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Research Article

The Implementation of the Mangrove Quality Index: A Way to Overcome Overestimation and Classification Concerns in Detecting Mangrove Forest Cover

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Abstract: The increasing applications of Geographic Information Systems (GIS) and Remote Sensing (RS) for mapping, predicting, and monitoring are practical for sustainable mangrove ecosystem management. This study evaluated various geospatial techniques for detecting healthy mangroves on the eastern coast of Sri Lanka, including single spectral indices, supervised/unsupervised classification, and developed methods using Landsat data. The use of medium-resolution satellite data and the uniqueness of the mangrove ecosystem are generally involved in discriminating healthy mangroves from non-mangrove areas. This study focused on detecting degraded narrow patches of mangroves on the Eastern coast of Sri Lanka using Landsat 8 remote sensing data and five vegetation indices. The accuracy of the results was assessed using randomly generated points. The study used ArcGIS Desktop software for processing, analyzing, and integrating spatial data to meet the research objectives. The mangroves were detected using Landsat 8 OLI satellite images from 2018 and 2021. The results showed high overestimation/underestimation and misclassification of mangroves, thus applying Mangrove Quality Index (MQI). Findings of MQI provide insights into overall mangrove health and identify three degradation classes of mangroves on the Eastern coast of Sri Lanka. The application of MQI in well-developed and degraded mangrove ecosystems merits further investigations, which provide reliable information for conservation priorities.

Keywords: Geospatial Technologies; Remote Sensing; Satellite Data, Mangrove Mapping; Spectral Indices.

1. Introduction

Geospatial technologies had developed since ancient times when the first maps were created. In contemporary times, geospatial technologies serve as advanced tools that aid in the geographical mapping and analysis of the earth and human societies. Most studies on mangrove ecosystems rely heavily on geospatial technologies, particularly remotely sensed data. Multi-seasonal satellite data, in particular, play a crucial role in providing comprehensive life history information on aquatic vegetation [1]. Remote sensing techniques have proven highly effective for mapping mangroves [2]–[4]. Medium-resolution satellite sensors such as Landsat, SPOT (*Satellite Pour l'Observation de la Terre*) [5], and Sentinel 1 and 2 [7] have been utilized to monitor, detect, and analyze mangroves worldwide. Among the high-resolution imagery IKONOS [8], Quick Bird, and Worldview 2 [9] have been used for the same purposes. Kuenzer et al. emphasized that the availability of a large number of narrow bands (<10nm) in airborne hyperspectral imagery opens a new window for mangrove mapping and detecting mangroves at the species level [10].

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Zhang et al. further showed the use of active systems like RADARSAT and ENVISAT ASAR along with optical data to classify mangrove species [11]. Mangrove restoration, a recently established program to rejuvenate the coastal belt, requires regular monitoring to investigate and study the regeneration of mangroves, which can be studied using Radar Sat-2 images and are more suitable for identifying the dynamics of regenerating mangroves [12]. Mangrove composition mapping is expensive and facilitated by LiDAR data [13]. Thus, the accessibility, purpose, and cost decide which type of satellite data is appropriate for a separate study. Selecting an appropriate classification method is challenging based on the satellite data type. Geospatial tools are essential in mangrove mapping to build conservation models and enhance conservation measures.

Regular monitoring of mangroves is not an easy task and is time-consuming. On the other hand, mangrove forests are difficult to access and survey due to the boggy waterlogging environment. Thus, remote sensing data are the most suitable source to detect and monitor mangroves. Besides, remote sensing in mangrove mapping and further analysis is a performance of satellite sensors beyond manual mapping. Mangrove mapping methods usually depend on a single-day imagery analysis. Mangroves being habitable in the coastal belt, generally adapted to tidal changes. High tides may affect the identification of mangroves in the satellite imagery, likewise the low tide. Single-day imagery thus suffers either from low tide or high tide. This can lead to underestimation or overestimation in mangrove mapping if the imagery is captured during high tide.

Further emphasizing the difficulties in mangrove mapping using moderate resolution, 30-meter satellite data highlighted the need for high-resolution imagery to gain more accurate mapping results corresponding to different tidal levels [14]. However, due to natural or human disturbances, accessing high-resolution satellite imagery to detect fragmented mangrove patches costs highly. If the study area is large enough, double the cost [15]. Remarkably, studies have used medium-resolution multispectral data in mangrove mapping over a large area [1], [16]. In that context, freely accessible medium-resolution satellite images like Landsat 7 and 8 need to examine for improved mangrove detection methods or suitable spectral indices rather than relying only on commonly applied NDVI.

The destruction of Sri Lanka's mangrove ecosystem is occurring faster than before; promoting awareness of geospatial technology and expanding its research applications is essential. Currently, the use of geospatial tools for decision-making and resource management in Sri Lanka is at a basic level, and there are challenges in applying these technologies to detect healthy mangrove forests. More research is needed to protect the mangrove ecosystem, beginning with identifying the appropriate method to identify healthy mangrove forests. This study was conducted on the eastern coast of Sri Lanka to assess the suitability of different methods for detecting healthy mangroves through geospatial techniques, including using single spectral indices, supervised or unsupervised classification with standard ground-truthing, or developed methods using freely accessible Landsat data.

2. Material and Methods

2.1. Study Area

The Eastern coast of Sri Lanka is ideal for natural resources comprising shallow coastal areas, rivers and estuaries, lagoons, and expansive beaches.

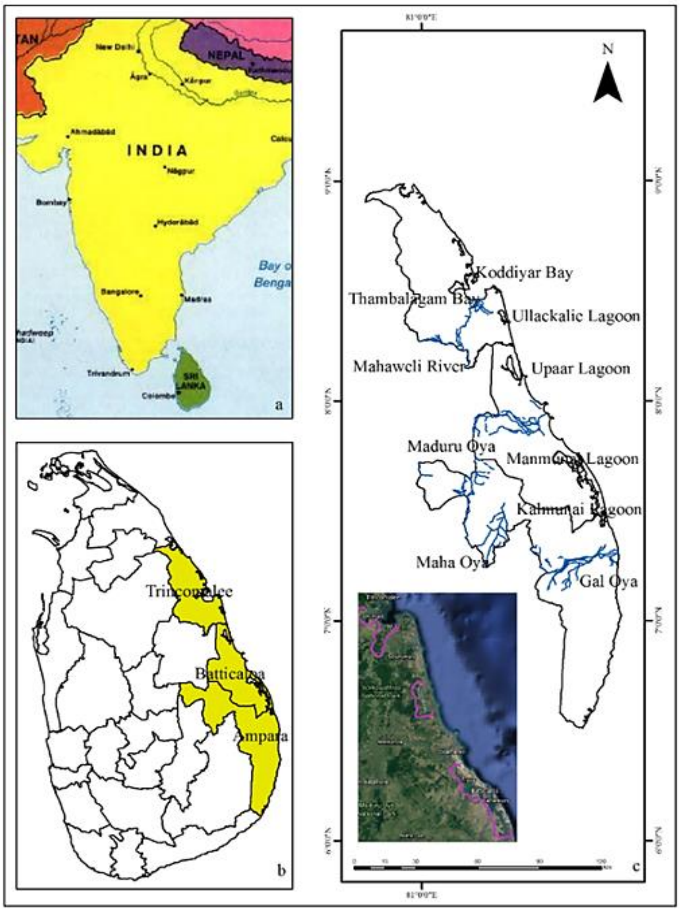


Figure 1. The relative and absolute location of the study areas. (a) the relative location of Sri Lanka in the Indian Ocean (uppermost left); (b) Study areas in Sri Lanka (lowermost left); and (c) the east coast of Sri Lanka (right)

The Eastern coast comprises three districts Trincomalee, Batticaloa, and Ampara (Figure 1). Mangroves are visible around Thambalagam bay, Mahaweli estuary, Manmunei, and Kalmunei lagoon areas. Mangroves in Trincomalee are a single layer with a simple hierarchy [17]. Medium-height mangroves (< 5m) are distributed along the coastal belt on muddy, sandy, and rocky beaches. Mangrove regeneration takes place in Batticaloa. The total extent of mangroves in Trincomalee, Batticaloa, and Ampara was 50.84 km2 (23.95 km2, 20.71 km2, 6.18 km2) in 2007 [18].

2.1. Data Analysis

2.2.1. Satellite Data Processing and Extraction

The study utilized the digital image processing software ArcGIS Desktop to process, analyze, and integrate spatial data to achieve the research objectives. To detect mangroves, Landsat 8 OLI satellite images from 2018 and 2021 (Table 1) were obtained from the USGS Earth Explorer (https://earthexplorer.usgs.gov). The images underwent atmospheric correction prior to analysis. The extracted vegetation area was then classified using supervised classification and divided into 12 classes to differentiate exclusive mangrove forests. Vegetation data for each image were obtained using different vegetation indices. Mangroves were detected using band combinations 4, 5, and 6.

Table 1. Satellite Data Details

Year	Date of Acquisition	Path	Row	Spatial Resolution	Projection
2018	2018/09/06	140	55	30 x 30	"WGS84"
	2018/09/13	141	54	30 x 30	"WGS84"
	2018/06/25	141	55	30 x 30	"WGS84"
2021	2021/03/29	141	54	30 x 30	"WGS84"
	2021/03/29	141	55	30 x 30	"WGS84"
	2021/07/12	140	55	30 x 30	"WGS84"

NDVI is a valuable tool for distinguishing green vegetation from other surfaces. This is because the chlorophyll in green vegetation absorbs red light for photosynthesis and reflects near-infrared wavelengths due to scattering caused by internal leaf structure [19]. NDVI is more effective in wet and dry areas [20]. NDVI values range from -1.0 to +1.0, and very low NDVI values (-0.1 and below) correspond to a barren rock, sand, or urban/built-up areas. A value of zero in the given context represents water. NDVI values between 0.10 and 0.30 signify low vegetation density, whereas values between 0.60 and 0.80 indicate dense vegetation. NDVI values between 0.90 and 1.0 represent the highest possible green vegetation density [21]. The algorithm is;

$$\boldsymbol{NDVI = \frac{NIR - R}{NIR + R}} \tag{1}$$

RVI is also used to study vegetation, the most detailed vegetation index initially described by Birth and McVey [22] as a slope-based vegetation index like NDVI. The algorithm is;

$$\boldsymbol{RVI = \frac{NIR}{R}} \tag{2}$$

DVI is a more accessible vegetation index that weighs the near-infrared band due to the slope of the soil line. Zero values of DVI stand for bare soil, and positive values indicate vegetation. DVI calculating algorithm is;

$$\boldsymbol{DVI = \frac{SWIR1}{R}} \tag{3}$$

IPVI is functionally the same as NDVI. IPVI computation is faster than NDVI computation. The value range between 0 and 1. The algorithm is as follows;

$$\boldsymbol{IPVI = \frac{NIR}{NIR + Red}} \tag{4}$$

SAVI corrects soil brightness in areas with low vegetation cover detected by NDVI. SAVI is designed as a ratio between the red and near-infrared values with a soil brightness correction factor (L) defined as 0.50. The algorithm is;

$$\boldsymbol{SAVI = \frac{(NIR - Red)}{(NIR - Red + L)} \times (1 + L)} \tag{5}$$

2.2.2. Accuracy assessment

Accuracy of the mangrove detection is carried out by creating random points checked across the actual land area using Google Earth, which the date aligned to Landsat satellite images. In order to verify the accuracy, ground truthing was carried out in the field.

2.2.3. Mangrove Quality Index

In order to avoid the weaknesses or challenges in healthy mangrove detection, a mathematical formula is applied for better results.
MQI Score of a specific category

$$\boldsymbol{MQIS_i = \sum_{i=1}^{j} 2\ w_i z_i} \tag{6}$$

Overall MQI

$$\boldsymbol{Overall\ MQI = \sum_{i=1}^{c} MQIS} \tag{7}$$

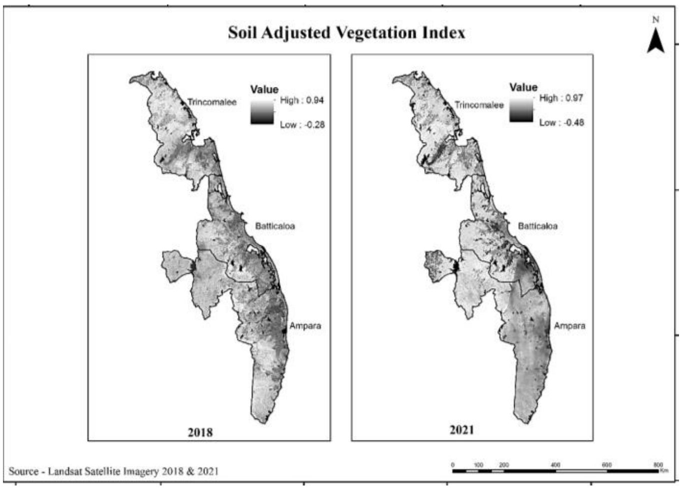
*c is the number of categories.

The application of the Mangrove Quality Index (MQI) involves several steps. Firstly, the disturbance level is classified using geoinformatics. Then, socio-ecological variables of the mangrove ecosystem are identified and evaluated using principal component analysis, resulting in 43 variables. Equations 6 and 7 calculate the MQI for each variable category and the overall MQI. Data for socio-economic variables are obtained from an unpublished survey conducted in the study area. The MQI results are rated on a scale ranging from 1 (worst) to 5 (excellent). The method is validated using NDVI classification for the study areas. It is worth noting that the Eastern coast mangrove ecosystems are classified according to their disturbance level based on available literature.

3. Result and Discussion

3.1. Issues Involved in Disturbed Patches of Mangrove Mapping

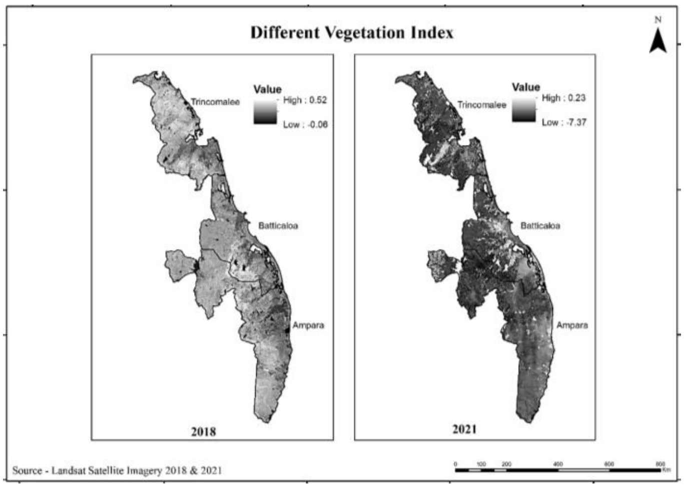
Based on the Landsat images, the data was extracted, spectral indices were calculated, and relevant maps were produced in accordance (Figure 2-6).



Soil Adjusted Vegetation Index

Source - Landsat Satellite Imagery 2018 & 2021

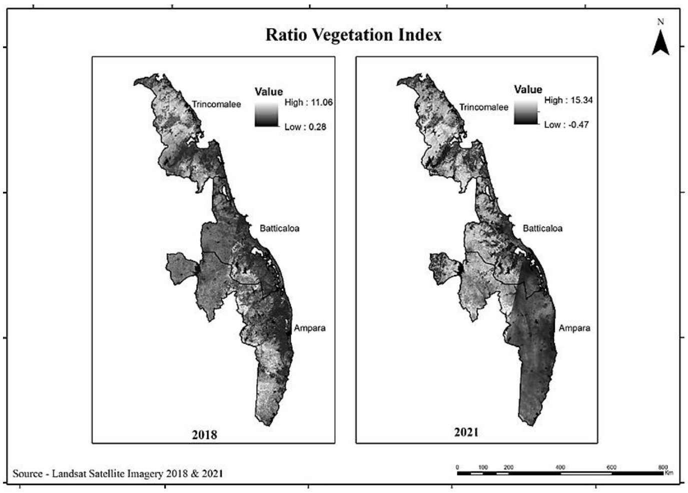
Figure 2. Overestimated/underestimated Mangrove Detection 2018 and 2021 – SAVI Index.



Different Vegetation Index

Source - Landsat Satellite Imagery 2018 & 2021

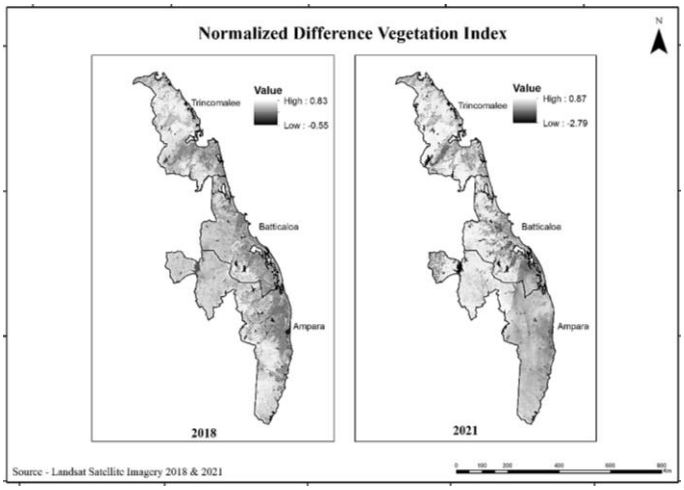
Figure 3. Overestimated/underestimated Mangrove Detection 2018 and 2021 – DVI Index.



Ratio Vegetation Index

Source - Landsat Satellite Imagery 2018 & 2021

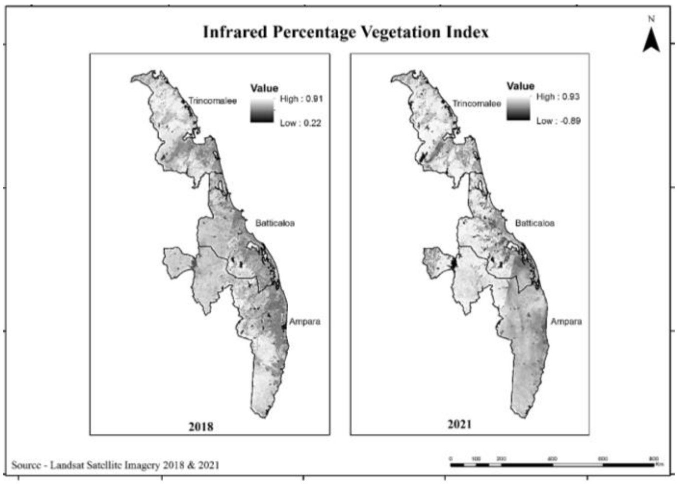
Figure 4. Overestimated/underestimated Mangrove Detection 2018 and 2021 – RVI Index.



Normalized Difference Vegetation Index

Source - Landsat Satellite Imagery 2018 & 2021

Figure 5. Overestimated/underestimated Mangrove Detection 2018 and 2021 – NDVI Index.



Infrared Percentage Vegetation Index

Source - Landsat Satellite Imagery 2018 & 2021

Figure 6. Overestimated/underestimated Mangrove Detection 2018 and 2021 – DVI Index.

Both the 2018 and 2021 maps were placed together to compare the results. SAVI, NDVI and IPVI for 2018 mostly misclassified the dry vegetation cover as high mangrove areas. DVI and RVI underestimated mangrove areas by not detecting actual mangrove extents. Overall, the 2018 image did not recognize the coast's mangrove forests. Mangrove identification for 2021 also failed to detect actual mangrove forests using IPVI, DVI and RVI. Underestimation and misclassification of mangroves are highly visible. Though the over-classification of mangroves via SAVI and NDVI could be seen in 2021, exact mangrove forest patches were already classified within the area.

Table 2. The overall Accuracy of Spectral Indices

Spectral Index	2018 (%)	2021 (%)
SAVI	76.92	86.20
DVI	77.77	66.66
IPVI	69.23	80.00
RVI	75.00	100.00
NDVI	60.37	76.92

Overall accuracy thus cannot prove the accurate statistics of mangrove extents (Table 2); instead, the accuracy results are correct for other vegetation types associated with sandy-salt mixed environments (Halosere and Xerosere). The misclassification shows that the detected land cover extents exceed the true extent of mangroves in the study areas (Table 3). For example, Pathmanandakumar found that the mangrove extent in Trincomalee District is approximately 15 km2 [17]. Table 3 clearly shows the contrasting overestimated forest cover, including mangroves. This shows that simple land cover classification for environmentally particular areas is unsuitable for detecting micro-biomes like mangroves.

Table 3. The Extent of Areas Leads to Overestimation

Spectral Index	2018 (km2)	2021 (km2)
SAVI	3431.83	2750.52
DVI	1341.09	587.46
IPVI	4576.56	3137.22
RVI	727.68	186.52
NDVI	4576.56	3137.22

3.2. Advancements in Remote Sensing of Mangrove Ecosystems

Mangrove is a unique vegetation type always challengeable in identification using spectral indices, especially the degraded and healthy mangroves from other salinity preferable wetlands plants. Several classification methods have been examined for extracting mangrove land cover using Landsat data. These include unsupervised classification using the k-means clustering algorithm, supervised classification using the maximum likelihood decision rule, and the band ratio algorithm using the maximum likelihood decision rule. Among these, the band ratio supervised classification method has been found to produce the most accurate results for detecting mangrove land cover. Besides, Combined Mangrove Recognition Index (CMRI) was recently applied to detect mangroves in Sundarbans, India [23]. CMRI is calculated using NDVI and NDWI's unique range of classes for better-distinguishing mangroves from non-mangroves. The submerged Mangrove Recognition Index (SMRI) is another index that effectively distinguishes submerged mangroves that perform better with high-resolution images than those medium-resolution Landsat data [24]. The tidal effect is only a factor that disturbs effective mangrove detection using medium-resolution data [14]. The other factors are soil and water physio-chemical properties, plankton ecosystem, biotic characteristics, and socio-economic factors. Developing a better index for mangrove quality is far more critical since there are few challenges in applying typical vegetation indices and classification algorithms for degraded narrow mangrove patches.

Following Ibrahim et al. [25], mangrove quality was assessed for five distinct factorial categories consisting of 43 variables, namely; (i) biotic variables, basal area, mangrove tree height, tree volume, crab abundance, above-ground biomass; (ii) soil variables; pH, sulfur, calcium, phosphorus, potassium, nitrogen, carbon, magnesium; (iii) aquatic ecosystem variables; abundance of phytoplankton, diatoms, dinoflagellates, copepods, jellyfish, no of phytoplankton species, diatoms, dinoflagellates, copepods, jellyfish; (iv) hydrology variables; pH, turbidity, electric conductivity, total dissolved solids, temperature, dissolved oxygen, total suspended solids, chemical oxygen demand, biochemical oxygen demand, salinity, ammonia, phosphate, nitrate, fecal coliform; and (v) socio-economic variables; fishing hours/days and weight of fish catches, monthly income, age, education. Where the results of the calculation range from 1 standing for the worst condition, while up to 5 indicates excellent.

Accordingly, the 1-5 scale showed the Mangrove Quality Index (MQI). MQI for the study area revealed that each variable group ranges between worst and good levels. Mainly, three distinct areas were identified in the study area; a) least disturbed, b) moderately disturbed, and c) most disturbed. The least disturbed areas obtained an MQI of 5, moderately disturbed areas an MQI of 4, and most disturbed areas reached an MQI of 2. The least disturbed area is the Mahaweli estuary and Thambalagam bay (Figure 7), while the moderately disturbed areas are the Irrakkandi lagoon, Upparu lagoon, and Periya Kalapuu. The most disturbed areas are the Batticoloa complex, Ullackalie lagoon, and Pothuvil (Figure 7). Validation of the MQI carried out performing NDVI. The reliability of the MQI results can be seen with the NDVI validation. The NDVI values close to 1 in areas ranked five showed the mangrove vegetation was denser and healthy, while the NDVI value nearing (-1) in areas ranked two showed the area is less dense with mangrove vegetation and sparse distribution hence supporting the overall MQI values obtained to indicate the East coast mangrove ecosystem health.

Table 4. The Extent of Areas Leads to Overestimation

Disturbed level	Areas	NDVI
Least Disturbed	Mahaweli estuary, Thambalagam bay	0.50 - 0.80
Moderately Disturbed	Irrakkandi lagoon, Upparu lagoon, Periya Kalapuu	0.10 - 0.60
Most Disturbed	Batticoloa complex, Ullackalie lagoon, Pothuvil	-0.50 - 0.30

Table 5. Mangrove Species Distribution by Disturbed Category

Mangrove species	Eastern coast	Least disturbed	Moderately disturbed	Most disturbed
Aegiceras corniculatum (T)	√	√	-	√
Avicennia marina (T)	√	√	√	√
Avicennia officinalis (T)	√	-	-	√
Bruguiera cylindrica (T)	√	√	-	-
Bruguiera gymnorrhiza (T)	√	-	-	√
Bruguiera sexangular(T)	√	-	-	√
Ceriops decandra (T)	√	-	-	-
Rhizophora apiculate (T)	√	-	√	√
Rhizophora mucronate (T)	√	√	√	√
Heritiera littoralis (T)	√	-	√	√
Lumnitzera racemose (T)	√	√	√	√
Pemphis acidula (T)	√	-	-	√
Excoecaria agallocha (T)	√	-	√	√
Sonneratia apetala (T)	√	√	-	-
Scyphiphora hydrophyllacea (T)	√	√	-	-
Xylocarpus granatum (T)	√	-	-	√
Hibiscus tiliaceus (A)	√	√	√	-
Achrosticum aurem (A)	√	√	-	√
Acanthus illicifolis (A)	√	√	-	√
Cerbera manghas (A)	√	-	-	√
Dolichandrone sp (A)	√	-	-	√
Arthrocnemum sp (A)	√	√	-	-
Suaeda monoica (A)	√	√	-	-

Mangrove detection using medium-resolution satellite imagery has been identified as complex compared to high-resolution imagery. Since Landsat medium-resolution images are freely accessible, most undergraduates and graduate students have used Landsat imagery for their studies. However, mangroves confined to a patchy distribution, degraded and regenerating mangrove mapping only using spectral indices could lead to misclassification and underestimation. Misclassification, underestimation, and overestimation of mangroves may be due to the high density of natural forests and gallery forests along the numerous waterways and alluvial, clay-mixed sandy soils. RVI, IPVI, and DVI could be recognized as unsuitable for micro-scale biome-like mangrove mapping among the spectral indices. Though SAVI and NDVI detected mangroves, the integration of natural riverine and gallery forest is still visible. Regarding the accuracy of each spectral index (Table 2), SAVI can be considered an excellent index to identify mangroves adapted to specific soil conditions, but the overestimation still existed. Overall, it is clear that misclassification led to overestimating the extent of mangroves in 2021 (Table 3), while overall accuracy for 2018 could not be accurate due to the difficulty in finding cloud-free imagery.

In contrast, unsupervised classification-based mangrove detection is far more accurate than single vegetation indices. Previous studies also proved that supervised or unsupervised classification at first is suitable for detecting different types of land covers [17]. Identifying several land cover types helps to detect the respective small-scale biome, like mangroves. However, the weaknesses of each method show that current methods are more reliable for studying small-scale biomes like mangroves using freely available satellite data. These weaknesses result from the unique characteristics of mangrove species and the ecosystem. NDVI is identified as an excellent spectral index to detect mangrove and non-mangrove areas.

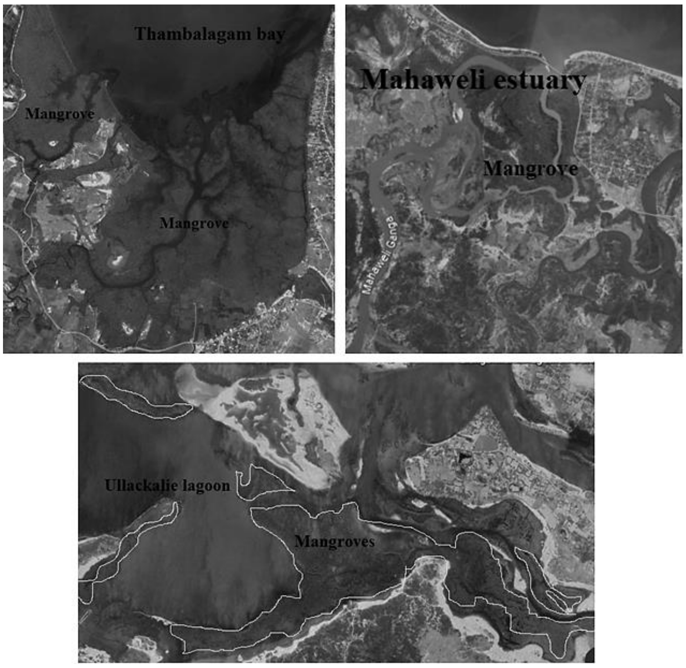


Figure 7. Overestimated/underestimated Mangrove Detection 2018 and 2021 – NDVI Index.

However, detecting and quantifying healthy mangrove vegetation in dry zone areas mixed with salty environments is challenging. Besides, the Eastern coast has about 16-19 mangrove species, but most mangroves are mixed with associates (Table 5) that grow landward than submerged and heavily disturbed or patched. Thus, the detected area may have other vegetation types, such as salt marsh and other wetland and land plant species. Mapping mangroves need a particular focus on exclusive or true mangroves than mangrove associates. Valid mangrove species are highly vulnerable to changing climate effects, sea-level changes, impacts of species interactions, and human activities such as ad hoc landing, illegal fishing methods, land encroachments for housing and shrimp ponds [26], which is significant in Batticaloa in the Eastern coast [27]. Discriminating mangroves with high green values with non-mangrove areas is typically frequent. Unless validated by meticulous ground-truthing in the mixing zone, remote sensing studies may lead to overestimating such mangroves as small-scale biomes. Ground-level information collection generally has difficulties like a time-consuming, difficult to reach some locations, and requiring human and financial resources.

Therefore, the MQI is a valuable tool for identifying the priority areas for mangrove conservation, and the mangrove species distribution in each area can provide valuable information for conservation efforts. The study suggests promoting awareness of geospatial technology in Sri Lanka to expand its research applications, particularly for protecting mangrove ecosystems. It is also essential to identify the appropriate method for identifying healthy mangrove forests, and the study highlights the suitability of the SMRI for detecting degraded and submerged mangroves. Overall, the study's findings suggest that using geospatial techniques and applying the MQI can provide valuable insights into the conservation of mangrove ecosystems on the Eastern coast of Sri Lanka.

4. Conclusion

The study investigated the suitability of vegetation indices to detect degraded mangroves distributed as narrow patches on the Eastern coast of Sri Lanka and found the challenges of discriminating mangroves from non-mangrove areas. Overestimation and misclassification are the main issues associated with the medium-resolution remotely sensed data, mangrove characteristics, and land vegetation primarily distributed in the study area's salty and sandy soil environments. If ground-truthing and field sampling is not applied, using medium-resolution satellite imagery data has no validity in detecting healthy mangroves. In order to avoid these circumstances, applying MQI, comprehensive and based on socio-ecological mangrove ecosystem variables, revealed the possibilities of detecting healthy mangrove ecosystems. This is an effective tool that ensures mangrove ecosystem health status is helpful for the management, restoration, and conservation planning of mangrove ecosystems fulfilling the needs and safeguarding the livelihoods of local communities more sustainably.

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