The application of Landsat imageries and mangrove vegetation index for monitoring mangrove community in Segara Anakan Lagoon, Cilacap, Central Java

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Abstract. The only place for estuarine-mangroves in Java Island, Segara Anakan Lagoon, experiences the vast decline of mangrove cover. Satellite remote sensing has a critical role in monitoring that change as it allows to record vast areas over time. However, most studies tend to utilize satellite data to investigate the change of mangrove areas into other land-use types rather than identify the mangrove community's shifting. This study utilized the mangrove vegetation index (MVI) for monitoring the changes of mangrove communities at the life-form level using satellite data. The study used multi-temporal Landsat images as it has historical systematic archive data. The threshold value of the index for each class is defined by referring to the field data. The class referred to the life-form classification consisting of mangrove trees, Nypa, and understory. The image analysis was conducted using Google Earth Engine (GEE), while R software was used for determining threshold values through statistical analysis. The result shows that the MVI can differentiate between some life forms of mangroves, with the overall accuracy reaching 78.79% and a kappa coefficient of 0.729. Further, the multi-temporal maps showed the decline of mangrove tree areas, which the understorey and Nypa community have replaced.

Keywords: life-form community, mangrove changes, mangrove vegetation index, remote sensing

1. Introduction
Segara Anakan Lagoon (SAL) is the only place for estuarine mangrove on Java Island. This place provides shelters and life supports for marine biota as it is blessed with rich nutrients [1, 2]. Moreover, the lagoon plays an important role in the productivity of the coastal waters over the southern part of...
Central Java [3]. Mangroves occupy three-quarters of the lagoon’s area, while waters cover the remaining area [4]. However, a recent study showed the decline of mangrove extent with only 43.8% of the remaining area in 2003 [5]. The main causes were various anthropogenic activities, such as agriculture, aquaculture, industry, and settlement. Significant changes are found in the central part of SAL as the mangrove tree species such as *Avicennia alba* and *Sonneratia caseolaris* declined within a decade (2005 - 2015). In contrast, *Nypa fruticans* and understorey communities (*Acanthus* spp. and *Derris trifoliata*) have been increasingly dominant in the region [6, 7]. This dramatic change might be an alarm because understorey occupation, namely *Acanthus* spp., could be used as a bio-monitoring agent for mangrove degradation due to they usually occupy the area of open land [7]. Moreover, an occurrence of *Acanthus* spp. or *Derris trifoliata* is a sign of decreasing soil salinity [6, 7].

To our knowledge, the changes in mangrove communities have been less documented in published literature. Previous studies emphasized only the conversion of mangrove areas to other land-uses or covers [5, 8-10]. An attempt to provide mangrove maps at SAL with more detailed information was conducted by [11-13]. However, there are no available maps or spatial data regarding the expansion of *Acanthus* spp. and *Derris trifoliata* in SAL.

The remote sensing technique has a critical role in monitoring mangroves as it allows to record vast and difficult areas over time [14]. Image classification technique, namely supervised and unsupervised, has been widely used to identify mangrove covers [15-20]. However, this technique is less consistent in the result and the accuracy level as it depends on the classifier algorithm, the computer capacity, the proper knowledge of the study area, as well as the specific skill for interpreting the image [18, 21]. Hence, it is not easy to generalize the same technique for other images in various times and locations. Therefore, there is a need to explore more techniques that are applicable for addressing those limitations.

Spectral indices have shown the ability to detect and distinguish vegetation, for example, NDVI [22], SAVI [23], and EVI [24]. These approaches allow users to apply automated mapping. Spectral indices are a combination of satellite image bands, which can enhance the vegetation signal. Several indices have been designed to discriminate mangroves from terrestrial vegetation, such as MRI [25], MI [26], and MVI [21]. However, these indexes have never been used to identify mangroves into more detailed information, such as life-form or community types. Therefore, this study will explore the ability of those spectral indices to discriminate mangrove covers based on life-form or community types.

## 2. Methodology

### 2.1. Study Area

The lagoon is located on the south coast of Central Java separating by Nusakambangan Island from the Hindian Ocean (Figure 1). Terrestrial forests mostly cover Nusakambangan Island. On the contrary, the lagoon is covered mainly by the mangrove forest and waters with low elevation. The lagoon has two main outlets in the east and west parts connecting the lagoon to the ocean. The west part is highly influenced by the discharge from the Citanduy river transporting huge sediment [4, 27-29]. In contrast, the east part is highly influenced by the ocean as the Donan river has less discharge. The east outlet is deeper and wider than the west part. As a consequence, the main shipping lane lies in the east outlet. The center of the population is also placed in the east of SAL as it was established as a municipality of Cilacap. This city is one of the main hubs for sea transportation in the southern part of Java and Indonesia.
2.2. Method

This study was conducted in two stages. The first stage is developing the threshold model, and the second is implementing the threshold model. The first stage aims to define the threshold value of the spectral index for discriminating mangrove within the images based on life-form classification. Further, the second stage aims to implement the threshold model into the spectral index image at four time periods for presenting the change of mangrove communities in SAL.

2.3. Threshold Model

The first stage combined multi-images of Landsat-8 OLI between 2017 and 2019 to generate cloud-free data and used it to produce spectral index images. The technique to combine multi-images to produce a cloud-free image referred to the given script in the Google Earth Engine (GEE). This study utilized Landsat satellite data as its consistency to provide multi-temporal data for almost four decades. MVI (Mangrove Vegetation Index) developed by [21] was used in this study to explore its possibility for discriminating mangroves into several classes at the life-form level as it combined SWIR (Short Wave Infra-Red), NIR (Near Infra-Red), and green spectrum for developing the index. They found that their spectral index was superior to others for discriminating mangroves from terrestrial vegetation. It also supports the review study carried out by [14] that shows specific spectrums such as SWIR, NIR, and green can distinguish several types of mangroves due to their sensitiveness with leaf pigment, internal structure, and water content. The formula of MVI is as follows:

\[
MVI = \frac{|\text{NIR} - \text{GREEN}|}{|\text{SWIR} - \text{GREEN}|}
\]  

The life-form classification is based on Saenger [30] that distinguishes mangroves into trees and shrub/understorey. This study modified the class into mangrove trees, mixed mangrove trees, palm-like mangrove (Nypa), and understorey, as highlighted in the SAL mangrove communities. The MVI threshold value for each class was developed by grouping MVI pixels within the field data based on statistical analysis. The basic statistical analysis was used to compare the mean, first quartile, third quartile,
median, maximum, and minimum value of each class. Hence, those values were used to define the threshold for each class. The field data was provided from the Research Center for Oceanography-Indonesian Institute of Sciences survey in 2019. The data is processed data deriving from 150 drone images comprising the cover percentage of mangrove trees, Nypa, and understorey. The mangrove trees were defined by the cover percentage of mangrove tree canopy greater than 50%. While mixed mangrove was defined by the cover percentage of mangrove trees canopy between 30% and 50%. The remaining classes, Nypa and understorey class, were defined by the cover percentage of each object greater than 50%. Based on the knowledge from the field data, we also defined a polygon sample for each mangrove class to build a reflectance curve as the additional information. The polygon sample consisted of 285 pixels extracted from seven bands of the Landsat data. The reflectance curve is useful to provide information on which bands can discriminate objects, particularly mangrove communities.

The accuracy assessment was conducted by using overall accuracy along with the Kappa coefficient. The overall accuracy and Kappa (K) coefficient [31] were calculated based on the formula as follows:

\[
\text{Overall accuracy} = \frac{\text{number of correct points}}{\text{total number of points}} \tag{2}
\]

\[
K = \frac{N \sum_{i}^{n} M_{i,i} - \sum_{i}^{n} (G_{i} - C_{i})}{N \sum_{i}^{n} (G_{i} - C_{i})} \tag{3}
\]

Where:
\(i\) = the class number.
\(N\) = the total number of classified pixels that are being compared to ground-truth.
\(M_{i,i}\) = the number of pixels belonging to the ground-truth class \(i\), that has also been classified as class \(i\).
\(C_{i}\) = the total number of classified pixels belonging to class \(i\).
\(G_{i}\) = the total number of ground-truth pixels belonging to class \(i\).

The data for assessment was generated from visual interpretation on google satellite images based on local observation/knowledge. All the processes in this study used open-source platforms, namely GEE and R, for image processing and statistical analysis, respectively.

2.4. Multi-temporal Mapping
We used Landsat data for four periods (t0, t1, t2, t3) in the second stage. Similar to the first stage, each period used a cloud-free image. The data of t0, t1, t2, and t3 were generated from the Landsat-5 TM between 1987 and 1990, Landsat-5 between 1997 and 2000, Landsat-5 between 2007 and 2010, Landsat-8 OLI between 2017 and 2019, respectively.

The MVI and the threshold model were used to produce mangrove maps at four periods. The multi-temporal map presented the change of mangrove communities in SAL at the life-form level. The change analysis was conducted in R using a portion of a tool from the LULCC library. The result of the analysis is the table presenting the change of area in each life-form class.

3. Result and discussion

3.1. Mangrove Vegetation Index Threshold
The reflectance curve of mangrove communities and terrestrial vegetation in Segara Anakan Lagoon is shown in Figure 2. As we know that SWIR is the key band that can discriminate between mangrove and non-mangrove [21], the reflectance of this band also shows the unique signatures in the Landsat 8 OLI imageries among different life forms of mangroves (Figure 2). This range is sensitive to water content as it absorbs infrared light and becomes more strong in the SWIR range [14, 21, 32, 33], [34] and [21] were convinced that mangroves could be distinguished from other vegetation by their water content and greenness level. They found that the combination of water index and greenness was able to produce a mangrove map accurately. This finding also strengthens the previous studies that stated mangroves were associated with the water content and greenness characteristic.
Figure 2. The reflectance curve of mangrove communities and terrestrial vegetation.

Compared to SWIR, Green (G) (500 nm) and near-infrared (NIR) (800 - 900 nm) cannot discriminate mangrove trees from terrestrial vegetation as the reflectance line of those has coincided. It means the discrimination cannot be determined only by its leaf pigments and internal structure characteristics as highlighted by the visible and near-infrared spectrum. Hence, this finding emphasized the critical use of SWIR for detecting mangroves even more specifically for its other life-form class, namely *Nypa* and understorey. Further, the reflectance of terrestrial vegetation has a narrower difference between SWIR and NIR than other mangrove communities. The water absorption could influence this in the SWIR region. The water content in the leaf and its soil background contributed to the absorption in the SWIR region. It is consistent with spectral response characteristics in mangroves, as mentioned in [14].

[21] used the response difference between SWIR, NIR, and G to enhance the mangrove features. The difference between NIR and G is used to enhance the greenness variation among mangrove and terrestrial vegetation. Further, the difference between SWIR and G is used to express the distinct moisture of mangroves due to their environment. Based on their formula, mangroves have specific thresholds that contrast to other land covers. Even this threshold is wider than others. Hence, it raises the possibility to detail the threshold into the more specific classes. A wide range of signatures for mangroves can be applied for further mangrove identification based on the spectral properties of the canopy [34].

This study utilized MVI [21] to identify further mangroves based on life-form class. The basic assumption of life-form classification is that the characteristics of plant structures can represent the balance of water content, soil fertility, temperature, and light penetration [30]. The mangrove community in the eastern LSA is dominated by true mangroves consisting of *Rhizophora apiculata*, *Ceriops* spp., *Bruguiera gymnorrhiza*, and *Aegiceras corniculatum*. However, the Central and West regions are dominated by associate mangrove species that are more resistant to fresh water and dry environments, namely *Nypa fruticans* and understorey mangrove communities such as *Acanthus* spp., *Derris trifoliata* [6-7]. The characteristics of these different communities will affect the physical
properties of plants, such as water content and greenness level. Therefore, this characteristic has the potential to be detected from the use of certain wavelengths in satellite imagery.

By using drone imageries, identified mangrove life forms or mangrove communities can be corresponded with MVI values generated from Landsat imageries, and presented in Figure 3. The optimal minimum threshold of MVI for mangroves feature in Sentinel-2 and Landsat-8 OLI images are 4.5 and 4.6, respectively [21]. This threshold is quite consistent in the SAL image. Based on Figure 3, mangrove trees, Nypa and understorey communities are well separated from other classes. In contrast, mixed mangroves and the Nypa community have shown an overlap threshold. This overlap occurred as the Nypa and understorey occupied the gap between mangrove trees within a pixel of Landsat as its pixel size is relatively fit enough to represent mixed energy. Further, this situation caused the spectral response between Nypa and mixed mangrove classes to be difficult to distinguish. This feature can be found mainly in the central and western parts of SAL.

![Figure 3: The boxplot of MVI value for each class of mangrove communities.](image)

Mangrove trees, Nypa, and understorey are determined based on the 1st (lower) and third quartile (upper). This value is the limit for determining the MVI value of the three classes. It is different from the mixed mangrove class because the data distribution overlaps with that of Nypa. Therefore, it was determined that the upper limit of mixed mangrove coincided with the minimum limit of mangrove trees (7.39), and the lower limit was determined based on the 1st quarter value of mixed mangrove (6.69), which coincided with the upper limit of the Nypa threshold. Furthermore, the lower limit of the Nypa class threshold is determined at a value that coincides with the upper limit of the understorey threshold based on the 3rd quartile value of its data. The threshold values for each of these classes can be seen in detail in table 1.

| Class       | MVI threshold       |
|-------------|---------------------|
| Mangrove Trees | 7.391 - 16.950   |
| Mixed Mangrove  | 6.691 - 7.390   |
| Nypa           | 5.631 - 6.690   |
| Understorey    | 3.47 - 5.630    |
3.2. Accuracy
The defined threshold was used to generate the mangrove map based on the life-form class. The overall accuracy shows the performance of this map as it reaches 78.79% with a Kappa coefficient of 0.729. The accuracy assessment is based on 49 points of data generated from visual interpretation in the google satellite images. This accuracy is lower than [21] for discriminating mangroves from terrestrial vegetation. However, it has better performance than [35] as they used NDVI for classifying mangroves species with an overall accuracy of 65% for Landsat-8 OLI. Their studies also found SPOT-5, Sentinel-2, and WorldView-2 resulting in map accuracy 75%, 78%, and 93%, respectively. Further, they also found that the NDVI threshold of Laguncularia racemosa, Rhizophora mangle, and dead mangroves were well separated.

The misclassification occurred mainly in the transitional area between understorey and terrestrial vegetation. It could happen as the minimum MVI value of understorey (3.47) coincides with the maximum value of terrestrial vegetation (3.5) [21]. For example, we found these features in the western part of SAL and the north part of the central lagoon (Figure 4). This location is occupied by an understorey adjoining rice fields.

Figure 4. Misclassification in the eastern part (a) and north part of the central lagoon (b).

3.3. Spatial historical change of mangrove
In total, 22% of mangroves cover consisting of mangrove trees community, and mixed mangrove has declined over three decades (t0-t3). According to Table 2, mangrove trees and mixed mangrove communities have lost 45% and 10% during this period, respectively. Mangrove trees community has experienced an increase from 1,952.37 ha (hectares) to 2,147.85 ha between 1990 and 2000 (t0-t1). However, it came to the greatest loss of 38% in a later decade between 2000 and 2010 (t1-t2). In contrast, mixed mangrove has increased 18% in the last decade before initially has declined by 17% in the first decade (t0-t1). This could be related to the reforestation in the eastern part and the natural regeneration of Rhizophora apiculata seedlings, as mentioned by [6]. They also concluded that those processes caused increasing densities in mangrove trees, but the trees remained small and shrubby.

| Class          | t0    | (t0-t1) | t1    | (t1-t2) | t2    | (t2-t3) | t3    | (t0-t3) |
|----------------|-------|---------|-------|---------|-------|---------|-------|---------|
| Mangrove trees | 1952.37 | 10%     | 2147.85 | -38%    | 1338.39 | -19%    | 1081.26 | -45%    |
| Mixed mangrove | 3721.68 | -17%    | 3091.86 | -8%     | 2829.42 | 18%     | 3333.24 | -10%    |
| Nypa           | 1493.37 | 1%      | 1502.55 | 40%     | 2109.42 | 39%     | 2922.39 | 96%     |
| Understorey    | 2166.66 | 50%     | 3254.76 | 22%     | 3968.46 | -10%    | 3576.42 | 65%     |
Based on Figure 5, a significant change occurred in the western and central parts of SAL. The mangrove cover was gradually changed from mixed mangrove community into \textit{Nypa} and understorey. The \textit{Nypa} and understorey communities were sharply increased in the last three decades by 96% and 65%, respectively. The biggest gain of understorey occurred in the first decade (50%) before it has slightly declined to 10% in the last decade. However, the understorey area is still the largest in the last observation (t3) as it reached 3,576.42 ha. The growth of \textit{Nypa} and understorey could be related to the moderate and low salinity environment [6]. This is also highlighted by the influence of the high discharge of freshwater from the Citanduy river [4].

The effect of the low-saline environment contributed to changes in the mangrove community on the newly emerged land in the eastern of SAL. The sedimentation process generated the emerged land as influenced by the Citanduy river [4, 28]. Initially, the emerged land was occupied by mixed mangroves in the t1 (1997-2000). Further, it was gradually replaced by understorey until t3 (2017-2019) as this community was more tolerant to the low-saline environment.

![Figure 5](image.png)

**Figure 5.** The multi-temporal maps of mangrove communities in SAL (a. t0, b. t1, c. t2, d. t3).

4. Conclusion

Although MVI is aimed to distinguish mangrove and non-mangrove from satellite imageries, this index can also be used to differentiate between some life forms of mangroves, i.e., \textit{Nypa} and understorey mangrove (\textit{Derris trifoliata} and \textit{Acanthus} spp.). These life forms have unique thresholds of MVI values. This is because those life forms' reflectance values in the SWIR band are significantly different from mangrove trees.

The application of this MVI may be important for mangrove mapping into more detail, i.e., life form levels, particularly around the study case, Segara Anakan Lagoon. This study contributes to providing a mangrove map of SAL which include \textit{Nypa} and understorey mangrove (\textit{Derris trifoliata} and \textit{Acanthus} spp.). Previous studies have indicated these mangrove species as invasive plant species and an indicator
for mangrove degradation. Therefore, providing this mangrove map might be essential work for future studies.

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