JOURNAL OF
HYDRO-METEOROLOGY

Check for updates

Research Article

Combining UAV and satellite images to assess forest changes: A case study in Phuoc Thuan commune, Xuyen Moc district, Ba Ria - Vung Tau province in the period 2020-2023

Tran Ngoc Huyen Trang[1,2,3]*, Dao Ngoc Duc[4], Le Van Trung[1,2], Vo Le Phu[1,2]*

[1] Faculty of Environment and Natural Resources, Ho Chi Minh City University of Technology (HCMUT); tnhtrang.sdh222@hcmut.edu.vn; volephu@hcmut.edu.vn; lvtrung@hcmut.edu.vn
[2] Vietnam National University Ho Chi Minh City (VNU-HCM); tnhtrang.sdh222@hcmut.edu.vn; volephu@hcmut.edu.vn; lvtrung@hcmut.edu.vn
[3] Department of Geodesy, Cartography and GIS, Ho Chi Minh City University of Natural Resources and Environment; tnhtrang.sdh222@hcmut.edu.vn
[4] Long Thanh Protective Forest Management Board; daongocduc1991@gmail.com

*Corresponding author: tnhtrang.sdh222@hcmut.edu.vn; volephu@hcmut.edu.vn;

Tel.: +84–98615481; +84–933902908

Received: 27 May 2024; Accepted: 8 July 2024; Published: 25 September 2024

Abstract: In recent years, Unmanned Aerial Vehicles (UAVs) technology has advanced substantially, which created new opportunities in developing monitoring applications for forest resources management. UAVs are capable of flying and capturing at varying altitudes, angles, and attaining precise images. These collected data are continuously, quickly, efficiently, and crucially provide insight into forest health situations. Importantly, these captured images cover other useful factors such as changes in the status of biodiversity, deforestation, and forest recovery. The aim of this study is to combine UAV images with satellite imagery for a powerful tool in monitoring and evaluating forest dynamics and resources. Accordingly, Landsat 8 images in 2020, UAV images 2023 and GIS technology were employed to create a forest map in Xuyen Moc district, Ba Ria - Vung Tau province allowing an evaluation of changes in forest area over a spanning period of 2020-2023. The results indicated that the forest area changed at a rate of 4.1% (9.37 ha) in which the largest change was bare land with a substantial decrease of 8.08 ha meanwhile restored forests increased a remarkable area of 7.85 ha over the period 2020-2023. These changes were detected by overlaying forest maps 2020 and 2023 with the accuracy is 90.6% and Kappa coefficient was 0.87%. The findings suggest that the latest application of UAVs coupled with GIS technology brought significant conveniences with images retrieved from UAVs, providing a quick, reliable and competitive approach to the management practices of forest resources.

Keywords: UAV; Forest map; Forest change map; Landsat.

1. Introduction

Forests, those priceless natural treasures and the lungs of our planet, play a vital role in the Earth's ecosystem [1–2]. Their influence extends to maintaining natural balance and mitigating climate change. However, forests are under threat, grappling with issues such as habitat loss, illegal logging, and forest fires. To safeguard and sustainably manage these vital ecosystems, monitoring forest developments becomes an essential and crucial task [3–4].

Unmanned Aerial Vehicles (UAVs) have gained popularity across various fields, including agriculture, forestry, surveying and mapping, urban management, and fast delivery of useful information for decision-makers [5–7]. Their efficiency and productivity have made them becoming an indispensable tool for a wide range of environmental and natural resources management. UAVs not only reduce production costs but also enhance accuracy and improve service quality and customer relationships [8]. These applications underscore the significant impact drones have on industries worldwide. Presently, UAV-based applications in the field of forest research encompass a diverse range of tasks, including resource inventory, disease mapping, forest development monitoring, species classification, and fire monitoring and assessment. These applications primarily focus on different domains as enumerated as below.

Resource inventory, UAVs are employed to assess and quantify forest resources, including tree density, canopy cover, and vegetation distribution. The study [9] conducted a study by using point clouds and digital elevation models, particularly the Canopy Height Model (CHM), to inventory forests between 2013 and 2015. Estimating tree height using UAV photos provides accurate information about biomass volume, supporting forestry management activities.

Disease mapping: By capturing high-resolution imagery, UAVs aid in identifying and mapping diseases affecting trees and other vegetation. The Convolutional Neural Network (CNN) algorithm on UAV images is frequently employed for disease detection in plants. Research has focused on various plant species, with grapes and watermelon being particularly notable. Over 10 types of diseases have been identified, with fungi accounting for more than 60% of cases, while the remainder are caused by viruses, nematodes, and abiotic factors [10].

Species classification: UAVs contribute to species identification and classification, crucial for biodiversity monitoring and conservation efforts. In a comparative study using the EfficientNetV2 model alongside other widely used transfer learning models (ResNet50, Xception, DenseNet121, InceptionV3, and MobileNetV2), the results demonstrate that EfficientNetV2 achieves recognition rates of up to 99% for seven plant species. This impressive outcome was achieved by the research team [11].

Forest development monitoring: Tracking changes in forest structure, growth, and regeneration over time is facilitated by UAVs. Investigating six forest plots with varying structures, the research reveals that changes in canopy height patterns directly mirror forest degradation. The fine texture corresponds to a uniform distribution of small tree canopies, indicative of ongoing regeneration after overexploitation [12].

Fire monitoring and assessment: UAVs play a pivotal role in monitoring forest fires, assessing their impact, and aiding in post-fire recovery efforts. Additionally, UAVs are instrumental in quantifying spatial distances within forested areas and estimating soil movements following harvest activities. The successful deployment of UAVs in forestry hinges on several key features such as Flexibility in flight planning, Cost-effectiveness, Reliability and autonomy, and Timely availability of high-resolution data [13, 14].

Satellite images play a crucial role in monitoring natural resources (water, land, forest), which perform numerous advantages for tracking and safeguarding valuable resources. Satellites equipped with a variety of sensors capture high-resolution imagery of the Earth's surface. Optical sensors provide visible and infrared imagery, while multispectral and hyperspectral sensors collect data across several narrow bands. This enables detailed land cover classification and vegetation analysis [15]. To monitor forest changes from the past (specifically, when UAV images were not available in 2020) up to 2023, Landsat 8 satellite images can be freely downloaded from online platforms [16, 17]. The 8th generation satellite - Landsat 8 was successfully launched into orbit on November 2, 2013. Landsat 8's primary mission is to deliver crucial information across various domains, including energy and water management, forest monitoring, environmental resource assessment, urban planning, disaster recovery, and agriculture. Multispectral image bands with a 30-meter resolution offer valuable insights for creating forest maps and evaluating forest health [18, 19].

Forest monitoring involves precisely identifying the various types of forests and the land designated for existing forest development. It aims to quantify changes in forest volume over time, considering each forest type and the primary objectives of the campaign. This information is crucial for strategic forest management, protection, and development planning. The process typically includes gathering data on tree density, forest cover, fluctuations in forest area, and other relevant factors such as vegetation, animal species, and environmental conditions [20]. Monitoring forest developments plays a critical role in assessing forest health and management. It enables the detection of forest degradation and identification of threats to the forest environment, including environmental destruction, illegal mining, and forest fires. By collecting data and closely monitoring forests, forest managers and environmental organizations can implement measures to safeguard forests, strengthen their capacity to combat forest fires, and propose effective management policies for the protection and preservation of forest ecosystems [21]. A forest status map is a thematic map that delineates the boundaries of forest status plots based on the current forest classification system. These maps are overlaid onto topographic maps, with each map corresponding to a specific scale. This practice aligns with Clause 6, Article 2 of Circular No. 31/2018/TT-BNNPTNT, issued by the Ministry of Agriculture and Rural Development on November 16, 2018 [22].

The forest change map is a widely employed tool for analyzing, managing, and monitoring forest dynamics. These maps draw upon data from diverse sources, including satellite images, aerial photographs, ground-based measurements, and other geospatial information. By leveraging image analysis techniques and geostatistical methods, forest change maps facilitate the identification, classification, and quantification of forested areas, enabling the assessment of their temporal changes over time [23]. Forest change maps serve the purpose of documenting and monitoring alterations in both the extent and condition of forests within a specific region. These maps offer insights into the fluctuations whether growth or decline of forested areas over time. Researchers, governmental bodies, and environmental organizations rely on these maps to gain an overview of the forest state and track the ecosystem changes occurring within these vital ecosystems [24].

2. Materials and Methods

2.1. Study area

The study area is located in Phuoc Thuan commune, which falls within the Xuyen Moc district of Ba Ria - Vung Tau province, situated in the Southeast region of Vietnam (Figure 1). The study area covers 2.23 km^2 within the total land area of Phuoc Thuan commune, which spans 52.02 km^2. The forest area of this current study is a part of the renowned primeval forest of Binh Chau - Phuoc Buu. Being referred to as the "green lung" of Xuyen Moc district, this forest area is the harbors of about 800 plant species and over 350 animal species, including several rare and unique inhabitants.

2.2. Method for acquisiting image data using UAV and creating forest maps in 2023

UAV data was collected using a DJI Matrice M300 aircraft and a DJI Zenmuse L1 sensor (Figure 2). The Matrice 300 RTK is the most advanced UAV with a range of new safety features, high-tech solution design, expanding capabilities and exploring previously unexplored areas of work. DJI Zenmuse L1 integrates a Livox lidar sensor, high-precision IMU and a 1-inch CMOS sensor camera, 20MP resolution and mechanical shutter on a Zenmuse 3-axis stabilized gimbal. In particular, Zenmuse L1 can also be exploited to create real-time terrain-aware flight paths.

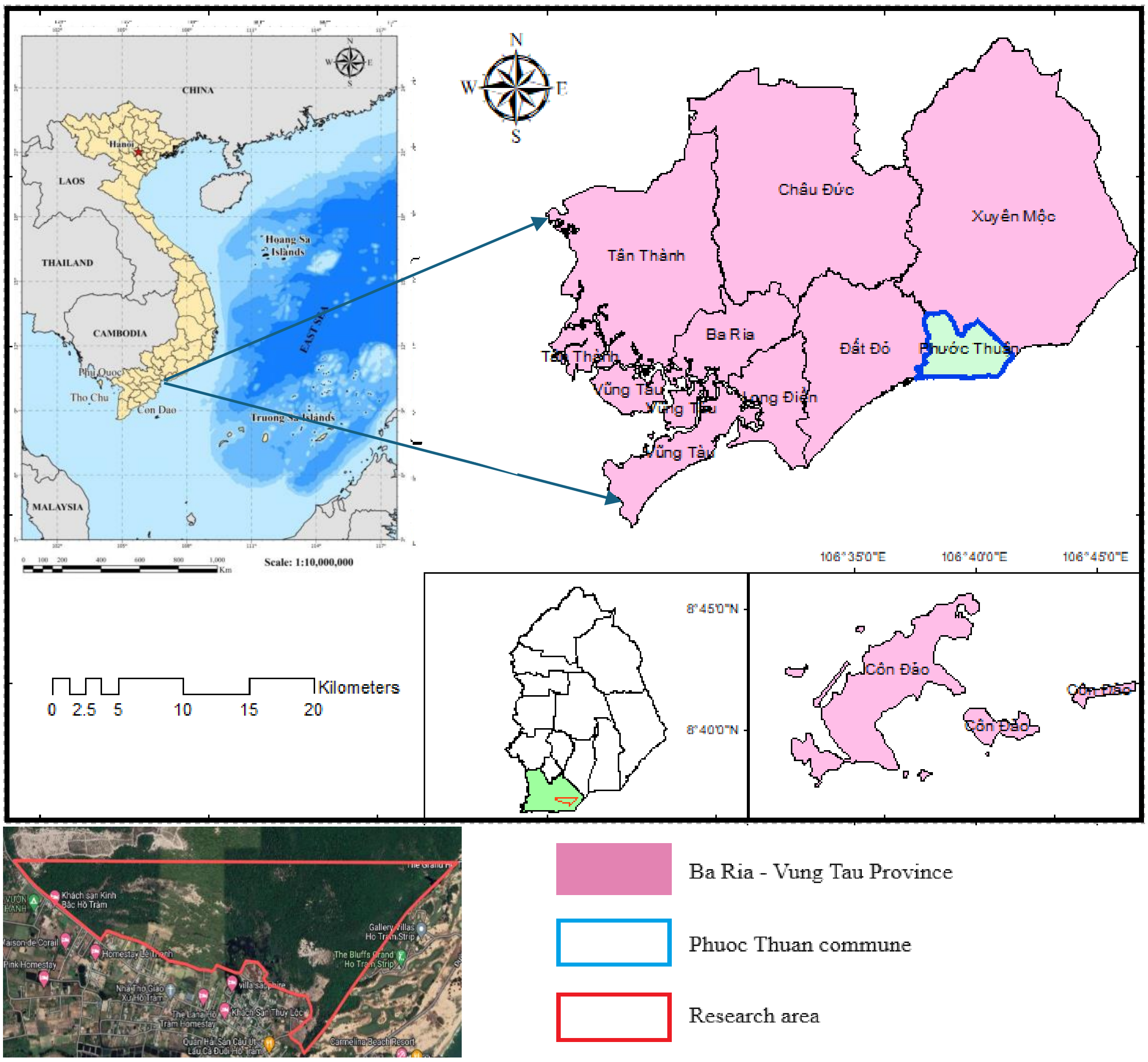

Figure 1. The study area is located in Phuoc Thuan commune, Xuyen Moc district, Ba Ria Vung Tau province.

Figure 2. DJI Matrice M300 UAV and DJI Zenmuse L1 sensor.

Using two benchmarks of basis cadastral coordinates, specifically Nui Le and Theo Neo, provided by the Survey and Mapping Data Center, serves as the foundation for establishing a base station. This base station facilitates the transmission of signals to the UAV, enabling them to conduct aerial photography using GNSS RTK technology (Figure 3). The Hi-Target V30 satellite positioning device serves as the base station, strategically positioned at the benchmark of basis cadastral coordinates. The base station plays a crucial role in receiving signals from multiple satellites simultaneously, across various frequency bands. Its primary objective is to ensure accuracy. Subsequently, it transmits and corrects signals to the UAV which now functions as a rover. Throughout the flight and image capture process, the UAV continuously receives satellite signals, akin to the base station on the ground. Simultaneously, it receives correction signals from the base station. By comparing and calculating this information, the UAV derives the most precise results in terms of coordinates and altitude for each image projection center [25, 26].

To survey the entire study area, from November 13 to 14, 2023, we conducted 10 flights at an altitude of 150 meters. Both the overlap along track and the overlap across track were set at 80%. The total implementation time for this comprehensive aerial survey exceeded 7 hours, resulting in a set of 1100 images.

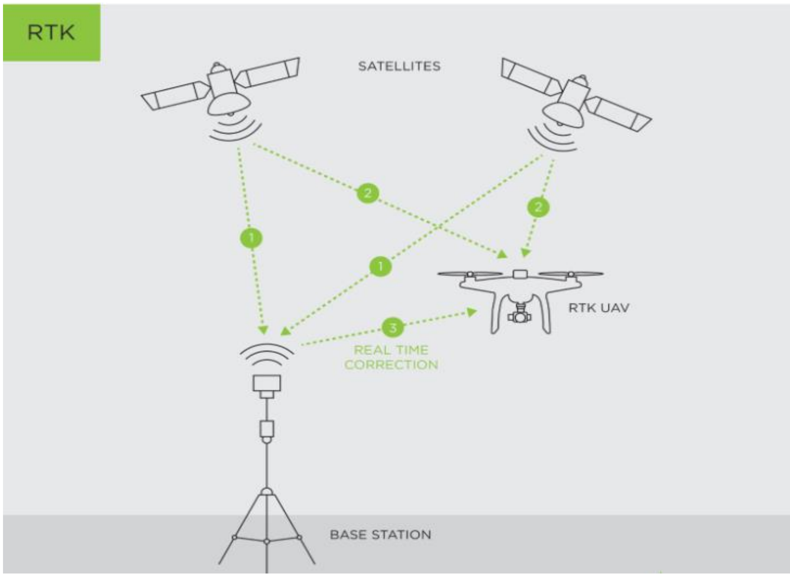

Figure 3. The operational principle behind the signal reception of UAV RTK [27].

Agisoft Metashape software was used to process images and create the orthomosaic of the study area. After collecting information about the research area, determine the task of image interpretation. UAV images, with their exceptionally high resolution, reveal distinct characteristics for each class of objects. When observing these images, the unique features of different objects become evident. Use direct reading and drawing diagnostics including color, shape, size, pattern, shadow, texture, indirect standards including distribution standards and relationships between objects to interpret using eyes and then digitize types: water, bare land, recovering forests, growing forests, old forests (Table 1).

Table 1. Identifying characteristics of the types to be interpreted.

Class	Image on orthomosaic	Identifying characteristics
Water		Ash gray color, very smooth structure.
Bare land		White mixed with green and black spots.
Recovering forests		Light green color, very fine structure.
Growing forests		Green color, smooth structure.

Class	Image on orthomosaic	Identifying characteristics
Old forests		Dark green color, quite smooth structure mixed with black shadow.

After digitizing the data of 5 layers, the forest map in 2023 was edited by using ArcGIS software.

2.3. Method for creating forest map in 2020 using satellite images

Download Landsat 8 image dated on 14 November 2020 with radiation correction, orthogonal geometry correction, using ground control points and DEM. Convert the image coordinates to the coordinate system with the local meridian axis of Ba Ria - Vung Tau province which is 107 degrees 45 minutes, then crop the image according to the boundary of the study area.

The Normalized Difference Vegetation Index (NDVI) is a crucial metric in remote sensing and environmental monitoring. It provides valuable insights into vegetation health and density. The NDVI quantifies the greenness or vegetation vigor of an area based on spectral data [28]. It is calculated using the reflectance values from two specific bands: Red band (usually around 650-680 nm wavelength); Near-infrared (NIR) band (typically around 750-900 nm wavelength) [29]. The NDVI formula is as follows:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{Red}}{\mathrm{NIR} + \mathrm{Red}} \tag{1}$$

NDVI images are calculated at a resolution equal to that of Landsat 8 images, which is 30 meters. Comparing documents on the boundaries of forest subdivisions reported by the local authority, combined with the opinions of experts in the field of forestry through expert consultation, NDVI thresholds were divided into five classes as shown in Table 2.

Table 2. NDVI threshold for forest classification.

Class	NDVI thresholds
Water	NDVI ≤ -0.07
Bare land	-0.07 < NDVI ≤ -0.01
Recovering forests	-0.01 < NDVI ≤ 0.05
Growing forests	0.05 < NDVI ≤ 0.11
Old forests	NDVI > 0.11

Maps created from satellite images always have certain errors that can stem from the image acquisition method of the device's sensor to the image classification process. Therefore, classification accuracy is often used to evaluate the quality of classified satellite images. Create 277 randomly distributed sample points on the classification results and Google Earth images, then build a classification error matrix.

Forest change map for the period 2020-2023 was created by overlaying the forest map in 2020 and the forest map in 2023. Use the query tool to search for unchanging and changing forest types, then label the areas of the forest change map.

3. Results

In 2020, a forest map was created using Landsat 8 satellite imagery. The map's accuracy was assessed post-classification, utilizing 277 sample points. These points were used to evaluate five distinct land cover types: water, bare land, recovering forest, growing forest, and old forest. The classification accuracy results are documented in Table 3.

Table 3. The results of post-classification accuracy assessment.

Land cover type	Classified total	Reference total	Number correct	Producers Accuracy (%)	Users Accuracy (%)
Water	9	9	9	100.0	100.0
Bare land	51	49	48	98.0	94.1
Recovering forests	32	35	30	85.7	93.7
Growing forests	68	85	65	76.5	95.6
Old forests	117	99	99	100.0	84.6

Overall accuracy (%) = 90.6%; Kappa coefficient = 0.87.

The overall accuracy and kappa coefficient, as indicated in Table 3, demonstrate a strong agreement between the classification results and the reference data source. In 2020, a thematic map was created for the study area, covering 2.23 km². Within this area, various land cover types were identified, including water (occupying 0.02 km²), bare land (covering 0.34 km²), recovering forest (encompassing 0.10 km²), growing forest (spanning 0.22 km²), and old forest (dominating the landscape at 1.55 km²) (Table 4). This comprehensive map provides valuable insights into the distribution and dynamics of land cover within the specific study area.

Table 4. Distribution of forest land types in the 2020 forest map.

Land cover type	Number of Polygons	Area (km^2)	Percentage of Area
Water	6	0.02	0.9
Bare land	111	0.34	15.2
Recovering forests	35	0.10	4.5
Growing forests	55	0.22	9.9
Old forests	53	1.55	69.5
Total	260	2.23	100.0

The 2020 forest map was established in the VN-2000 coordinate system, the map scale is 1:10,000 with map components such as north arrow, location diagram, legend (Figure 4).

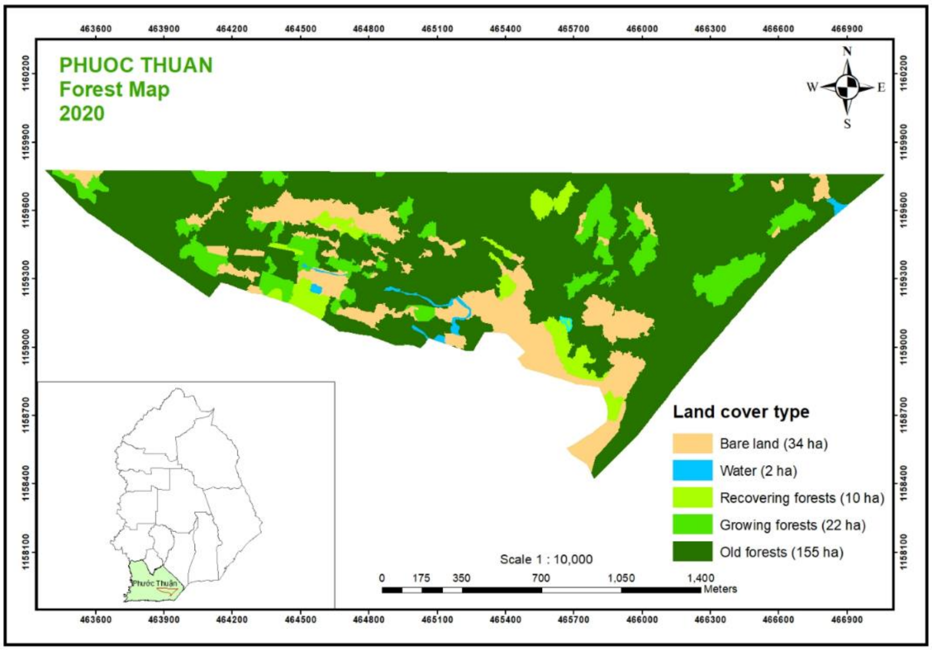

Figure 4. Forest map of Phuoc Thuan commune, Xuyen Moc district, Ba Ria - Vung Tau province in 2020.

Derived from an image map with an impressive resolution of 2.89 centimeters, the 2023 forest map exhibits exceptional sharpness. Consequently, the results of interpretation and digitization align remarkably well with the outcomes from field tests. In 2023, the forest cover spans a total area of 2.23 km^2. Within this area, water cover constitutes 0.9%, bare land occupies 11.2%, recovering forests account for 8.1%, growing forest encompasses 9.8%, and old forests comprise 70%.

Table 5. Distribution of forest land types in the 2023 forest map.

Land cover type	Number of Polygons	Area (km^2)	Percentage of Area
Water	6	0.02	0.9
Bare land	87	0.25	11.2
Recovering forests	57	0.18	8.1
Growing forests	52	0.22	9.8
Old forests	58	1.56	70.0
Total	**260**	**2.23**	**100.0**

From the forest map in figure 5, the dark green color represents old forests that occupy most of the area in the study area.

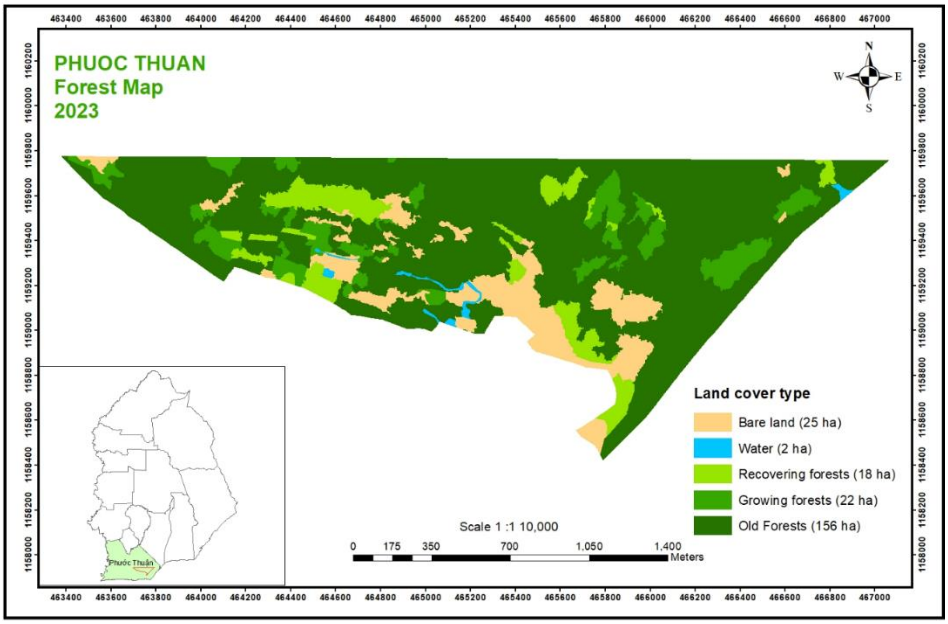

Figure 5. Forest map of Phuoc Thuan commune, Xuyen Moc district, Ba Ria - Vung Tau province in 2023.

Overlay the forest map from 2020 with the forest map from 2023 to detect changes in forest types. The variation results on the map in Figure 6 indicate that certain locations within the study area have experienced changes in cover types, as depicted by the scattered red polygons. The water surface did not change during this assessment period. In the period 2020-2023, the forest area to be changed is 9.37 hectares, accounting for 4.1% (Table 6a). Specifically, bare land decreased by a substantial area of 8.08 hectares, while restored forests increaseed by a remarkable area of 7.85 hectares (which includes the area from bare land changed to recovering forest and from recovering forest to growing forest). Additionally, growing forests had a slight decrease of approximately 0.39 hectares, while old forests increased around 0.62 hectares (Table 6b). These alterations reflect the dynamic and intricate nature of forest ecosystems, where various land categories undergone transformations over time.

Table 6a. Changes in land cover types.

ID	Land cover type 2020	Land cover type 2023	Area (ha)
1	Old forests	Bare land	0.11
2	Bare land	Recovering forests	8.19
3	Recovering forests	Growing forests	0.34
4	Growing forests	Old forests	0.73
Total			**9.37**

Table 6b. The change (increase or decrease) in the area of each type of land cover type.

ID	Land cover type	Area (ha)
1	Water	0.00
2	Bare land	-8.08
3	Recovering forests	+7.85
4	Growing forests	-0.39
5	Old forests	+0.62

In the span of three years, Table 6a illustrates a remarkable transition from bare land to recovering forest land. This shift is driven by investments in tree planting to protect the environment for both humans and creatures. Initially in a recovering state, the forest gradually regained ecological balance, growing in height and canopy. It then transitioned to a growing forest. Simultaneously, the forest evolved from a growing to an old forest. However, selective tree cutting occurs even in old forests to prepare space for new saplings, ensuring a balance between regeneration and conservation. This dynamic interplay reflects nature's intricate dance, emphasizing the need for sustainable forest management.

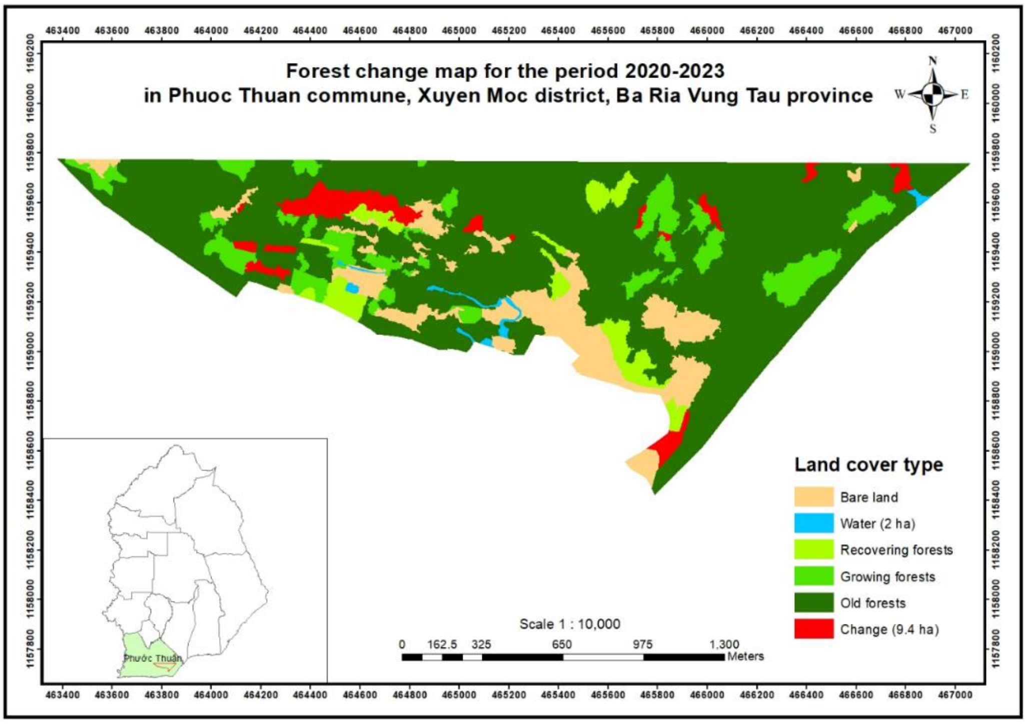

Figure 6. Forest changemap for the period 2020-2023.

4. Discussion

The purpose of error matrix for Landsat images is to compare the classification results on Landsat 8 images with Google Earth images (or in the field). The accuracy assessment of the forest by on-site examination (in the field) is not a good idea, because it is impossible to recognize what type of forest when standing in a location in the forest. Instead, we can only see the tree trunks, not the tree canopy. Meanwhile, UAV images have higher resolution than Google Earth images, visual interpretation on UAV images has achieved reliable results. Therefore, the accuracy of the 2023 forest map (by UAV) was not evaluated.

In this study, we examined the synergy of UAV data and Landsat 8 image data from a previous time to assess changes in forest types and other land covers, including water and bare land. Due to the relatively short research period (3 years), only approximately 4.1% of the total land area experienced alterations.

There is a fact that we are examining the feasibility of UAV deployment to monitor forest growth and development over time. Unfortunately, due to the absence of UAV data in 2020, we had to reply on Landsat 8 data as an alternative. Therefore, this is a limitation of this study in which imagery data is not the same type. Of course, this aspect was mentioned in the Conclusion section for future directions.

Compared to the results from the study [30], it shows that using a combination of UAV images with Quickbird and Ikonos satellite images will result in only a small difference in resolution when overlaying the map, thereby yielding more reasonable results. The 12-year study period also revealed significant changes in forest cover. The results demonstrate the transformation from forest land to urban land or vacant land with different construction forms. While it is necessary to pay for the use of high-resolution satellite images (Quickbird, Ikonos) to achieve similar resolution as UAV images, the Landsat 8 images used in our study are free and can be easily downloaded from the providers' platforms.

5. Conclusion

The research findings indicate that various methods can be employed to generate forest maps, including those for monitoring and managing forest changes. In this particular study, both UAV (Unmanned Aerial Vehicle) photos and Landsat 8 satellite images were effectively deployed to create forest maps for the years 2020 and 2023. The analysis revealed that 9.37 hectares of forest area underwent changes during this period, accounting for approximately 4.1% of the total area investigated. The observed movement trend aligns with natural laws and forest development principles. Forest maps generated using UAVs offer flexibility, allowing access to challenging and hazardous areas such as mudflats or regions with dense tree root networks. Additionally, UAVs capture images at a finer resolution compared to satellite images, resulting in better image quality. While UAVs provide advantages, using satellite images remains more cost-effective, and satellite data also facilitates the collection of historical image data. In summary, both UAVs and satellite imagery play crucial roles in forest mapping, each offering distinct benefits. Researchers and forest managers can choose the most suitable approach based on their specific needs and available resources.

In order to objectively assess the accuracy, it is essential to consider the differences in resolution and accuracy between UAV images and Landsat 8 satellite images, which are essential factors to perform a better and more reliable forest map. In order to achieve these, field verification data becomes crucial. Additionally, expanding the assessment over multiple periods and a broader research area will allow us to demonstrate the progression of changes and understand the underlying patterns of forest dynamics within the region. Notably, these study's results reflect the imagery data from Landsat 8 (2020) and UAV (2023), which are not the same type of data. These results provided an acceptable insight into perspective of data absent in the past. However, future directions of this barrier can be solved to tackle missing and absence of past data and information. Once this obstruction is unveiled, the data to provide the management practices of forest and natural resources will be more reliable and is a huge improvement.

Authors' contribution: Conceptualization: T.N.H.T., D.N.D., V.L.P., L.V.T.; Methodology: T.N.H.T., D.N.D., V.L.P., L.V.T.; Data processing: T.N.H.T., D.N.D.; Writing - original draft: T.N.H.T., D.N.D., V.L.P., L.V.T.; Writing, reviewing and editing: T.N.H.T., V.L.P.

Declaration: The authors collectively declare that this article is the result of their research, not previously published elsewhere, and not copied from previous studies; there is no conflict of interest among the authors.

Acknowledgements: The authors would like to express our thankfulness to Ho Chi Minh City University of Technology (HCMUT), VNU-HCM for the support of time and facilities for this study.

References

1. Paulinus, C.A.; John, J.I.I., Colman, C.I. Our forests, our environment, our sustainable livelihoods. *Eur. J. Acad. Essays*. **2015**, *2(4)*, 6–19.
2. David, O.E. Importance of forest and trees in sustaining water supply and rainfall. *Niger. J. Educ. Health Technol. Res.* **2016**, 1–8.
3. Per, A.; Terrence, B.; Michael, M. Challenges and solutions for forest biodiversity conservation in Sweden: Assessment of policy, implementation outputs, and consequences. *J. Land*. **2023**, *12(5)*, 1098.
4. Kandasamy, G.; Sabariswaran, K.; Mathiyazhagan, N. Influences of wildfire on the forest ecosystem and climate change: A comprehensive study. *J. Environ. Res*. **2024**, *240(2)*, 117537.
5. Mingyang, L.; Yibo, Z.; Chao, H.; Hailong, H. Unmanned aerial vehicles for search and rescue: A survey. *J. Remote Sens*. **2023,** *15(13)*, 1–35.
6. Tiberiu, P.B.; Gheorghe, F.B.; Constantin, B. The use of drones in forestry. *J. Environ. Sci. Eng*. **2016**, 557–562.
7. Trung, L.V.; Phu, V.L.; Trang, T.N.H.; Khai, H.Q. Opportunities and challenges of UAV application for monitoring the construction progress and updating the geographic database in urban area of Ho Chi Minh City, Vietnam. *IOP Conf. Series: Earth Environ. Sci.* **2023**, *1170*, 012014.
8. Asif, A.L.; Awais, K.J.; Rashid, A.L.; Haque, N. Unmanned aerial vehicles: A review. *J. KeAi Chin. Global Impact. Cognit. Robotics*. **2022**, *3*, 8–22.
9. Tristan, R.H.; Nicholas, C.C.; Peter, L.M.; Piotr, T.; Patrick, C. Unmanned aerial systems for precision forest inventory purposes: A review and case study. *For. Chron.* **2017**, *93*, 71–81.
10. Ruben, C.; Cagatay, C.; Ayalew, K. Plant disease detection using drones in precision agriculture. *Springer - Precis. Agric.* **2023**, *24*, 1663–1682.
11. Girma, T.; Isabella, G.; Gianni, G.; Fulvio, G.; Stefano, A.; Ivan, S. Automated identification and classification of plant species in heterogeneous plant areas using unmanned aerial vehicle-collected RGB images and transfer learning. *Drones* **2023**, *7(599)*, 2–19.
12. Clément, B.; Julie, B.; Pierre, C.; Lilian, B.; Hélène, D.; Johan, O.; Renan, L.R.; Louis, R.; Lucas, M.; Plinio, Läderach, S.P.; Gond, V. UAV-based canopy textures assess changes in forest structure from long-term degradation. *Ecol. Indic.* **2020**, *115*, 106386.
13. Chiara, T. et al. Forestry applications of UAVs in Europe: A review. *Int. J. Remote Sens.* **2016**, *33(8-10)*, 2427–2447.
14. Simon, E. et al. Towards operational UAV-based forest health monitoring: Species identification and crown condition assessment by means of deep learning. *J. Comput. Electron. Agric*. **2024**, *219*, 1–17.
15. Sunandana, R. Natural resource management using remote sensing and geographic information systems. *J. Environ. Sci. Eng*. **2023**, 79–91.
16. Amit, K.R.; Nirupama, M.; Akansha, S.; Krishna, K.S. Landsat 8 OLI satellite image classification using convolutional neural network. Proceeding of the International Conference on Computational Intelligence and Data Science (ICCIDS 2019), 2020, pp. 987–993.
17. Ridwan, M.A. et al. Applications of Landsat-8 data: A survey. *Int. J. Eng. Technol*. **2018**, 436–441.
18. Chaudhary, S.K.; Pandey, A.C.; Parida, B.R. Forest fire characterization using Landsat-8 satellite data in Dalma wildlife sanctuary. *J. Remote Sens. Earth Syst. Sci*. **2022**, *5*, 230–245.

19. Katsuto, S.; Tetsuji, O.; Nobuya, M. Detecting forest changes using dense Landsat 8 and Sentinel-1 time series data in tropical seasonal forests. *J. Remote Sens*. **2019**, *11*, 1–22.
20. Badea, O.; et al. Forest monitoring - assessment, analysis and warning system for forest ecosystem status. *J. Not. Bot. Horti. Agrobo*. **2013**, *41(2)*, 613–625.
21. Sumalika, B.; Qiongyu, H.; Anupam, A.; Myat, S.M.; Franz-Eugen, A.; Peter, L. A multi sensor approach to forest type mapping for advancing monitoring of sustainable development goals (SDG) in Myanmar. *J. Remote Sens*. **2020**, *12*, 1–21.
22. MARD. Circular No. 31/2018/TT-BNNPTNT of the Ministry of Agriculture and Rural Development: Regulations on forest boundary delineation. 2018.
23. Katsuto, S.; Wataru, M.; Takahisa, F.; Ronald, C. E. Mapping land use/land cover changes and forest disturbances in Vietnam using a Landsat temporal segmentation algorithm. *J. Remote Sens*. **2023**, *15(3)*, 1–17.
24. Hansen, M.C.; Ruth, S.D. Detecting long-term global forest change using continuous fields of tree-cover maps from 8-km advanced very high resolution radiometer (AVHRR) data for the years 1982-99. *J. Ecosystems*. **2004**, *7(7)*, 695–716.
25. Martínez, C.P.; Agüera, V.F.; Carvajal, R.F. Accuracy assessment of RTK/PPK UAV-photogrammetry projects using differential corrections from multiple GNSS fixed base stations. *J. Geocarto Int*. **2023**, *38(1)*, 1–21.
26. Remzi, E.; Remzi, A.; Remzi, A. A comparative analysis of UAV-RTK and UAV-PPK methods in mapping different surface types. *Eur. J. For. Eng.* **2021**, *7(1)*, 12–25.
27. Ferntech Commercial Company. RTK and PPK survey drones, what is the difference? Available online: https://www.ferntechcommercial.co.nz/news/rtk-and-ppk-survey-drones-what-is-the-difference.
28. Meeragandhi, G. et al. NDVI: Vegetation change detection using remote sensing and GIS – A case study of Vellore District. Conference: Elsevier Procedia 3rd International Conference on Recent Trends in Computing 2015 (ICRTC-2015) At: SRM University, Delhi Campus, 2015, 57, 1199–1210.
29. Bhandari, A.K.; Kumar, A.; Singh, G.H. Feature extraction using normalized difference vegetation index (NDVI): A case study of Jabalpur City. *J. Procedia Technol*. **2012**, *6*, 612–621.
30. Jumaat, N.F.H.; Ahmad, B.; Dutsenwai, H.S.; Land cover change mapping using high resolution satellites and unmanned aerial vehicle. *IOP Conf. Series: Earth Environ. Sci.* **2018**, *169*, 1–6.