tapanuli Tengah—PlanetSope, (b) Langkat—PlanetScope, (c) Asahan—Sentinel-2A, and (d) Asahan—Landsat-8

In general, the study at the four study locations shows that the contribution of non-spectral (socio-geo-biophysical) variables ranges from 18% to 37.5%. Only in the Langkat study location with PlanetScope imagery did the non-spectral variables contribute 18%, whereas in the other locations (Tapanuli Tengah —PlanetScope, Asahan — Sentinel-2A, and Asahan — Landsat-8) they contributed 29%-37.5% (Figure 2). From this evidence, it is clear that the role of socio-geo-biophysical variables is needed more in medium-resolution imagery (Sentinel and Landsat), which has a resolution of 10-30 m. The condition of mangrove cover in the Tapanuli Tengah study location is slightly more complex, with the mangrove ecosystem fragmented into small mosaics and randomly distributed, making it difficult to accurately identify the mangrove class. Integrating socio-geo-biophysical variables into a machine learning approach could provide an ecological context for detecting mangrove ecosystems [8].

Based on the role of each variable, the four research locations—pa Tengah, Langkat (both using PlanetScope), Asahan–Sentinel-2A, and Asahan–Landsat-8—showed several consistent spectral and non-spectral variables, with both groups contributing significantly to the decision tree model for land cover classification in mangrove ecosystems. Differences in sensor spatial resolution appear to result in significant differences in weighting. Several spectral and non-spectral variables exhibited very high stability across all images and all locations studied. These variables will serve as "foundational" variables in land cover classification in mangrove ecosystems (Figure 3).

Variables	Tpn	Rank	Lkt	Rank	Ash-S	Rank	Ash-L	Rank
NDVI	1.000	1	0.894	1	0.913	2	0.903	3
SAVI	0.999	2	0.862	2	-	16	-	17
SI	0.985	3	-	14	0.639	9	0.679	10
NDWI	0.831	4	0.783	7	0.776	7	0.853	4
Substrate	0.808	5	0.844	4	0.911	3	0.921	1
Salinity	0.729	6	0.086	13	0.462	11	0.563	11
GARI	0.717	7	0.816	6	0.825	6	0.911	2
NGBLUE	0.550	8	-	14	-	16	-	17
Settlement proxy	0.523	9	-	14	-	16	0.071	15
Altitude	0.377	10	0.317	11	0.273	13	0.318	12
Coastal proxy	0.267	11	-	14	0.561	10	0.713	9
River proxy	0.147	12	0.236	12	0.325	12	0.291	13
VDVI	-	13	0.702	9	0.934	1	0.723	8
VARI	-	13	-	14	0.885	5	0.742	6
Road proxy	-	13	-	14	0.175	14	0.198	14
NRGI	-	13	0.651	10	0.886	4	0.740	7
NDBI	-	13	-	14	0.776	7	0.853	4
GNDVI	-	13	0.774	8	-	16	-	17
CMRI	-	13	0.848	3	-	16	-	17
ARVI	-	13	0.818	5	-	16	-	17
Slope	-	13	-	14	0.120	15	0.024	16

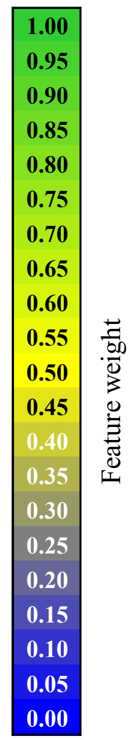


Fig. 3. Heatmap of the comparison of each variable in each study site

3.1.1 Consistent variables across all sites

3.1.1.1 Spectral variable

In general, this study found that the NDVI variable was consistently present across all study locations and ranked between 1 and 3, with weights ranging from 0.89 to 1.00. This dominance indicates that the NDVI variable is superior at detecting mangrove vegetation and its ecosystem. This reflects the important role of NDVI in capturing spectral variations caused by physiological variations in mangrove vegetation (chlorophyll, biomass, leaf water content). The GARI variable also emerged as another important variable, ranked 2-7 and consistently detected variations in greenness and chlorophyll content in mangrove stands. This study also found that the NDWI variable showed a strong role in stability across locations, making an important contribution to mangrove detection, and ranked 4-7. These findings confirm NDWI's sensitivity to detecting variations in vegetation water content and humidity, which are highly relevant in the mangrove ecosystem's tidal zone. This result is in line with the study of mangrove dendity detection performed by Hilmi *et al.* [9].

3.1.1.2 Non-spectral variables

For the non-spectral variable group, this study found that substrate variables play a significant role in identifying land-cover and land-use classes in mangrove ecosystems. Substrate is the primary non-spectral variable that determines whether an area is a mangrove ecosystem. Among all variables, the substrate variable ranks 1–5. This indicates that the presence of substrate is a primary indicator in mangrove ecosystems. Furthermore, this study found that the Salinity variable appears in all locations, with varying weights (0.086–0.729) and ranks (6-13). For Tapanuli Tengah, Salinity is a reasonably important variable. The inclusion of salinity is significant in mangrove detection using a machine learning approach [10]. This study also found that, although its weight is low, the altitude variable is stable, ranging from 0.273 to 0.377, and consistently ranks 10–12. In other words, elevation variations in coastal areas are relatively slight, so their influence is limited. The river proximity variable also shows a consistent role. However, its contribution is low, with a weight of 0.147–0.325, ranking 12–13, indicating that proximity to the river is not a major differentiating factor at the resolution scale used.

3.1.2 Robust variables at specific locations only

The SAVI variable appears to be present only in high-resolution PlanetScope imagery of Tapanuli Tengah and Langkat. This is understandable because high spatial resolution imagery can detect vegetation density, while SAVI is exceptionally reliable at detecting mangrove the soil background in the sparse mangrove classes. The SAVI variable consistently ranks second. SAVI has proven its superiority in detecting vegetation with low density, distinguishing variations in soil conditions between gaps in the vegetation canopy. The SI (Salinity Index) variable also plays an important role in mangrove classification in Tapanuli Tengah, with a weight ranking of 3. For the Asahan study site, although SI contributes a low weight, it consistently ranks 9th and 10th. In other words, the salinity index derived from Sentinel and Landsat imagery demonstrates its effectiveness when salinity gradation can be captured in greater detail. In the other study, it had also been proven that the Sentinel-2 image provided high accuracy in the detection of mangrove mapping [11]. Other spectral variables, such as GNDVI, CMRI, and ARVI, also make important contributions in Langkat–PlanetScope but are not present in Tapanuli Tengah. This indicates differences in spectral characteristics between locations. The NGBLUE variable has a medium weight in Tapanuli Tengah, ranking 8th, but its role is not apparent in medium-resolution images.

3.1.3 Robust variables specifically in Sentinel-2A and landsat imagery in Asahan

In a study using medium-resolution Sentinel-2A and Landsat imagery in Asahan, this study found location-specific features. In contrast to those found in high-resolution imagery in Tapanuli Tengah and Langkat, the VDVI variable ranked first in medium-resolution Sentinel-2A imagery. However, in the VDVI from Landsat imagery, it ranked only eighth. Another variable that played a fairly consistent role in classifying medium-resolution imagery was VARI, which ranked 5th for Sentinel imagery and 6th for Landsat imagery. NRGI and NDBI variables also consistently ranked 4th to seventh.

For the Asahan location, this study found that the distance-from-coastline variable consistently contributed at ranks 9 and 10. Other non-spectral variables, such as altitude, coastal proxy, and river proxy, generally had relatively low weights (0.14-0.32). These weights were relatively stable across Sentinel and Landsat imagery in Asahan. The Coastal proxy variable in Asahan, using Landsat imagery, had a reasonably high contribution of 0.71, ranking ninth or tenth, reflecting the influence of the extensive coastline, and was more detectable at 30 m resolution. On the other hand, the settlement proxy variable had a very low weight in Asahan using Landsat imagery, at 0.07. This is most likely due to the dominance of pixels originating from small mosaic land cover, such as a mixture of settlements and vegetation. This study also found that the Altitude variable contributed consistently with a low weight across all locations (<0.38). This shows that elevation variation is not a major differentiating factor in mangrove land-cover classification. Although the total weight of non-spectral variables is only 18–30%, the role of substrate and distance variables from the coastline remains a key factor in mapping mangrove distributions.

3.2 Parameter optimization of DT-ML

In tests using a combination of several decision tree machine learning parameters, including testing the type of sampling method, entropy-based class separation criteria (Information Gain, Gini Index, and Gain Ratio), the depth of the decision tree branches, and pruning strategies (pruning and pre-pruning), this study found unique characteristics of each location. The findings from this parameter optimization test at each location are described in the following sub-chapters (Table 1).

3.2.1 Tapanuli Tengah – PlanetScope

Of the five best combinations in Tapanuli Tengah, the best combination was found to be given by a combination consisting of automatic sample selection (Auto) with Information Gain (IG) criteria, a maximum depth of 29, without pruning or pre-pruning, a minimum leaf size equal to 1, and a minimum size for split = 11 which resulted in an accuracy of 90.83%. Of the five best combinations, with accuracies ranging from 90.5 to 80.8, the best sampling technique was automatic stratification, while the best class separation criterion was information gain (IG); IG provided 4 out of 5 criteria. The pruning aspect (pre-pruning and pruning) is an important choice in building the best model. For this location in Tapanuli Tengah, the most frequent combination was True-False for pruning and pre-pruning, but the best was without pruning and without pre-pruning (False-False). For the Minimum leaf size, it ranges from 1 to 100, but the best value is 1. Likewise, the minimum split size ranges from 1 to 100, but the best is a minimum leaf size of 11, with up to 20 pruning alternatives.

3.2.2 Langkat – PlanetScope

For PlanetScope classification in Langkat, this study also found high accuracy, with an OA accuracy of 99.37%. This accuracy was achieved using a combination of parameters, stratified sampling, entropy criteria with the Gini Index (GI), a maximum branch depth of 60, and both pruning and no pruning. In this combination, the minimum leaf size was 11, and the minimum split was 21. The second and third-ranked accuracy configurations showed accuracies above 99%, with a consistent pattern: both using the IG and GI criteria, and the model tended to require deep trees with pre-pruning activation. This stability confirms that PlanetScope's high-resolution imagery, with clear vegetation structure in Langkat, enables highly effective class separation even with parameter variations.

3.2.3 Asahan – Sentinel-2A

At the Asahan site, an OA of 92.1% was obtained using Sentinel imagery. The data subset was conducted with standardized sampling, using IG as the basic data criterion, with a maximum depth of 100, without pruning or pre-pruning, and a relatively large minimum leaf size (51). This indicates that the model is quite complex and performs better for medium-resolution data. The second-best configuration uses the Gini Ratio (GR) with automatic sampling, with a depth of 39. In other combinations, pruning and variations in leaf number (11–80) yield only a very small difference in accuracy (less than 0.2%). This indicates that the model remains stable and robust to the parameters at this location.

3.2.4 Asahan – Landsat

At the Asahan study site, Landsat imagery was used to optimize a combination of parameters using stratified sampling, with the IG parameter achieving the highest accuracy (91.67%). This combination used a maximum depth of 70 and no pruning. The leaf size and minimum split were relatively large (51–51), indicating that a less granular model was better suited to the coarser Landsat pixel characteristics. Subsequent configurations, including the use of GI with pruning, maintained accuracy of 91.41–91.54%, indicating that a shorter tree structure (depth 19–60) remained adequate.

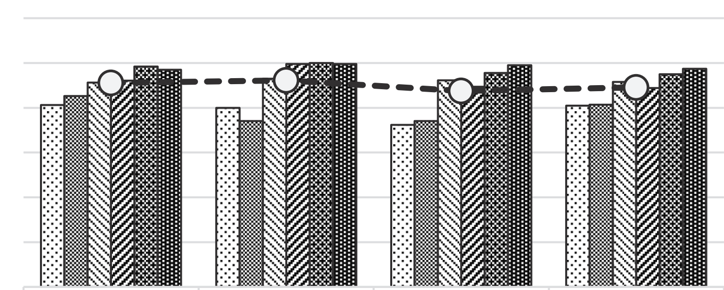
Table 1. Parameter optimization in each study site.

Rank	Samp. Type	Crit.	Max. depth	Pruning	Pre-pruning	Min Leaf size	Min. size for split	No of pre-prun.alt.	OA (%)
				Tapanuli Tengah - PlanetScope					
1	Auto	IG	29	False	False	1	11	20	90.8
2	Stratif	IG	50	False	True	1	1	0	90.7
3	Stratif	IG	19	True	False	90	21	20	90.7
4	Auto	IG	60	True	False	60	60	60	90.7
5	Auto	GI	9	True	False	100	100	10	90.5
				Langkat - PlanetScope					
1	Stratif	GI	60	True	True	11	21	10	99.4
2	Auto	IG	50	True	True	1	60	40	99.3
3	Stratif	GI	39	True	True	11	11	0	99.2
4	Stratif	GI	39	False	True	11	21	0	99.2
5	Stratif	IG	60	True	True	11	60	10	99.2
				Asahan - sentinel					
1	Stratif	IG	100	False	False	51	60	20	92.1
2	Auto	GR	39	False	False	11	60	40	92.1
3	Stratif	IG	100	False	False	1	70	10	92.0
4	Stratif	GI	9	True	False	51	80	30	92.0
5	Stratif	GR	50	True	False	21	41	50	92.0

Table 2. Parameter optimization in each study site (continue).

Rank	Samp. Type	Crit.	Max. depth	Pruning	Pre-pruning	Min Leaf size	Min. size for split	No of pre-prun.alt.	OA (%)
Asahan - Landsat									
1	Stratif	IG	70	False	False	51	51	60	91.7
2	Auto	IG	50	False	False	100	90	0	91.5
3	Stratif	GI	19	True	False	70	41	100	91.5
4	Auto	IG	80	True	False	60	70	30	91.4
5	Auto	IG	60	True	False	21	41	50	91.4

3.3 Accuracy assessment



	Tapanuli Tengah Site - PlanetScope	Langsat site - PlanetScope	Asahan Site - Sentinel-2A	Asahan Site - Landsat-8
Min Rec	81,3	80,0	72,4	81,0
Min Prec	85,2	74,1	74,1	81,4
KA	91,2	93,0	92,2	91,5
OA	92,1	99,6	89,3	88,8
Max Rec	98,4	100,0	95,5	95,0
Max Prec	97,0	99,6	98,9	97,4
AvgAll	91,1	92,2	87,5	89,1

Fig. 4. Comparison of the accuracy measures among four studies in Tapanuli Tengah, Langkat, and Asahan

3.3.1 Comparison between sensors

As depicted in Figure 4, this study demonstrates that differences in spatial resolution are important determinants of image classification performance in quantitative analyses. In Langkat Regency, the OA value can reach 99.6%, while the average recall and average precision are 95.5% and 96.0%, respectively. Similarly, the classification results in Tapanuli Tengah have an OA of 92.1% and average precision and recall of 91.9%. In terms of Kappa accuracy, high-resolution imagery consistently achieves Kappa scores of 93.0% in Langkat and 91.2% in Asahan. In general, PlanetScope imagery provides high precision (97.0–99.6%) and maximum recall (98.4–100%), enabling increased mangrove canopy variation and information within mangrove gaps.

3.3.1.1 Sentinel-2A: moderate accuracy and higher class variability

In testing Sentinel-2A and Landsat-8 imagery in Asahan, the accuracy was slightly lower than that of high-resolution imagery. OA values ranged from 88.8% to 89.3%. Minimum recall values ranged between 72.4% and 81.0%, while minimum precision values ranged between 74.1% and 81.4%.

3.3.1.2 Landsat-8: lower accuracy but more stable than sentinel-2A

Asahan—Landsat performed slightly lower than Sentinel-2A in OA (88.8%) and KA (91.5%), but had higher minimum precision and recall (Prec min = 81.4%; Rec min = 81.0%). The average precision (88.7%) and recall (88.6%) indicated better interclass stability than Sentinel, albeit with a lower maximum. Given the spatial resolutions of Landsat and Sentinel images (10 m and 30 m, respectively), these medium-resolution images are less able to capture the details of mangrove vegetation.

3.3.1.3 Sensor comparison

Overall, PlanetScope imagery performed best in terms of accuracy, precision, and consistency in recall. The Sentinel-2A sensor was in the moderate category, with high maximum values but low minimum values, reflecting interclass variability. Landsat-8 demonstrated slightly lower accuracy but better interclass stability than Sentinel-2A. This pattern confirms that spatial resolution significantly impacts mangrove classification performance: the higher the resolution (PlanetScope), the better the model's ability to capture canopy structure heterogeneity and land cover class differences.

4 Results and discussion

4.1 Feature Importance across spectral and non-spectral variables

From a variable group perspective, this study shows that spectral variables contribute significantly to land cover classification in mangrove ecosystems, accounting for approximately 63% to 82% of the data, with non-spectral variables contributing the remaining 18% to 37%. The spectral variables that consistently and stably dominate across all locations and sensors are NDVI, NDWI, and GARI. These spectral variables are highly sensitive in describing variations in canopy health (canopy condition), leaf moisture, mangrove chlorophyll, and mangrove vegetation biomass. In high-resolution PlanetScope imagery, variations in leaf greenness require NDVI for classifying stand density. In high-resolution imagery, SAVI and SI are quite prominent variables. This is because SAVI can detect soil conditions beneath the canopy (background soil), especially in stands with low canopy density. Similarly, SI is sensitive to soil salinity beneath the canopy.

In contrast, non-spectral variables such as substrate, salinity, altitude, and river proximity have lower weights but still appear at all locations. Substrate is the most important non-spectral variable (ranked 1–5), confirming its role as a major ecological determinant of mangrove existence. Other variables, such as salinity and coastal proxies, contribute more to medium-resolution sensors (Sentinel-2A and Landsat), where spectral variations are less able to distinguish classes finely. From the above findings, it can be concluded that spectral variables play a significant role in clearly separating vegetation from non-vegetation and in detecting mangrove density classes. On the other hand, non-spectral variables play a role in identifying mangrove and non-mangrove ecosystems, as a function of substrate and salinity variables, in separating them.

4.2 Model parameter optimization across sensors

Based on the importance (weight) of each variable at each location, this study identified patterns in the classification of mangrove landscape ecosystems. Wetland ecosystems with highly variable canopy densities require spectral parameters capable of detecting and identifying variations in leaf greenness, vegetation biomass volume, leaf moisture, and background soil moisture. The level of spatial resolution detail is also closely related to the pattern and condition of land cover in mangrove ecosystems. High-resolution sensors are best suited to heterogeneous landscapes composed of small mosaics. Meanwhile, for intact, homogeneous ecosystems, sensors with moderate spatial resolution are more effective at accurately detecting the landscape.

Non-spectral (socio-geo-biophysical) variables are crucial in distinguishing mangrove ecosystems (wet and brackish/saline) from other ecosystems. The presence or absence of substrate and salinity levels are key determinants in detecting mangrove ecosystems. Distance from the coast or river mouth provides spatial information about mangrove locations. The branch depth of a decision tree (19-60) with or without pruning is also highly determined by the combination of mangrove ecosystem complexity and the spatial resolution of the imagery used.

Medium-resolution images, which are lower-resolution, generally require more branches. However, a large number of branches will lead to overfitting of mixed pixels. Therefore, limiting the maximum branch depth of the decision tree remains necessary to optimize results from medium-resolution imagery. Therefore, model complexity, landscape complexity, and sensor spatial resolution are crucial considerations, particularly when adjusting branch depth, determining pre-pruning and pruning implementation, and setting the threshold for class separation.

4.3 Classification accuracy comparison across sensors

In general, this study shows a significant performance difference between high-resolution and medium-resolution imagery. PlanetScope imagery was consistently more accurate than Sentinel-2A and Landsat-8 imagery in classifying mangrove ecosystem classes and their canopy density. PlanetScope accuracy testing in Langkat and Tapanuli Tengah yielded OA, KA, average recall, and precision above 90%. PlanetScope in Langkat achieved OA accuracy of 99.6% and KA of 93.0%, with an average precision-recall>95%; in Tapanuli Tengah, it achieved OA accuracy of 92.1% and KA of 91.2%. Medium-resolution imagery yielded lower accuracy, with OA values ranging from 88.8% to 89.3%. This was due to the high degree of confusion in mixed classes. Landsat-8's precision was slightly higher than that of Sentinel-2A. In general, this study confirms that accuracy is strongly influenced by spatial and spectral resolution. Landsat-8, which has lower spatial resolution than Sentinel imagery, appears to have a spectral resolution advantage over Sentinel imagery. This is evident in its higher recall than Sentinel-2A. The mangrove distribution maps derived in the four study sites are depicted in Figures 5~8.

Several studies have shown that Decision Tree algorithms and Decision Tree-based Random Forest algorithms often produce superior performance compared to other machine learning methods [12]. SVMs and Random Forests only perform better at higher resolutions in more complex environments. To achieve more realistic accuracy with a cross-validation approach that also reduces overfitting, the Decision Tree algorithm achieves high cross-validation-based accuracy, demonstrating its effectiveness on heterogeneous data [13]. It should be noted that each algorithm has its own advantages and limitations, which contribute to varying levels of accuracy. There are trade-offs among accuracy, computational efficiency, and the model's interpretability. In fact, Random Forest algorithms can achieve high accuracy. However, because they are ensemble-based, they require longer computational times and are not suitable for applications that require interpretability, as Random Forests tend to be "black-box"; the model selection is unknown. In contrast, Decision Tree and Naive Bayes models can be easily copied and used for other scenarios and applied to classification at other times and places, for target conditions with the same variables. Therefore, the selection of the appropriate algorithm should be guided by the specific needs and constraints of the application being worked on.

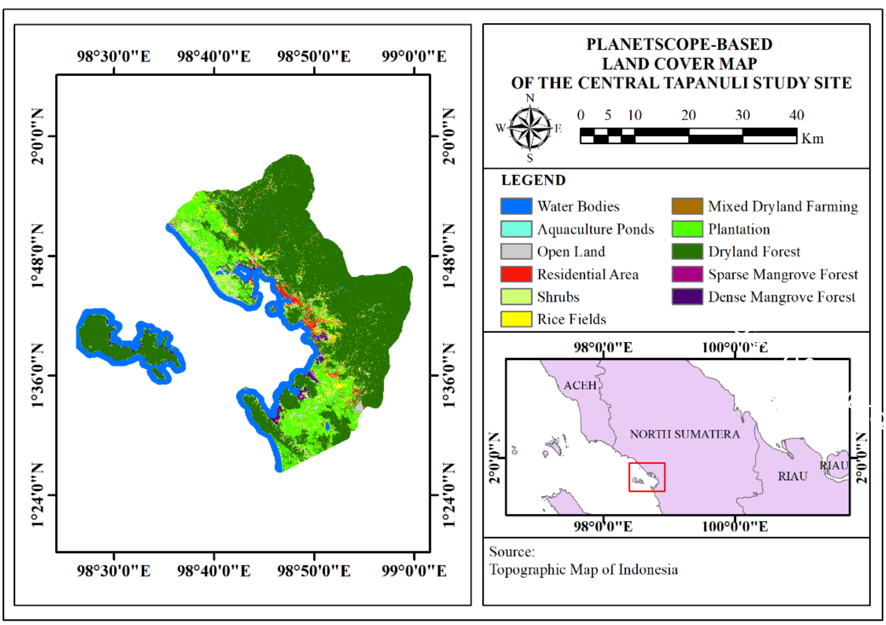


Fig. 5. PlanetScope--based classified image of TapanuIi Tengah study site

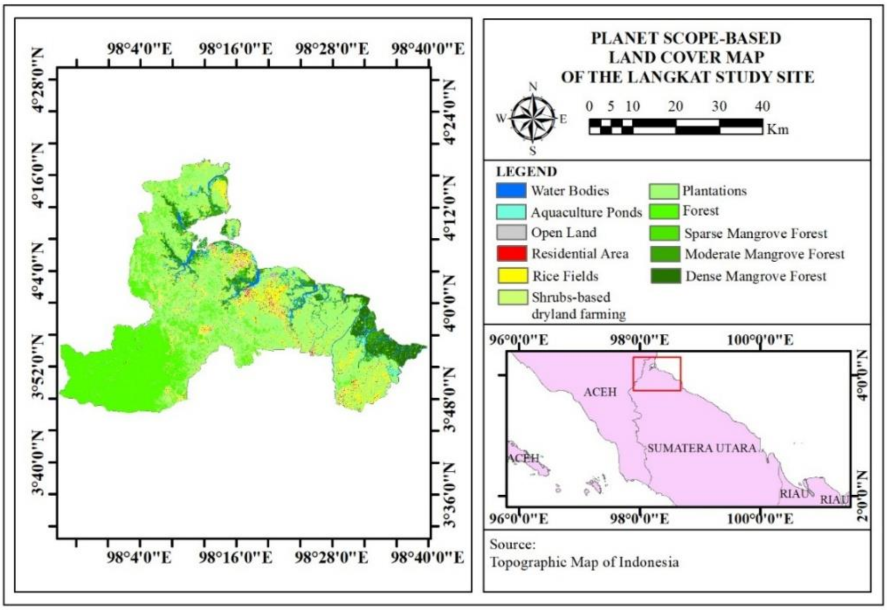


Fig. 6. PlanetScope-based classified image of Langkat study site

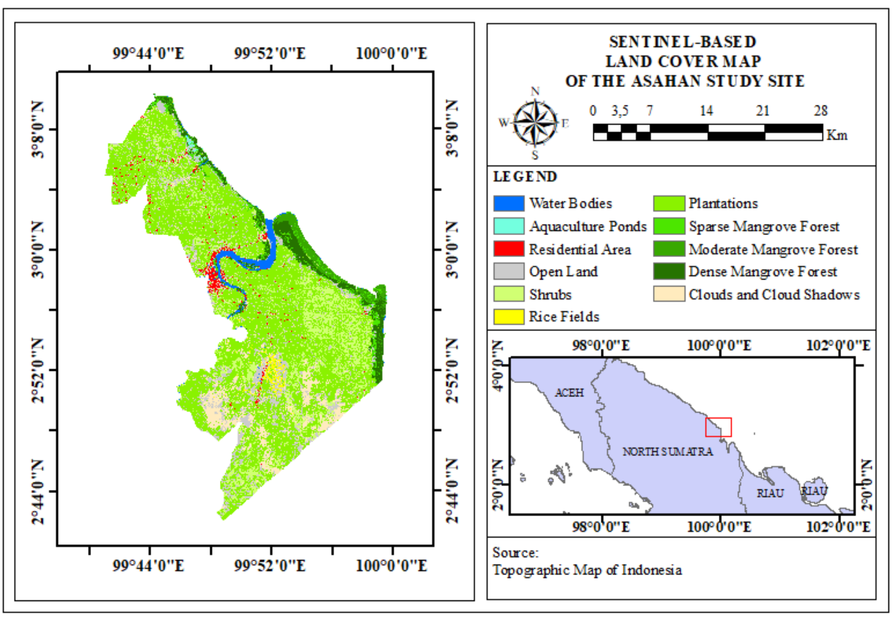


Fig. 7. Sentinel-2A-based classified image of Asahan study site

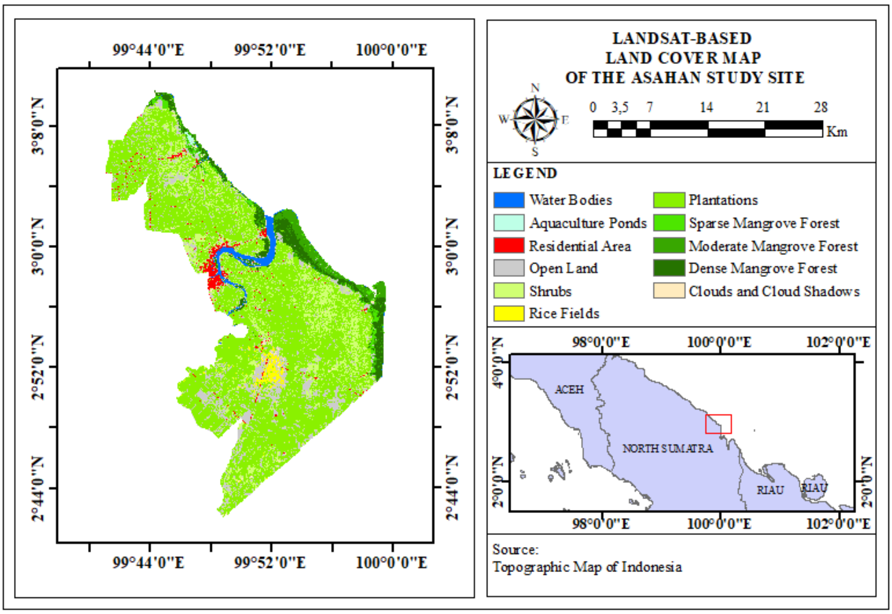


Fig. 8. Landsat-8-based classified image of the Asahan study site

5 Conclusions and future work

5.1 Conclusion

Based on the results and discussion described previously, this study concludes that the higher spatial resolution of the sensor (PlanetScope) consistently yields higher accuracy in identifying mangrove ecosystems and their canopy cover density. PlanetScope achieves OA, KA, average recall, and precision greater than 90%, whereas Sentinel-2A and Landsat-8 achieve OA, KA, average recall, and precision between 87.5% and 89.1%. Spectral-derived variables play a larger role (63%-82%) and are very important for detecting variations in mangrove ecosystems, including tree canopy health and land conditions (soil dryness-moisture). The most important spectral variables in PlanetScope imagery are NDVI, GARI, and SAVI. Non-spectral variables with 18%-47% roles play a key role in identifying mangrove ecosystems, especially substrate and salinity variables, complementing the limitations of spectral variables.

5.2 Future work

Further studies are recommended to (a) integrate multiple sensors (PlanetScope–Sentinel–Landsat) to improve classification accuracy through spatial or spectral fusion; (b) evaluate other machine learning models such as Random Forest, Gradient Boosting, and Deep Learning to compare the robustness of each algorithm, and (c) Incorporate multiseason temporal data to capture mangrove phenological dynamics and improve model generalization.

References

1. S. Hamilton, Assessing the role of commercial aquaculture in displacing mangrove forest. Bull. Mar. Sci. **89**, 2, 585–601 (2013). doi: 10.5343/bms.2012.1069.
2. D.L.A. Gaveau, B.Locatelli, M.A. Salim, H. Yaen, P. Pacheco, D. Sheil, Rise and fall of forest loss and industrial plantations in Borneo (2000–2017). Conserv. Lett. **12**, 3 (2019). doi: 10.1111/conl.12622.
3. L. Goldberg, D. Lagomasino, N. Thomas, T. Fatoyinbo, Global declines in human-driven mangrove loss. Glob. Chang. Biol. **26**, 10, 5844–5855 (2020). doi: 10.1111/gcb.15275.
4. K.M. Carlson *et al.*, Committed carbon emissions, deforestation, and community land conversion from oil palm plantation expansion in West Kalimantan, Indonesia. Proc. Natl. Acad. Sci. U. S. A. **109**, 19, 7559–7564 (2012). doi: 10.1073/pnas.1200452109
5. D.R. Richards, B.S. Thompson, L. Wijedasa, Quantifying net loss of global mangrove carbon stocks from 20 years of land cover change. Nat. Commun. **11**, 1 (2020). doi: 10.1038/s41467-020-18118-z.
6. M. Hirschmugl, M. Steinegger, H. Gallaun, M. Schardt, Mapping Forest degradation due to selective logging by means of time series analysis: case studies in Central Africa. Remote Sens. (Basel). **6**, 1, 756–775 (2014). doi: 10.3390/rs6010756.
7. T.V. Tran, R. Reef, X. Zhu, A review of spectral indices for mangrove remote sensing. Remote Sens. (Basel). **14**, 19, 4868 (2022). doi: 10.3390/rs14194868.
8. P.P. Wu, K. Mengersen, M.J. Caley, K. McMahon, M.A. Rasheed, G.A. Kendrick, Analysing the dynamics and relative influence of variables affecting ecosystem responses using functional PCA and boosted regression trees: A seagrass case study. Methods Ecol. Evol. **10**, 10, 1723–1733 (2019) doi: 10.1111/2041-210X.13269.
9. E. Hilmi *et al.*, Mapping of mangrove ecosystem in Segara Anakan Lagoon using normalized different vegetation index and dominant vegetation index. Omni-Akuatika. **18**, 2 (2022). doi: 10.20884/1.oa.2022.18.2.926.
10. Y. Zheng, W. Takeuchi, Improving remote sensing-based estimation of mangrove forest gross primary production by quantifying environmental stressors: Sea surface temperature, salinity, and photosynthetic active radiation. Aug. **24**, (2021). doi: 10.21203/rs.3.rs-817946/v1.
11. A.B. Baloloy *et al.*, Estimation of mangrove forest aboveground biomass using multispectral bands, vegetation indices and biophysical variables derived from optical satellite imageries: Rapideye, Planetscope and Sentinel-2. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences. **IV–3**, 29–36 (2018). doi: 10.5194/isprs-annals-IV-3-29-2018.
12. S. Uddin, H. Lu, Confirming the statistically significant superiority of tree-based machine learning algorithms over their counterparts for tabular data. PLoS One. **19**, 4, e0301541 (2024). doi: 10.1371/journal.pone.0301541.
13. M.I. Khaldi, A. Erraissi, M. Hain, M. Banane, In-depth comparison of supervised classification models - performance and adaptability to practical requirements. International Journal of Advanced Computer Science and Applications. **16**, 8 (2025). doi: 10.14569/IJACSA.2025.0160862.