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THE STATE OF MANGROVE FOREST IN SOC TRANG PROVINCE, VIETNAM BASED ON SATELLITE IMAGERY BETWEEN 2000–2020

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Mangroves are vital for coastal defense, controlling erosion and carbon storage, yet they're endangered by human actions. This study used Landsat remote sensing imagery to investigate changes in Soc Trang, Vietnam's mangrove cover from 2000 to 2020. The findings showed expansion in the region's mangrove area, with Vinh Chau township experiencing substantial growth. These findings reflected wider changes seen across Vietnam. Mangroves in Mekong Delta has been decelerating since 2013, alongside with mangrove increase, due to afforestation and reforestation efforts. This shows successful mangrove conservation policies in Soc Trang. In this study, a map displaying the province's current mangrove status was produced. Multi-temporal satellite imagery is an important key for planning, improving understanding and boosting the role of mangroves in ecosystem services. The shift from mangrove decrease to increase may result from protective and restoration efforts, calling for broader Southeast Asia analysis.

Keywords: Mangrove forests, remote sensing, land cover changes, Vietnam, land use change, environmental monitoring

INTRODUCTION

Mangroves, unique in their adaptation to intertidal zones of tropical and subtropical regions, are crucial due to their considerable ecological and economic benefits. They play a critical role in soil stabilisation and coastal protection against natural disasters, proving more efficient at soil preservation than artificial structures. Furthermore, mangroves act as powerful carbon sinks, particularly efficient in tropical climates, sequestering carbon in both aboveground and below-ground biomass, as well as sediments (Donato et al. 2011, Alongi 2012, Kauffman et al. 2013, Pham et al. 2017, Pham & Yoshino 2017, Pham et al. 2018, Phan & Nguyen 2019, Phan et al. 2021).

However, over the past 50 years, these vital ecosystems have been rapidly vanishing worldwide due to increasing human activities such as urbanisation, aquaculture expansion and population growth (Giri et al. 2015, Chen et al. 2017, Alongi 2002). Among all regions of the world, Asia has suffered the most significant loss (1.9 million hectares) of mangroves, with over 100,000 ha lost from 2000 to 2012 (FAO 2007, Richards & Friess 2016).

Similar to most Southeast Asian countries, Vietnam's mangrove forests have seen a dramatic decrease of 400,000 ha in the early 20th century (Tuan et al. 2003), dwindling to 135,186 ha by 2020. These forests remain under considerable threat due to high population growth, aquaculture expansion, and migration into coastal areas.

Landsat remote sensing images supply data about the earth's surface with their extensive coverage, objective and cyclical information. Consequently, this imagery is widely used in numerous fields, including monitoring forest cover changes. A multitude of research papers have utilised satellite imagery to evaluate changes in mangrove areas, yielding accurate and objective results (Mohd-Hasmadi 2018, Ginting 2022). Several recent studies have examined the fragmentation or expansion of mangroves in Vietnam (Nardin et al. 2016, Mai & Nguyen 2017, Phung & Ton 2021).

Soc Trang is a coastal province of the Mekong Delta, having a sizeable area of mangrove forests. Due to various reasons, the coastal protective forests of Soc Trang province have rapidly transformed, affecting local production and the livelihoods of people. However, not many studies assessing the fluctuation of the mangrove area in Soc Trang, particularly using satellite images, have been conducted, which would yield fairly accurate and objective results (Pham 2011, Klaus 2015, Olivier 2010). Given this reality, the use of Landsat satellite images and GIS technology to assess the status of coastal mangroves in Soc Trang province is urgently needed.

This research aims to understand the changes to Soc Trang's mangrove forests from 2000–2020, and to identify the causes and to propose restoration strategies. Using remote sensing technology, the study will map the current state of these forests, examining human impacts. The study seeks to fill knowledge gaps and aid in their management, supporting local livelihoods and contributing to carbon mitigation globally.

MATERIALS AND METHODS

Study area

Soc Trang province, located on the southern estuary of the Hau River, is 231 km from Ho Chi Minh City and 62 km from Can Tho City. Transportation to and from the province is facilitated via National Highway 1A and Highway 60, which connect it to several surrounding provinces. With its geographical coordinates set between 9° 12'–9° 56' N and 105° 33'–106° 23' E, the province covers an area of 3,311.7629 km². This makes up roughly 1% of the total area of Vietnam and about 8.3% of the Mekong Delta. Comprising 11 districts and cities, Soc Trang boasts a coastline that stretches for 72 km and contains mangrove and Melaleuca forests. The primary study areas within the province are the coastal districts and towns of Cu Lao Dung, Tran De and Vinh Chau (Dinh 2010).

Data and method

Aerial photographs from 2000 and remotely sensed image data (Landsat 5 and Landsat 8, taken on March 3, 2000, and Landsat 8 operational land imager (OLI), taken on

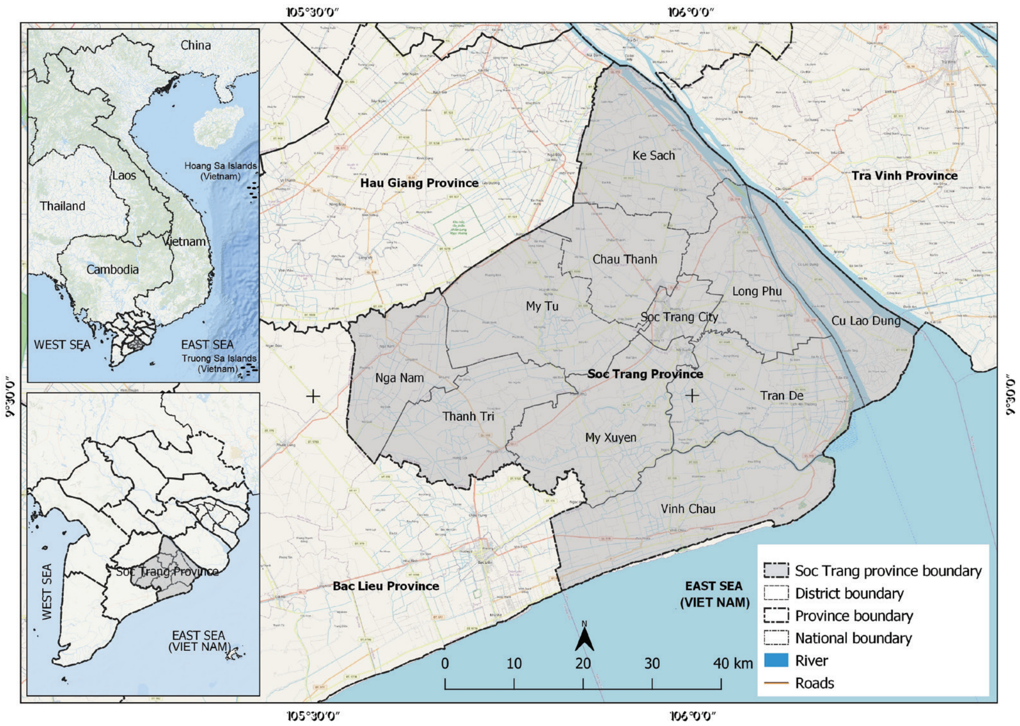


Figure 1 Location map of the study area showing the boundaries of its communes and landmarks (Pham 2011)

February 23, 2020) in the coastal area of Soc Trang province were downloaded from the United States Geological Survey (USGS). These images have a resolution of 30 m for conventional channels, and 15 m for panchromatic channels.

The analysis workflow consisted of three main steps: (1) collection and pre-processing of image data, followed by data analysis, processing and image interpretation, (2) mapping the forest status in 2000 and 2020 using the maximum likelihood classifier (MLC) and (3) preparation of a map illustrating changes in the mangrove area during the period from 2000 to 2020 (Figure 2). The study also applied a map overlapping algorithm and a method for calculating area statistics on quantum geographic information system (QGIS) to analyse the changes in forest status. Statistical variations were evaluated using Microsoft Excel software.

In this study, the characteristics of forests and other features within the study area were differentiated using image interpretation keys (Table 1). These keys utilise criteria such as shape, size, color, structure and brightness to discern the distinct attributes.

The training sample areas, as detailed in Table 1, comprise collections of pixels representing both forest and non-forest objects. These sample areas were used in image analysis and interpretation within the Google Earth Engine (GEE). This analysis identifies and categorises similar pixels and adjusts objects based on the reference provided by the training samples. A random split method is employed to minimise bias in the final classification results. The results of this process, expressed as scores, are integrated into the GEE program for automated calculations. These calculations leverage both the vegetation indices method and the random forest method. During the referencing process, GEE resorts to resampling, utilising the nearest neighbor (NN) algorithm as the default.

Simultaneously, the differentiation of objects in the image is facilitated by measured differences in reflectance characteristics through indices such as the normalised difference vegetation index (NDVI), normalised difference water index (NDWI), mangrove forest identification index (MFII) and combined forest identification index (CFII). These indices, together with their typical values, are presented in Table 2.

The calculation of the CMRI threshold is primarily based on the NDVI and NDWI indices. However, intermediate values are needed to enhance the contrast between mangrove areas and other objects, thereby necessitating the MNDWI index. The CMRI index is calculated

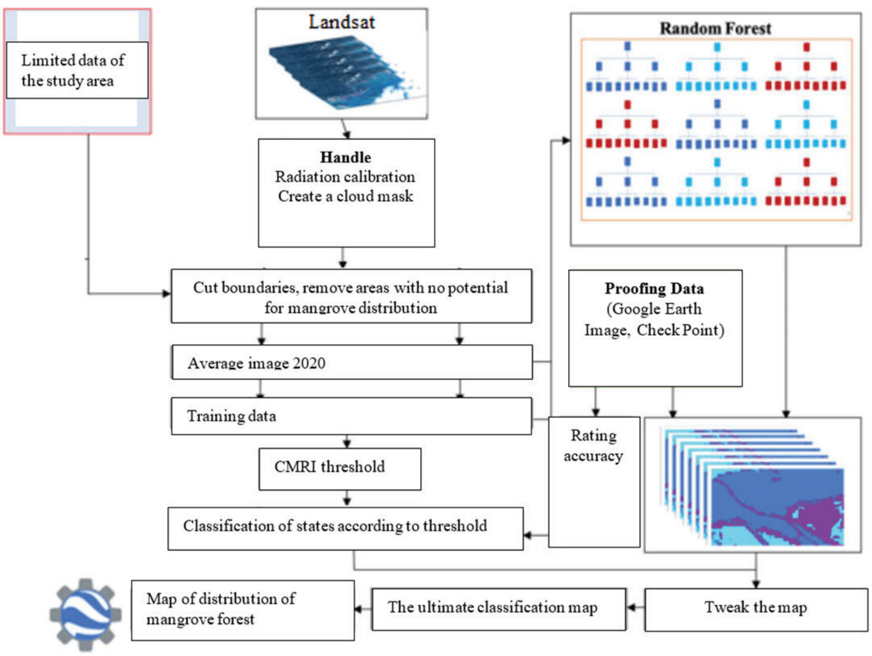


Figure 2 Diagram of research implementation

Table 1 Keys to deciphering remote sensing images

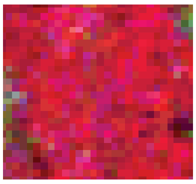
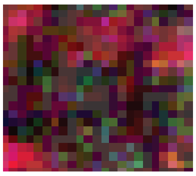
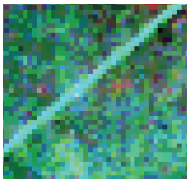
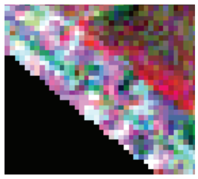
The key to deciphering	Forest (new plantation forest, thick forest)		Other subjects (eg. water surface, construction site, agricultural land)	
Object pattern (N-R-G* infrared color combination)				
Color, brightness	Red, bright	Dark, black	Green	Bright
Structure	Rough	Rough	Smooth	Rough
Distribution shape	Centralised distribution in clusters	Cluster distribution	Long and narrow (canal, river)	Plot format
Size/area	Large array	Large	Small	Small, adjacent

Table 2 Summary of indicators to determine the current status of forests in the study area

Index	Symbol	Formula	References
Normalised difference vegetation index	NDVI	(NIR - RED)/(NIR + RED)	Tucker 1979
Normalised difference water index	NDWI	(GREEN - NIR)/(GREEN + NIR)	Gao 1996
Modified normalised difference water index	MNDWI	(GREEN - SWIR)/(GREEN + SWIR)	Xu 2005
Modular mangrove recognition index	MMRI	(MNDWI| - NDVI)/(MNDWI + NDVI)	Diniz 2019
Combine mangrove recognition index	CMRI	NDVI - NDWI	Gupta 2018

by subtracting NDWI from NDVI, and its range is not limited from -1 to 1. Furthermore, NDWI may not efficiently eliminate signals from urban land use, leading to a mixture of extracted water features with urban noise. Thus, MNDWI is employed in this study to isolate water features. The MMRI combines two traditional indices, vegetation and water, to accentuate the mangrove contrast.

The resulting classification using the CMRI index provides the combined mangrove recognition index. Abbreviations being used include: NDVI for normalised difference vegetation index, IM for mangrove index, MMRI for modular mangrove recognition index, NIR for near infrared (used in band 4 at L5 (Landsat 5) and L7, band 5 at L8), SWIR for shortwave infrared (band 5 at L5 and L7, band 6 at L8), and Red refers to the Red band (band 3 at L5 and L7, band 4 at L8).

For statistical purposes and to gauge the concordance between different data sources or algorithms, the study utilises two measures: the overall accuracy (T) and the Kappa index (K). The K is employed to assess the interpretation accuracy relative to the field test results. A reliability rating scale according to the K, as per McHugh (2012) is implemented to evaluate the accuracy of the interpreted results relative to field test results (Table 3).

In calculating the Kappa coefficient, T epitomises the overall accuracy (derived from the sum of diagonal cells in the confusion matrix divided by the total pixel count within the sample area). The E is computed similar to T, but with data derived from the product matrix of row and column totals of the confusion matrix. The Kappa coefficient can be calculated using T and E. This coefficient allows for the publication of the accuracy of forest maps that are interpreted based on the field-verified sample areas.

The way to determine the global precision (T) is shown in the following formula:

$$T = \frac{\sum_{i=1}^{K} Oii}{n} * 100\%$$

where $\sum_{i=1}^{K} Oii$ = total number of correctly classified pixels, n = total number of pixels classified.

The way to determine the Kappa index is shown in the formula:

$$K = \frac{(T - E)}{(1 - E)}$$

where K = Kappa index, T = global precision given by error matrix, E = a quantity that represents a predictable (expected) accurate classification. The E contributes to an estimate of the likelihood of an accurate classification in the actual classification process.

When the Kappa coefficient equals 1, the classification accuracy is considered perfect. Observation accuracy is evaluated not only by the Kappa coefficient but also via a confusion matrix that represents a one-to-one comparison for accurate classification.

Reliability assessment involved comparing randomly selected points on Google Earth images to the classification results from 1990 to 2020, using the derived confusion matrix. Google Earth was used to gather representative samples of objects that were present in the past but are inaccessible for field observations currently. Additionally, data from the contemporary status monitoring system of the SERVIR-Mekong organisation were utilised for validation and accuracy assessment. The overall accuracy and Kappa index played essential roles in interpreting the image classification results and underlining confusion that might occur among objects during the classification process.

Object decoding resulted in discrete, unconnected regions within the same object. Therefore, these regions required linking or grouping to enable overlap and assessment fluctuation within the analytical algorithms. This connectivity allowed effective alternation between the three main subjects that the study intended to monitor. Prior to conducting statistics on the existing state of mangroves, it was critical to classify targets into three primary categories for facilitating change analysis and statistical processing. These categories included coastal mangroves, rivers/lakes/canals and other subjects (comprising all remaining targets). The area of each category was calculated at two tiers (district and commune) for each year.

Changes in coastal mangrove regions and the principal factors driving these shifts were analysed by creating overlapping maps of mangrove conditions grouped per decade using the union method. This approach aided in data overlap and comparison, identifying changing areas while maintaining the segregated and common regions for each year.

A reliability assessment was executed by using the error matrix, which compared random points on Google Earth images with the classification results for 2000 and 2020. The T and K helped in evaluating the image classification results, and illuminated potential object confusion throughout the classification process.

RESULTS

Result of remote sensing image analysis

The states of the coastal mangrove forests in Tran De, Cu Lao Dung and Vinh Chau districts were examined from 2000 to 2020 using indicators such as

Table 3 Reliability rating scale of Kappa index (McHugh 2012)

Value of Kappa	Level of agreement
K < 0.2	None
0.2 < K < 0.4	Minimal
0.4 < K < 0.6	Weak
0.6 < K < 0.8	Moderate
0.8 < K < 1.0	Strong
K = 1	Almost perfect

NDVI, NDWI, MMRI and CMRI, the threshold levels for which are provided in Table 4. The choice of indicators depended on the distinct differences in pixel values on the image between the state of the forest and surrounding conditions, at both points in time the images were acquired.

Results of the assessment of image interpretation accuracy

In the study, an assessment of the state of the mangroves was conducted for the years 2000 and 2020. As part of this assessment, test scores for classification accuracy were collected based on image data from Google Earth, as shown in Figure 3. The comparative methodology ensured the locations of the checkpoints remained unchanged during the observation period for reliable results.

In the study, a total of 85 test points were utilised as represented in Figure 3. The outcome of the accuracy assessment for image interpretation across the years is demonstrated through the classification error matrix exhibited in Table 5.

Accordingly, using Landsat image data for forest state classification yielded results with a global accuracy of over 85%, and a solid level Kappa coefficient (K = 0.67 in 2000 and K = 0.85 in 2020). In 2000, among the analysed checkpoints, there were 34 sites categorised as forest and 60 sites belonging to other categories. By 2020, there was a shift in the distribution of sites between categories, specifically with 51 sites falling under forest and 44 sites categorised otherwise (these are marked with red circles in Figure 4b). The data from the checkpoints also

Table 4 Results of threshold values of indicators in forest state classification

Parameters/statistics		2000	2020
Segment	Scale parameter	0.1	0.1
	Tightness	0.5	0.5
	Shape	15	15
Classify	NDVI	≥ 0.22	≥ 0.22
	NDWI	> 0.2	-
	MMRI	< -0.45	< -0.7
	CMRI	-	< 0.09

NDVI = normalised difference vegetation index, NDWI = normalised difference water index, MMRI = modular mangrove recognition index, CMRI = combine mangrove recognition index

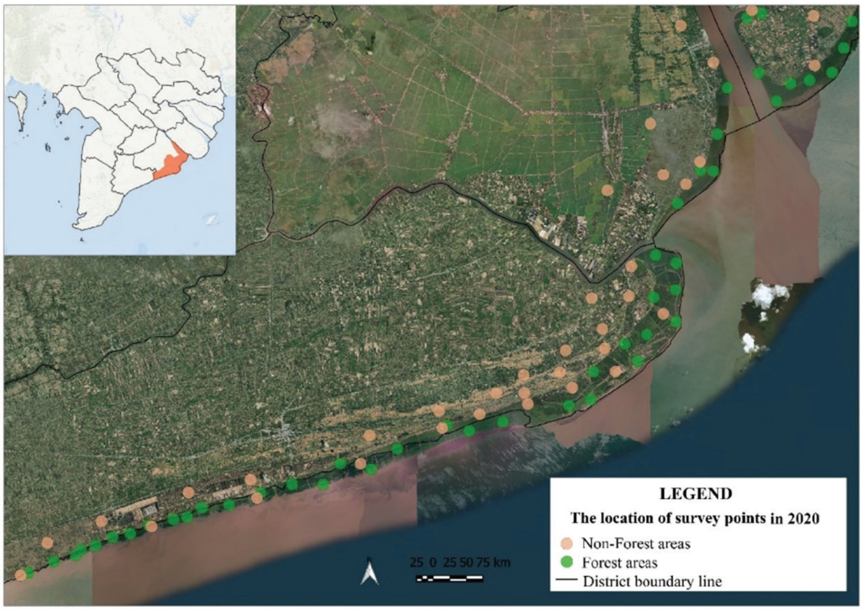


Figure 3 Location map of the study area showing the boundaries of its communes and landmarks (Pham 2011)

Table 5 Error matrix of forest status classification from remote sensing images

2000 (Landsat 5)				
Current status		Test results		Accuracy (%)
		Forest	Other subjects	
Result of guessing	Forest	25	9	73.5%
	Other subjects	5	55	91.7%
Reliability (%)		83.3%	85.9%	85.1%
Kappa's coefficient		0.67		
2020 (Landsat 8)				
Current status		Test results		Accuracy (%)
		Forest	Other subjects	
Result of guessing	Forest	47	4	92.2%
	Other subjects	3	41	93.2%
Reliability (%)		94.0%	91.1%	92.6%
Kappa's coefficient				0.85

suggested an increase in forest cover over time, as demonstrated in an overview provided in Figure 4.

Actual state of coastal mangrove forest in Soc Trang province between the period 2000–2020

The forest state interpretation results indicated that the spatial distribution and area of the forest have continuously changed over the years. Generally, the mangrove forest in Soc Trang province's coastal area has seen regeneration and expansion over time. The maps depicting the current state of the coastal mangrove forest for the years 2000 and 2020 are displayed in Figures 5 and 6.

Specifically, the area and percentage of forest status are described in detail in Table 6.

According to the statistical data, the forest area in the study period increased to 1776.89 hectares between 2000 and 2020. Vinh Chau township saw the most significant increase in forest area, with an increase of 1431.58 ha. Among the three studied areas, only Tran De district experienced a decrease in its forest area, losing 9.85 ha. However, this lost forest area constituted just 1.52% of Tran De district's total forest area in 2000.

a) The state of forest in 2000 b) The state of forest in 2020

Figure 4 Changes in forest status over time as seen from satellite images

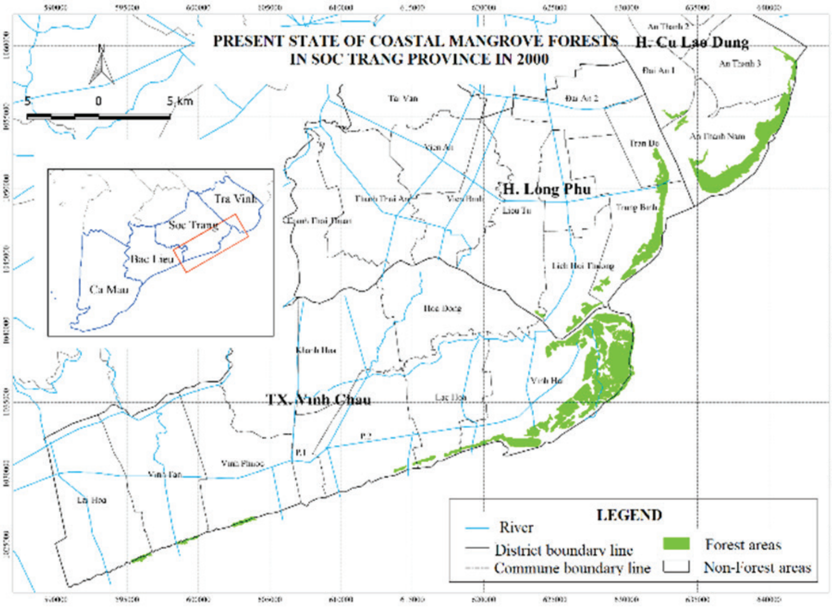


Figure 5 Map shows the current state of coastal mangrove forest in Soc Trang province in 2000

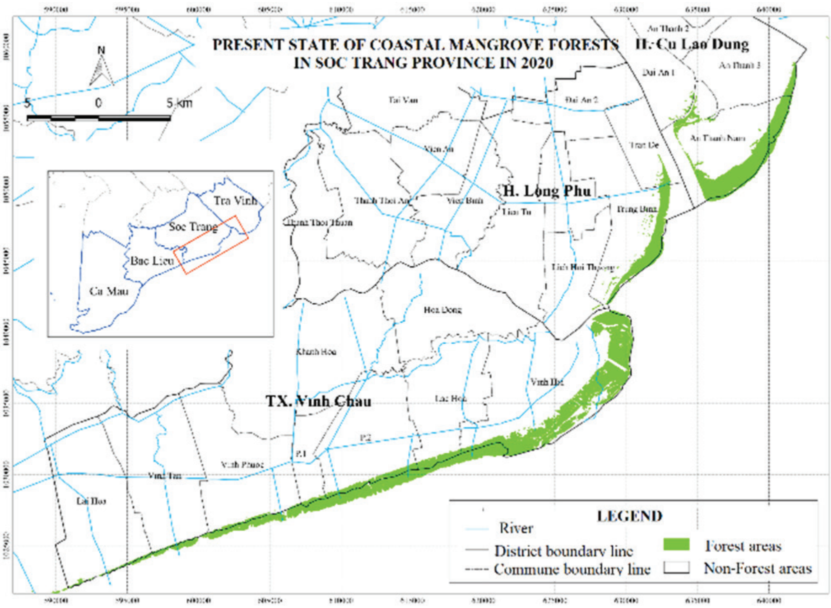


Figure 6 Map shows the current state of coastal mangrove forest in Soc Trang province in 2020

Table 6 Coastal forest area of Tran De, Cu Lao Dung districts and Vinh Chau township

State	District	Acreage (ha)		Changed area (ha)
		2000	2020	
Coastal forest	Tran De	647.5	637.65	-9.85
	Cu Lao Dung	972.48	1327.64	+355.16
	Vinh Chau	2252.26	3683.84	+1431.58
Total		3872.24	5649.13	+1776.89

Changes in coastal mangrove forest in Soc Trang province between the period 2000–2020

Based on the calculations presented in Table 6, the overall coastal forest area has undergone noticeable changes during the study period. An assessment of this variability is depicted through the volatility map in Figure 7.

Changes in the specific coastal forest areas at the commune level are represented in Table 7. The areas depicting forest converted to other uses are highlighted in bold, and the regenerated forest areas are emphasised in both italic and bold. From the observations in Table 7, it was noted that there have been shifts in the forested landscapes within the study area. For instance, in the Tran De district, the area of forest that has been repurposed exceeded the area that has been rehabilitated. Only in the Trung Binh commune, the regenerated forest area outnumbered the lost area. In two other districts, Vinh Chau and Cu Lao Dung, the area under forest restoration has notably enlarged. Particularly worth mentioning is Ward 1 of Vinh Chau district, where there was no forested area in 2000, and the forested region had grown to a notable 152.74 hectares by 2020, with no corresponding increase of land allocated for other uses. The most marked progress in forest rejuvenation happened in Ward 2 of the Vinh Chau district, as it swelled from 16.37 hectares in 2000 to an impressive 654.88 hectares in 2020, summing up to an increase of 638.51 hectares, with a mere 0.3 hectares of forest loss. The Cu Lao Dung district experienced an increment in the overall forest area over two decades, the coups being majorly concentrated in the An Thach Nam commune. In contrast, the Dai An 1 commune had witnessed a diminishing forest area.

Based on the assessment results and data analysis, there have been fluctuations in forest area size in different locations between 2000 and 2020, with some areas experiencing increases, while others have seen decreases. However, the overall trend appears to lean towards the restoration and expansion of forest areas, primarily through new plantations.

Primarily, mangroves have been restored from aquatic environments, specifically accounting for an increase of +1776.89 thousand hectares across two districts, Cu Lao Dung and Vinh Chau town. This significant restoration, which makes up 99.4% of the total mangrove restoration between 2000–2022, is largely due to sediment deposition on the coastal sea surface that has occurred since 2000, offering favorable conditions for mangrove development. Another key influence is the introduction of mangroves

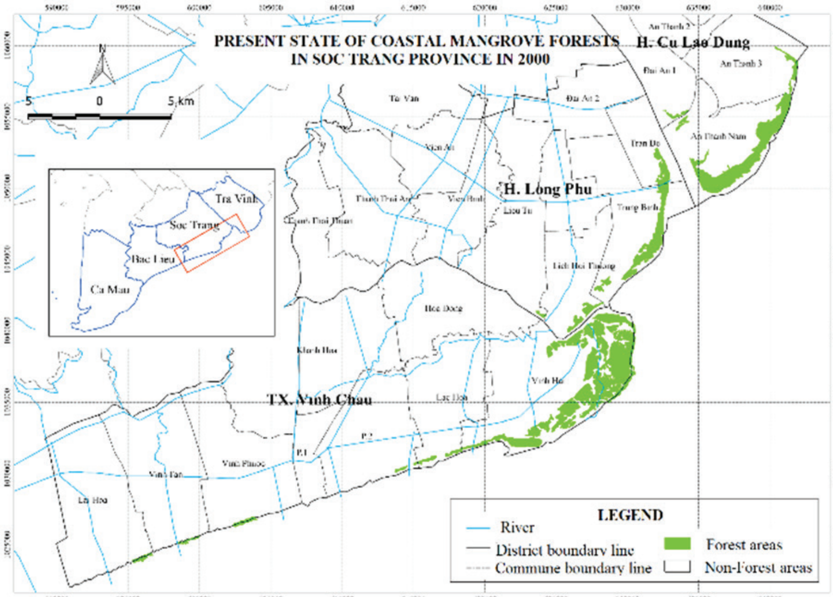


Figure 7 Map shows changes in the state of coastal forest in Soc Trang province between the period 2000–2020

Table 7 Matrix of forest area variation in the study area for the period 2000–2020

Distric	Commune	State of year 2000	State of year 2020	
			Forest	Other objects
Tran De	Lich Hoi Thuong	Forest	2.14	88.88
		Other objects	0.26	4810.44
	Tran De	Forest	48.37	74.71
		Other objects	7.3	1748.45
	Trung Binh	Forest	333.88	88.25
		Other objects	245.76	3855.52
Vinh Chau	Vinh Tan	Forest	19.99	3.15
		Other objects	88.5	5125.39
	Lac Hoa	Forest	43.1	5.48
		Other objects	247.22	3867.72
	Lai Hoa	Forest	27.43	4.97
		Other objects	46.81	5410.53
	Ward 1	Forest	0	0
		Other objects	152.74	1283.99
	Ward 2	Forest	16.37	0.3
		Other objects	638.51	4168.46
	Vinh Hai	Forest	1263.88	827.63
		Other objects	776.71	5084.94
	Vinh Phuoc	Forest	34.23	5.34
		Other objects	297.47	4940.12
Cu Lao Dung	An Thach Nam	Forest	746.39	133.48
		Other objects	488.41	3089.79
	An Thach 3	Forest	37.53	30.56
		Other objects	40.71	3635.31
	Dai An 1	Forest	2.88	22.86
		Other objects	9.86	4081.07

into formerly abandoned shrimp ponds or the practice of cultivating mangroves alongside aquaculture operations.

DISCUSSION

In general, fluctuations in the area of mangrove forests in Soc Trang province mirror alterations in the overall mangrove coverage across Vietnam. As Ton-Son (2020) noted the rate of decline in mangrove forest coverage in the Mekong Delta, which slowed down between 1998–2013. In fact, since 2013, the mangrove area has demonstrated a growth tendency, increasing by approximately 1568.5 ha year^{-1}. Observations of Ca Mau mangrove forests in the Ngoc Hien region (2004–2013) showed a decline in mangrove area from 2004 to 2009. However, due to afforestation efforts, there was an ingress in mangrove areas between 2009 and 2013. Despite this, the net change in mangrove area remained negative (-0.34%). This pattern can be attributed to factors such as aquaculture expansion, recent policy changes, reforestation programs, international recognition of protected areas, certifications, the proliferation of integrated shrimp mangrove production systems and logging cycles (Hauser et al. 2017). Similarly, Van et al. (2015a, b) recorded corresponding findings in the Ca Mau peninsula, utilising satellite imagery from multiple sources

Pham & Brabyn (2017) observed an increase in mangrove areas in the Can Gio region between 2000 and 2011, which was captured using Satellite Pour l'Observation de la Terre (SPOT-4 and

SPOT-5) imagery. The authors attributed this increase specifically to the colonisation by *Rhizophora apiculata*. However, they also found that spatial consistency in the variations of above-ground biomass due to *Avicennia alba* and *Sonneratia alba* was lacking, suggesting that this might be due to factors like soil accretion.

A study by Thu and Populus (2007) found that about 50% of the mangrove forest area in Tra Vinh of the Mekong Delta, Vietnam, was lost over the duration of 36 years (1965–2001). However, the annual rate of reduction from 1965 to 1995 was lower than that from 1995 to 2001. Over the period from 1965 to 2001, the total area of mangrove deforestation was 14,208 ha, while the area reforested was 5784 ha.

Within the Red River Delta, the mangrove forest area from 1986 to 2019 exhibited a significant increasing trend with a change rate of 39.07 ha year^{-1}. In contrast, the outer northern part of the Red River Delta displayed a declining trend (Long C et al. 2021). Compared to 2000, the mangrove forest area increased by 2020, but the increase was not substantial. This indicated that the mangrove protection policy has yielded positive results, particularly in Soc Trang province (Klaus 2009, Klaus 2015, GIZ 2018, Tran & Dinh 2019).

CONCLUSIONS

Globally, and especially in Vietnam, the state of mangrove forests has been studied and evaluated for the purposes of environmental protection, underscoring their significance in coastal protection, storm prevention, erosion control, land reclamation and climate regulation. These studies have utilised various methods. Notably, the use of multi-temporal satellite imagery facilitates the timely and relatively precise assessment of variables distributed over space, including changes in vegetation cover, specifically that of mangroves.

Analytical results revealed that from 2000 to 2020, the mangrove area in Soc Trang province has increased. According to statistical data, the forest area saw an increase of 1776.89 hectares within the study period. Vinh Chau township experienced the most substantial increase in forest area (an increase of 1431.58 ha). The interpretation of the forest status indicated that spatial distribution and forest area have consistently evolved over the years. Generally, the forest in the coastal region of Soc Trang province has been rehabilitated and expanded over time.

Based on these research results, the authors have established a map demonstrating the current state of the coastal mangrove forest in Soc Trang province. The findings presented a somewhat optimistic picture of the changing dynamics of South Vietnam's mangroves in general, and specifically in Soc Trang province, reflecting a transition from a negative trend to a positive one. Measures taken for the protection and restoration of mangrove forests have started to yield initial results. The analysis indicated that protection efforts have made the most significant contribution, primarily by reducing deforestation. Restoration efforts, on the other hand, have produced less noticeable impacts thus far. A more nuanced analysis of changes in areas with short intervals between surveys, especially within the past decade, would assist in evaluating whether this trend is representative of Southeast Asia as a whole.

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