JEE Journal of Ecological Engineering

Journal of Ecological Engineering 2024, 25(1), 161–174
https://doi.org/10.12911/22998993/174943
ISSN 2299–8993, License CC-BY 4.0

Received: 2023.10.18
Accepted: 2023.11.07
Published: 2023.12.04

High-Resolution Seagrass Species Mapping and Propeller Scars Detection in Tanjung Benoa, Bali through UAV Imagery

I Wayan Gede Astawa Karang[1,2*], Ni Luh Putu Ratih Pravitha[1], I Wayan Nuarsa[1], Basheer Ahammed K.K.[3], Pramaditya Wicaksono[4]

[1] Faculty of Marine Science and Fisheries, Udayana University, Jimbaran, Bali, Indonesia
[2] Center for Remote Sensing and Ocean Sciences (CReSOS), Udayana University, Denpasar, Bali, Indonesia
[3] Department of Geography, Central University of Jharkhand, Cheri Manatu, 835 222, India
[4] Department of Geographic Information Science, Faculty of Geography, Universitas Gadjah Mada, Yogyakarta, 55281, Indonesia
* Corresponding author's e-mail: gedekarang@unud.ac.id

ABSTRACT

As a part of the marine ecosystem, seagrass plays a significant role in the coastal environment. However, due to increased threats from natural causes and anthropogenic pressures, seagrass decline will likely begin in many areas of the world. Therefore, several studies have been carried out to observe seagrass distribution to help resolve the issue. Remote sensing is often used due to its ability to achieve high accuracy when distinguishing seagrass distribution. Still, this method lacks in species classification because not all satellites and similar aerial vehicles have fine spatial resolution to distinguish distinct species of seagrass. In this study, we aim to address the issue by utilizing unmanned aerial vehicles (UAV), which are known for providing finer resolution and better imagery. Samuh Beach at Tanjung Benoa, Bali, Indonesia, was chosen as the study site location because it experiences high levels of marine tourism and anthropogenic activities. From the UAV flight mission, the images obtained were processed. The result's accuracy was also tested with an error matrix. The species found in this study are *Enhalus acoroides*, *Halodule pinifolia*, *Thalassia hemprichii*, *Cymodocea rotundata*, and *Syringodium isoetifolium*, with 65% overall accuracy of the species classification map. This result indicates that UAVs can be a strong option for similar studies in the future. In addition to that, this study was able to observe the scars on the seagrass beds left by boat propeller activities from marine tourism. However, further research is needed to gain a better understanding of these objects.

Keywords: seagrass distribution, UAV, species classification, scars, boat propeller, Tanjung Benoa, anthropogenic pressures.

INTRODUCTION

Seagrass meadows, as flowering marine plants, are known for their vital roles in coastal environments [Wicaksono et al., 2019]. As part of the coastal ecosystem, seagrass makes a significant contribution to ocean biological productivity [Chayhard et al., 2018]. Along with mangroves and marsh plants, seagrass stores about 30% of the ocean's total NPP, with carbon being buried in the sediment [Duarte & Cebrián, 1996]. Additionally, they also offer feeding grounds, habitats, and nurseries for fish and other marine organisms [Riani et al., 2012]. Some species of seagrass are also found to have the ability to store carbon, for example, *Enhalus acoroides*, whose underground root systems are good for long-term carbon sequestration [Wicaksono et al., 2019]. In Indonesia, seagrass can be found in numerous locations, including Bali Island. Seagrass in Bali is distributed around the island, from the West Bali National Park Area to Sanur Beach in the south. According to Sudiarta and Sudiarta [2011], the area of seagrass on the Bali coast is approximately 1316 ha. Although seagrass has shown many vital functions for the ocean and coastal ecosystems, its sustainability is under alarming threat from both the natural causes and the anthropogenic pressures caused by economic development and the growing of population [Knudby & Nordlund, 2011]. Seagrass decline in Indonesia has been reported in numerous places, such as Banten, Kalimantan, and Sulawesi, with the cause still unknown [Riani et al., 2012]. It is likely to be the result of climate change or anthropogenic activities in the coastal area. Marine tourism, as one of the anthropogenic activities that take place near the seagrass meadows, can be a pressure for the underwater plants. According to Sondak & Kaligis [2022], tourism activities such as anchoring, mooring, gleaning, and the use of boat propellers can increase the risk of seagrass degradation and species loss. Bali has a high number of marine tourism activities, such as water sports, which include boating. This could be threatening because the locations of the activities are typically close to the seagrass meadows.

The ongoing decline of seagrass prompts more studies to find the distribution of seagrass around Indonesia, particularly in Bali. Understanding seagrass distribution is important given that they can function as anthropogenic imbalance indicators, therefore the information may provide information that is useful for their conservation [Knudby & Nordlund, 2011]. Traditionally, assessment of seagrass spatial distribution is carried out with field surveys and observations. However, a recent study conducted in North Bali has highlighted the limitations and challenges of traditional research methods, mainly due to adverse weather conditions and a shortage of necessary tools [Rosalina et al., 2022]. In response to these issues, remote sensing techniques are being employed due to their high accuracy when detecting seagrass distribution [Yang & Huang, 2011]. A study by Lazuardi et al. [2021] used images derived from Sentinel-2A MSI for the mapping of benthic habitat in Gili Sumber Kima, Bali, Indonesia and they classified seagrass cover with great accuracy, approximately 70% for the 2015 map and 83% for the 2019 map. This suggests that satellite images may well be utilized as a data source to accurately identify objects in the ocean.

However, remote sensing studies on seagrass distribution in species classification mapping is still lacking in many aspects. For example, most remote sensing images derived from satellite systems, such as Landsat 8 OLI/TIRS, ASTER, or Sentinel-2, typically have a medium spatial resolution of 10 to 30 meters [Yang et al., 2020]. This resolution may not be sufficient to distinguish between different seagrass species, which can make species detection and mapping more challenging. The low dominance of seagrass species also makes identification with remote sensing more challenging due to several issues, such as the requirement of high spatial resolution with a small scale of pixel size to map specific strips of seagrass and the low variability between the species classes compared to the cover classes [Phinn et al., 2008; Lyons et al., 2011].

Furthermore, remote sensing with satellites is unable to capture the damage to seagrass meadows caused by anthropogenic activities since the acquisition and analysis of the images take a long time, whereas the threats must be monitored frequently [Oguslu et al., 2018]. For instance, anchoring and the use of boat propellers in marine tourism leave scars when the boat propeller hits the sediment or the submerged vegetation [Li, 2018]. The scars can be the cause of seagrass habitat loss and degradation because the boat propeller forms line channels by excavating the sediments [Hallac et al., 2012]. By doing so, the burial of seagrass can increase the likelihood of mortality and reduce its capacity to recover from declines.

To overcome the limitations, such as the medium spatial resolution of Landsat 8 OLI/TIRS, ASTER, and Sentinel-2, we need finer spatial resolution from remote sensing imagery. According to Dekker et al. [2006], remote sensing with a high spatial resolution sensor is recommended because it can distinguish the small and narrow seagrass beds that are common in estuary areas. Some satellites with high spatial resolution are Quickbird-2 (2.4×2.4 m), IKONOS (4×4 m), and WorldView-2 (2.4×2.4 m) [Roelfsema et al., 2014]. However, even satellites with finer resolution also have their disadvantages. As an example, WorldView-2 makes it difficult to acquire images under certain conditions, such as high tide and sun glint [O'Neill et al., 2013]. Another drawback of using high-resolution satellite imagery data for site mapping is the prohibitively expensive cost [Nahirnick et al., 2019]. Overcoming those situations can be done by utilizing another type of airborne, namely the UAV or drone.

UAV (unmanned aerial vehicle) can be an alternative tool for remote sensing imagery with their capacity to acquire images at a very fine spatial resolution (0–5 cm), greater flexibility, and lower operational costs [Nahirnick et al., 2019]. While cloud coverage can be an obstacle for satellite remote sensing, UAVs are still able to provide images with sharper and better quality because they are carried out at altitudes under the clouds [Riniatsih et al., 2021]. Another disadvantage of satellite remote sensing is their infrequent temporal revisit cycle, whereas anthropogenic threats must be monitored consistently. While some of the satellites collect data in days intervals (e.g., Landsat ETM+ with a 16-day intervals [Théau, 2008]), UAV imagery can be collected on any day with good weather and low tides, providing the data on-demand [Yang et al., 2020]. With their spatial resolution up to centimeter scale, UAVs also can taxonomically identify seagrass or other marine organisms and vegetation [Román et al., 2021]. This makes UAVs a powerful alternative tool in seagrass distribution mapping. Despite their high spatial and temporal resolution, UAVs still have some limitations. According to Nahirnick et al. [2019], mapping and monitoring underwater vegetations with UAV must be carried out in clear shallow water and within a small area of seagrass beds. Meanwhile, remote sensing with satellites can be applied to a larger area.

Tanjung Benoa is a coastal area in Bali where seagrass meadows can be found. This location is known for its marine tourism activities. As an urban estuary, Tanjung Benoa is heavily influenced by anthropogenic activities from the surrounding area [Suteja et al., 2021]. The activities can be harmful to seagrass, especially those with boat propellers involved. A better understanding of seagrass distribution and species identification is required to improve seagrass meadow monitoring in Tanjung Benoa. The study can be conducted by utilizing UAV or drones as remote sensing tools to acquire images of the seagrass. UAVs are preferred over high-resolution satellites because they give even finer resolution, up to a centimeter scale. Previously, similar research on shallow water mapping was done at another location in Bali. Karang et al. [2022] used the Sentinel-2B satellite to map the shallow water benthic habitat in Nusa Lembongan, while Indayani et al. [2020] studied the absorption and reflectance features of seagrass leaf conditions as well as the location of the spectral channel. There is also a study with images derived from a high-spatial resolution satellites, Wolrdview-3, but the overall accuracy that lies between 62.72% and 73.00% was not statistically significant [Ginting et al., 2023]. However, those approaches are still unable to distinguish different species of seagrass and other submerged aquatic vegetation. Therefore, the goal of this study is to map seagrass distribution in Tanjung Benoa at the species level as well as evaluate the impacts of anthropogenic activities on the seagrass meadows.

MATERIALS AND METHODS

Study site

The study site of this research is located at Samuh Beach, Tanjung Benoa, Bali, as illustrated in Fig. 1. Samuh Beach was selected due to the massive anthropogenic activities, such as marine tourism (including water sports), that take place there. Aside from its function as a tourist destination, there are also several traditional fishing boats harbored at Samuh Beach [Watiniasih et al., 2019]. This makes the location suitable for detecting scars left by boat propellers with UAV utilization. Moreover, a study by Karang et al. [2019] discovered that the seagrass coverage at Samuh Beach is more prevalent than other benthic habitat classes. Therefore, mapping the distribution of seagrass species is feasible at this location. Data from the UAV was acquired during August-September 2020. Field observations were also carried out to validate the obtained data, as shown in Fig. 1, encompassing a total of 1278 observed points. The observed data included information on coordinates and species identification. These data will be utilized for input classification (50%) and accuracy testing (50%).

Data description

Recorded area, flight path, flight altitude, and ground sample distance (GSD) were determined prior to the UAV flights as part of preparations. GSD was measured according to the Eq. (1).

$$GSD = \frac{FLIGHT\ HEIGHT}{FOCAL\ LENGHT} \times PIXEL\ SIZE \quad (1)$$

In this study, a UAV was flown at a height of 30 meters with a camera that had a width of 3.57 mm and a pixel size of 1.56 mm. The GSD measurement was calculated to be 1.31 cm. To avoid surface water reflection issues, UAV flights were conducted in the morning (8-9 AM) and afternoon (4–5 PM), as recommended by Chayhard et al [2018]. Weather conditions, wind speed, and sun altitude were all considered before launching

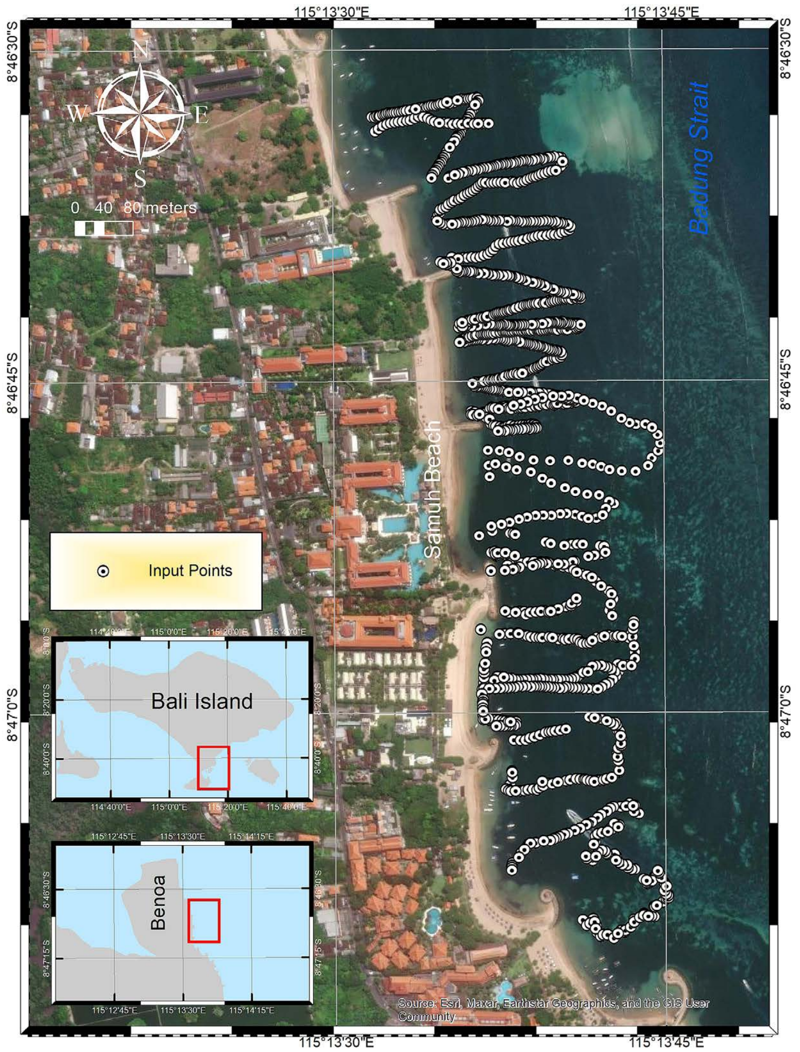

Figure 1. Overlay of research location with field data points. The white ring markers indicate the observation points, totaling 1278 samples

the UAV. A speed of 2 m·s^{-1} was used, with front lap and side lap set to 80% to optimize the connecting process of the resulting images. Increasing the front ap and side lap improves the quality of the resulting mosaics and digital surface models, as described by Joyce et al [2018]. The resulting mosaic is then displayed RGB.

Prior to proceeding with subsequent analysis, a meticulous image selection process was undertaken, involving the careful inclusion and exclusion of images based on specific criteria. These criteria included being tilted at an angle greater or less than 90 degrees, blurry, or accidentally capturing the drone's antenna. The obtained images were then processed through image mosaicking and seagrass species classification. During image mosaicking, Agisoft Metashape software was used to provide seamless merging of various images into a single coherent unit. Following the approach by Xiaoxia et al. [2004], the seagrass species classification was performed in two steps: multiresolution segmentation and knowledge-based classification of the segments.

Drone-Sruveyed RGB Mosaics

The first process in image mosaicking consists of two initial steps: aligning pictures and matching the points across the pictures. From this process, a 3D model and sparse point clouds are obtained. Those two products are used to generate dense clouds. In order to distinguish the elevation of the terrain and land surface, higher and lower points are segregated, facilitating the creation of a Digital Terrain Model (DTM) from the Digital Surface Model (DSM). After that, dense clouds are used to build a mesh. This step helps repair the hollow surfaces caused by uneven light exposure in certain parts of the images. Building a mesh was performed using Triangular Irregular Networks (TIN) data model approach. By utilizing the processed point cloud model and dense mesh, a Digital Elevation Model (DEM) is generated. This DEM is used to create the orthomosaic, which is important to create an accurate visualization as well as assess the entire study. After successfully completing the DEM creation process, the output can be exported and projected onto a different geographic coordinate system. As the final step, all the images are mosaicked into a single orthomosaic and processed further using eCognition software [adapted from Ahmed et al., 2020; Bao et al., 2019; Wang et al., 2021; Zhang et al., 2018].

Object-based image classification

For seagrass species classification, this study applied the Geographic Object Based Image Analysis (GEOBIA) approach. According to Nahirnick et al. [2019], this method can classify and identify seagrass species based on their visual characteristics, such as textures, colors, shapes, and distance from other objects. The first step in performing GEOBIA is image segmentation. Images are divided into several objects based on their pixel-character similarity. This process used multiresolution segmentation based on region growth. During the process, the image parameters such as scale, compactness, and shapes are set to 20, 0.3, and 0.7, respectively. The next step is segment classification using ROI selection, where benthic classes were defined into seagrass, seagrass species, sand, and reef. The objective of this stage is to precisely align chosen segments with the specified classes for accurate subsequent classification. The objective of this stage is to precisely align chosen segments with the specified classes for accurate subsequent classification. Upon segment selection, an essential process of feature adjustment is undertaken. This step focuses on the curation and refinement of attributes that will be employed for classifying segments that extend beyond the chosen ROI samples. The selected features were classified with the nearest neighbor approach. In the final step, the classification results from previous steps were dissolved and exported as shapefile for further processing in QGIS software. The final shapefiles containing the study area were calculated in QGIS software with calculated geometry after merging the shapefiles to combine the features of two or more images into one.

Analyses

To verify the accuracy of the classification results, images classified by drones were compared to field data. This study employed an accuracy assessment that comprised the overall accuracy, producer's accuracy, and user's accuracy [Congalton and Green, 2019]. These metrics were calculated using the Eq.2 – Eq.4.

$$Overall\ accuracy\ (\%) = \frac{\sum_{i=1}^{k} n_{ii}}{n} \times 100 \quad (2)$$

$$Producer's\ accuracy_j\,(\%) = \frac{n_{jj}}{n_{+j}} \times 100 \quad (3)$$

$$User'saccuracy_i\,(\%) = \frac{n_{ii}}{n_{i+}} \times 100 \quad (4)$$

where: n_{ii} – the total correctly classified test samples from a class; n – the total accuracy test samples; n_{jj} – the total reference sites correctly classified from a class; n_{+j} – the total accuracy test samples from a class; n_{i+} – the total accuracy test samples. Kappa analysis (K) is calculated using Eq. 5.

$$K = \frac{N\sum_{i=1}^{n} m_{i,i} - \sum_{i=1}^{n}(G_i C_i)}{N^2 - \sum_{i=1}^{n}(G_i C_i)} \quad (5)$$

where: i – the class number, N – the total number of classified values compared to truth values, $m_{i,i}$ – the number of values belonging to the truth class, i that have also been classified as class, i (i.e., values found along the diagonal of the confusion matrix), C_i – the total number of predicted values belonging to class i, and G_i – the total number of truth values belonging to class i. The species mapping stages can be summarized on the flowchart as illustrated by Figure 2.

Scars detection

The current study aims to evaluate the impacts of anthropogenic activities on seagrass beds, particularly the scars generated by boat activities involving propellers. The damages caused by propellers can be widespread due to their long-term effects, potentially occurring in any area of the estuary and its surrounding regions [Glasby and West, 2018]. Samuh Beach, the study area, serves as a boat harbor with a significant number of boats harbored, making it susceptible to seagrass bed collapse caused by propeller contact with submerged vegetation and soft bottom sediment, as well as dredging new channels or maintaining existing ones [Hallac et al., 2012]. A previous study by Li [2018] demonstrated the ability to detect scars using an Unmanned Aerial System (UAS). A subset image taken by UAS at Core Banks barrier islands in Beaufort, New Carolina, covering approximately 0.7 square kilometers, provided a zoomed-in depiction of the scars. In this study, the identification of scars within the seagrass beds was conducted using on-screen digitization techniques. A QGIS software was employed to display the drone images. Scarring criteria were established based on visual characteristics observed in the drone images. Scars were identified as areas exhibiting a noticeable reduction in seagrass density, characterized by disrupted or absent seagrass blades. The digitized scar polygons were spatially analyzed to calculate scar area and distribution, including parameters such as length, pattern, and width of the coverage area.

RESULTS AND DISCUSSION

Drone missions were executed, yielding a total of 2976 images across sixteen separate flights. These images were then organized into five distinct stages. The image compilation from

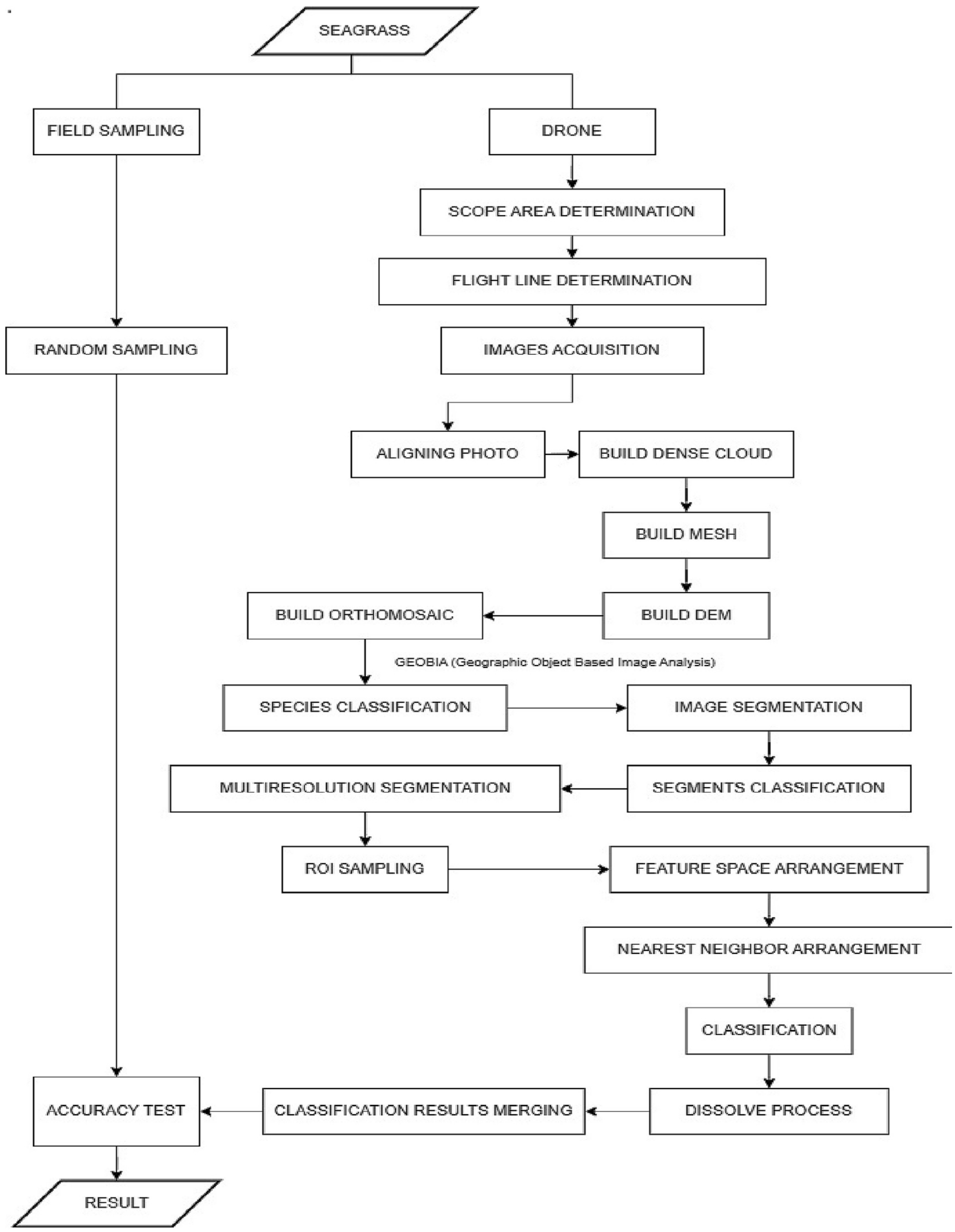

Figure 2. The flowchart diagram of the research process

all missions is shown in Figure 3. We have undertaken the compilation of a comprehensive orthomosaic through the aggregation of 2976 individual images collected during 16 distinct missions. Through a meticulous process of image compilation, we have created a unified representation of the seagrass habitat that provides an encompassing view of the study area. This orthomosaic image result is then processed again to obtain the finalized image that contains the species classification of seagrass.

The results of image classification are displayed in Figure 4. *Enhalus acoroides* was identified as the dominant species, covering an area of 11.5 hectares, followed by *Thalassia hemprichii* (6.1 hectares), *Cymodocea rotundata* (4 hectares), *Syringodium isoetifolium* (1.6 hectares), and *Halodule pinifolia* (1.5 hectares). This seagrass species can be found dominating an area of seashore because their shoots tend to grow in extension, up to the water surface, making them the biggest contributor to the overall reflectance among the other species [Wicaksono & Hafizt, 2013]. In this study, the species are distributed from the northern part of Samuh Beach, all the way to the southern part. Compared to the other species, *Enhalus acoroides* and *Thalassia hemprichii* distribution are denser, as shown in the picture. Some of the species, e.g. *Halodule pinifolia* and *Syringodium isoetifolium* can be seen to be covered by the most dominated species.

According to Wicaksono et al [2019], when the leaves of seagrass are stacked and layered, the coverage can be overestimated, compared to when the leaves are standing. *Syringodium isoetifolium* has cylindrical leaves shape that become flexible

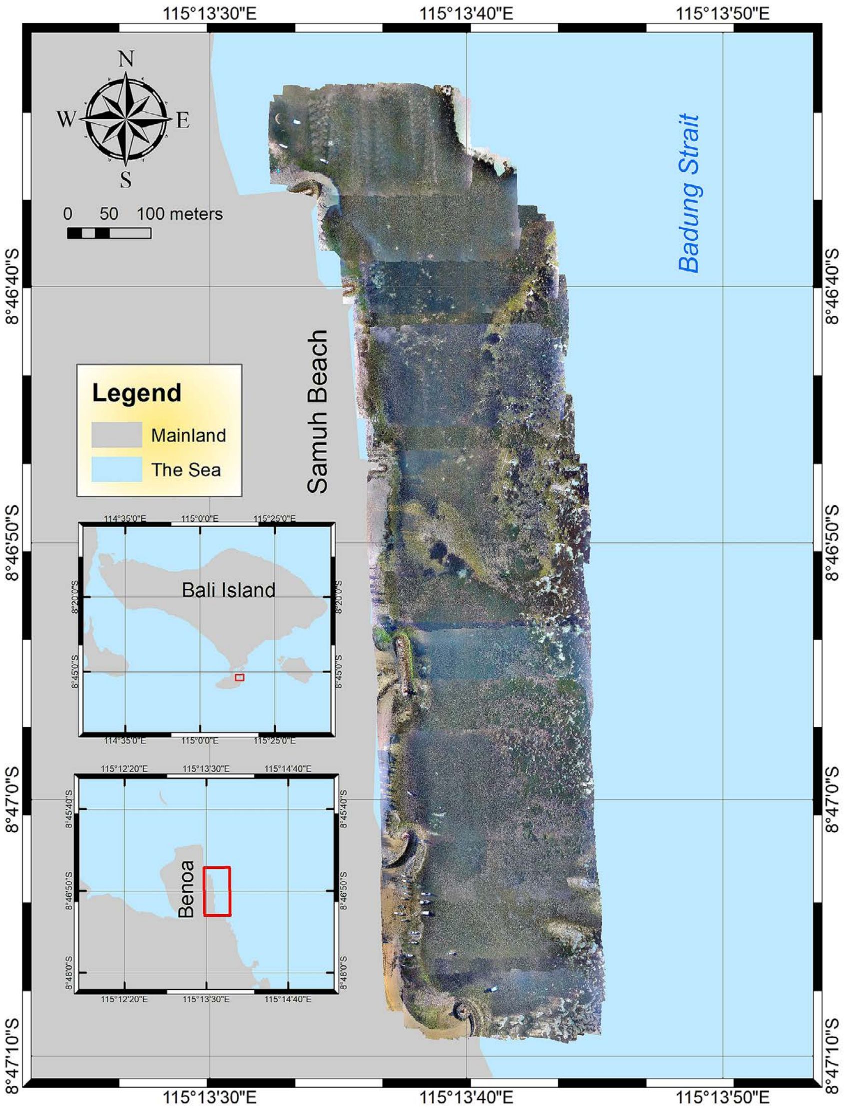

Figure 3. Drone images compilation from all missions

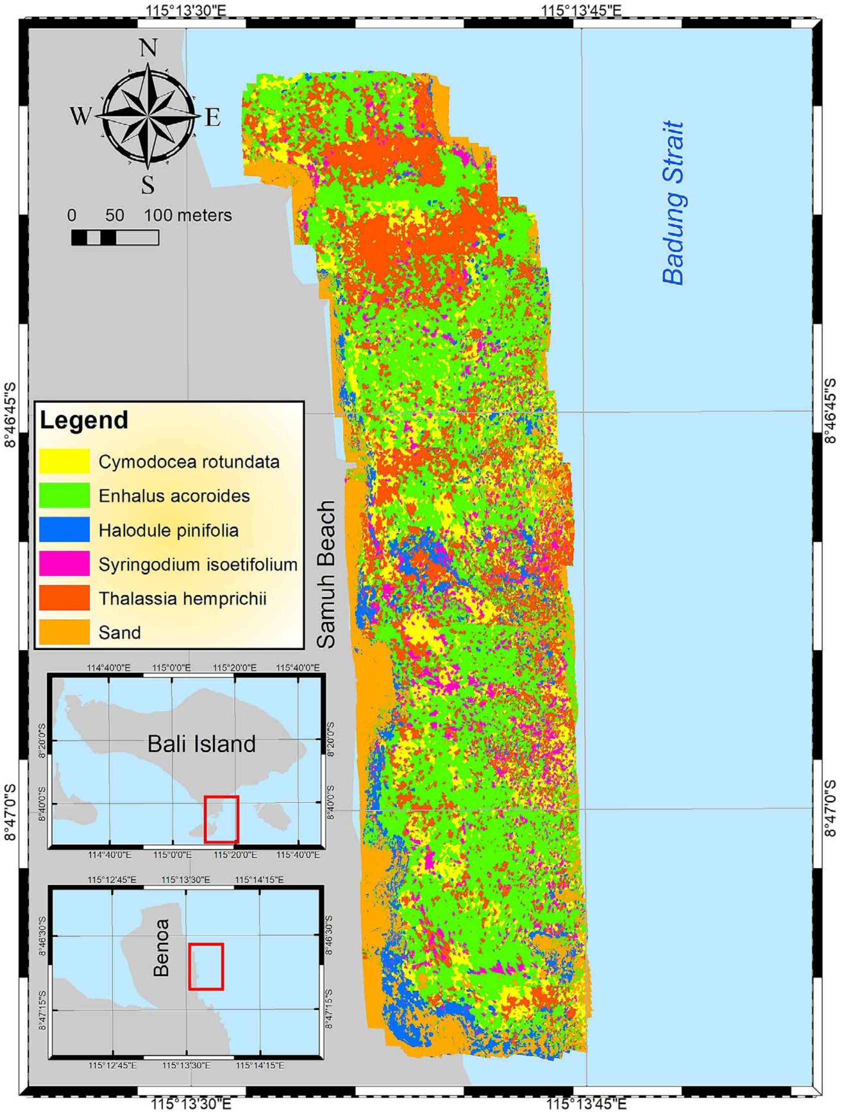

Figure 4. The result of seagrass species mapping using UAV at Samuh Beach, Bali, Indonesia

when current passes through them [Khairunissa et al, 2021]. It is possible that they got covered by other species during the image recording, resulting in the lower coverage. Furthermore, *Halodule pinifolia* which is also the species with lowest coverage along with the *Syringodium isoetifolium*, was observed in low density in the northern part of Samuh Beach. This aligns with Khairunnisa et al. [2021] findings which stated that the species flourishes in a stable substrate, whereas is unavailable in the beach's northern section. Additionally, some regions near the shore had no seagrass, likely due to boat activities that involve propellers usually occur at the shoreline, which resulted in low seagrass coverage.

The present study's finding also succesfully identified similar seagrass species from research of Sari et al [2023] and Karang et al [2019] who applied in situ observation to obtain their study data. However, this study was unable to identify some of other species they found, such as *Cymodocea serrulata*, *Halodule uninervis*, *Halophila ovalis*, and *Thalassodendron ciliatum*. Another research conducted with drone in Bali, at Ceningan Strait, also found similar species of seagrass, e.g. *Thalassia hemprichii*, *Syringodium isoetifolium*, and *Cymodocea rotundata* [Wijantara et al, 2022]. Furthermore, by combining the imagery data with machine learning, seagrass distribution identification with UAV can be advanced. This combination was demonstrated by the study of Tahara et al. [2022], which used UAV photography and deep neural network technique to accurately map seagrass beds and distinguish between similar-looking species. This further suggests that drone-based methods are comparable to satellite-based methods for seagrass mapping. Table 1 displays the results of the seagrass classification accuracy assessment, where the study achieved an overall accuracy (OA) of 65% and a Kappa index (K) of 0.52. The result is similar to the one generated by Wijantara et al [2022], with their overall accuracy of 68% and kappa coefficient of 0.55. The Kappa index falls within the medium category, indicating that the classification was carried out well, according to the standards set by Congalton & Green [2008] and LIPI [2014], as cited by Karang et al. [2022]. Furthermore, this accuracy is significantly higher than that achieved using high-resolution satellites, such as WorldView-2 and WorldView-3, as reported by Azizah et al. [2016] and Kumara et al. [2018], respectively. The overall accuracy obtained from the study of seagrass species classification in Tunda Island, Banten by Azizah et al. [2016] only reached 35.6%, meanwhile similar study by Kumara et al. [2018] in Nusa Lembongan has significantly lower overall accuracy with 17,11%. This further indicates that UAV imagery is capable to achieve even better accuracy than the satellite imagery. The spatial resolution of 1.31 cm/pixel for the drone images used in this study was also superior to that of high-resolution satellite imagery, which had resolutions of 0.31 m, 0.5 m, and 30 m for WorldView-3, WorldView-2, and Landsat 8, respectively. The improved spatial resolution was likely the primary factor in the higher accuracy achieved in this study.

However, the OA of this study is lower than that reported by Nababan et al. [2021], where the highest OA values were 77.4% for 12 benthic habitat classes and 81.1% for 9 benthic habitat classes. Meanwhile this study only used 7 benthic habitat classes. The significant difference in OA may be attributed to the use of the support vector machine (SVM) algorithm in addition to object-based image analysis (OBIA), which could improve the accuracy of the results. A report by Zhang and Xie [2013] demonstrated that the SVM algorithm can produce better accuracy in species-level research. This further indicates that the OBIA and SVM combination might be explored further in future studies to provide even more accurate seagrass mapping results. Additionally, another study by Tahara et al [2022] also showed that combining UAV photography with a deep neural network for seagrass species distribution mapping can improve the result accuracy compared to conventional methods.

Utilizing UAVs and satellite imagery for seagrass distribution and species identification studies may be helpful for the conservation and management of seagrass beds. This study's finding demonstrated a promising result of UAV imagery in seagrass species classification with high accuracy when identifying two species, *Enhalus acoroides* and *Halodule pinifolia*. High-resolution imagery from the UAV also allows data collection to be carried out in remote and challenging water areas. However, UAV imagery also lacks in some aspects. This study highlighted the UAV limitations, particularly in seagrass species classification, as the data processing resulted in some misidentified species. UAV imagery, for example, failed to identify *Cymodocea rotundata* and *Syringodium isoetifolium* because both species were misclassified as *Enhalus acoroides*. This indicates that UAV imagery is still unable to

Table 1. Seagrass species classification accuracy assessment

Specification	*Enhalus acroides*	*Thalasia hemprichii*	*Cymodocea rotundata*	*Haludule pinifolia*	*Syringodium isoetifolium*	Sand	Total	UA (%)
Enhalus acroides	209	19	10	2	23	1	264	79.17
Thalasia hemprichi	30	106	3	0	16	3	158	67.09
Cymodocea rotundata	39	20	22	1	5	2	89	24.72
Haludule pinifila	5	1	6	19	2	2	35	54.29
Syringodium isoetifolium	10	1	2	1	46	0	60	76.67
Sand	4	0	3	10	2	14	33	42.42
Total	297	147	46	33	94	22	639	
PA (%)	70.37	72.11	47.83	57.58	48.94	63.64		
Overall Accuracy (OA) in %					65			
Chance Agreement (CA)					0.28			
Kappa (K)					0.52			

distinguish between those three species. Furthermore, in this study, non-seagrass classification was found to have a low accuracy rate, with only 42% of the Sand class correctly identified. The difficulty in distinguishing *Halodule pinifolia* from the sand class due to their small leaf shapes may have been attributed to this missclassification. Nevertheless, this study still highlighted the potential of UAV imagery for seagrass species classification while also noticing the limitations of UAV imagery data processing in distinguishing between seagrass and non-seagrass classes.

Not only that, this study also found that UAV imagery can also be utilized to identify the impact of tourism activities on seagrass beds at Samuh Beach. The UAV imagery were able to detect the scars left by boats and other vehicles used in marine tourism activities. Those scars were later identified as the result of pressure on seagrass beds. Figure 5 shows the recorded scars on seagrass beds in Samuh Beach.

The scars were found in the form of vertical lines, covering the seagrass beds, and forming tracks that followed boats' tracks. They covered the seagrass beds at Samuh Beach at approximately 0.05 ha and 24.7 ha wide in total, with a ratio with overall seagrass coverage of 1:494. To make it more apparent, the overlay image of the scars on seagrass beds is shown in Fig. 6. In the image, the scars can be seen covering multiple areas of seagrass beds, further indicating the threat its possesed.

The scars were denser near the shallow water area, especially at the northern part of Samuh Beach, where high levels of boat activity are observed due to the presence of a harbor. The scars were found in several areas, but not in the sandy part that is adjacent to the seagrass beds. The study also referenced a previous finding by Hallac et al. [2012] in Florida Bay, which revealed the presence of non-continuous scar lines. It indicated that the appearance of scars appearance depends on how the water sports are performed. Water tourism agency tends to use certain areas for each sport, and it causes the seagrass decline to be more prevalent in those areas. We suggested the area for water sports tourism to be decided with greater consideration, by taking into account the seagrass recovery and endurance, as well as the sea level elevation. In this study, the application of UAVs has demonstrated significant advantages in seagrass research of Samuh Beach.

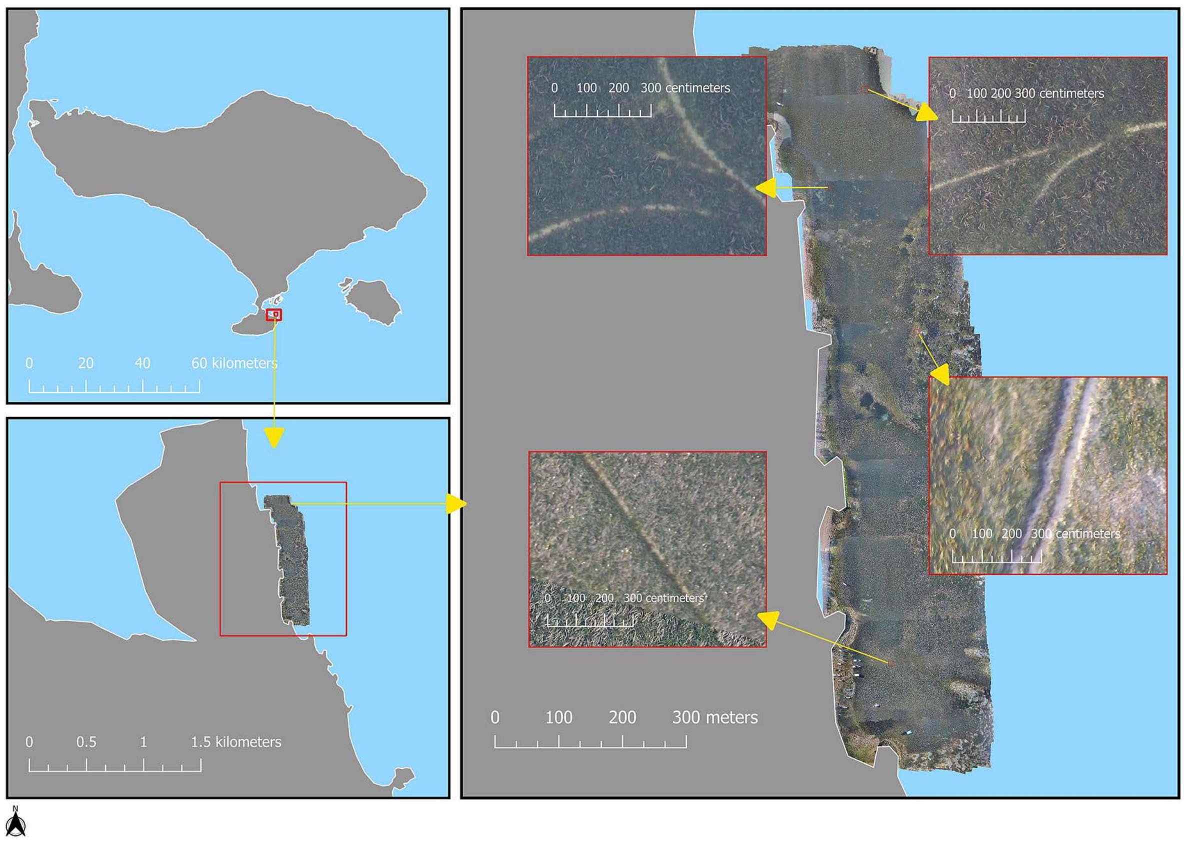

Figure 5. Example of scars detection at seagrass beds in Samuh Beach, Bali, Indonesia

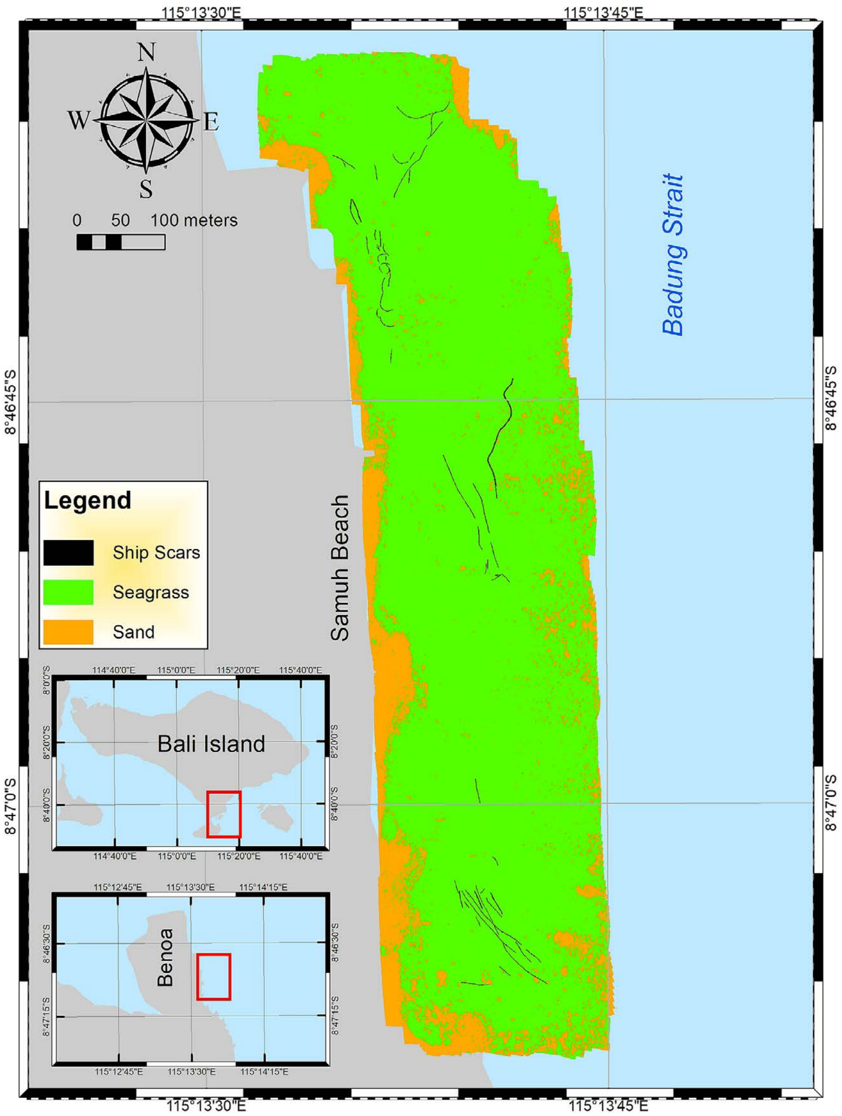

Figure 6. Overlay of seagrass and scars detection at Samuh Beach, Bali, Indonesia

The acquisition of 2976 hig-resolution images through sixteen separate flights aalowed for the compilation of a detailed orthomosaic, enabling comprehensive coverage and mapping of seagrass habitats. The high spatial resolution and detailed visual data obtained UAVs facilitated precise species identification and habitat monitoring. Furthermore, the ability to access remote or challenging coastal areas provided valuable insights into the distribution and condition of seagrass beds. However, the study highlights certain limitations in UAV-based research. The UAV imagery may not provide sufficient taxonomic resolution to accuratey distinguish between different seagrass species. A observed in the study, *Cymodocea rotundata* and *Syringodium isoetifolium* were misclassified as *Enhalus acoroides*, indicating the inability of UAV imagery to distinguish these species accurately. Interm of technical issues, weather dependence, battry life and flight time, data processing complexity and regulatory restrictions were experienced in this seagrass study. For example, adverse weather conditions can restrict UAV flights, and UAV have limited flight time due to battery constraints. As mentioned by Nahirnick et al [2019], mapping with UAV is advised to be done on a small area of seagrass beds. This can be a hurdle to carry out a remote sensing study with UAV in a larger area. Furthermore, UAV flight also requires optimal weather and environmental condition to avoid a number of issues, such as sunglint. The quality of the aqcuired data can be affected by sunglint, because of its visible appearence on the surface of the water body [Doukari et al., 2021]. Avoiding this problem can be accomplished by flying the

UAV in the morning and afternoon, following the recommendation of Chayhard et al [2018].

CONCLUSIONS

This study represents the first investigation of species classification using UAV photography at Samuh Beach. Mosaicked images compiled from drone missions successfully identified five species of seagrass, namely *Enhalus acoroides, Halodule pinifolia, Thalassia hemprichi, Cymodocea rotundata*, and *Syringodium isoetifolium*. This study also mapped the results of anthropogenic activities that posed a threat to the seagrass. Scars discovered on the seagrass bed were likely generated by boat propellers passing through the area. However, additional research on these scars is necessary to gain a better understanding of the impact of human activities, particularly marine tourism, on the seagrass bed at Samuh Beach.

Acknowledgements

The authors are grateful to LPPM, Udayana University for supporting this research with Udayana University PNBP research grant and USAID through Sustainable Higher Education Research Alliances (SHERA) Program Center for Collaborative Research Animal Biotechnology and Coral Reef Fisheries (CCR ANBIOCORE).

REFERENCES

1. Ahmed S., Al-Durgham K., Al-Nahar A. 2020. Multi-source satellite images merging for urban land cover mapping. The Egyptian Journal of Remote Sensing and Space Science, 23(1), 77-85.
2. Azizah N.N., Siregar V.P., Agus S.B. 2016. Penerapan Algoritma Spectral Angle Mapper (Sam) Untuk Klasifikasi Lamun Menggunakan Citra Satelit Worldview-2. Jurnal Penginderaan Jauh, 13(2), 61-72.
3. Bao Y., Chen L., Zhang Z., Zhang J. 2019. An efficient image registration algorithm for multi-source remote sensing images. Remote Sensing, 11(9), 1108.
4. Chayhard S., Manthachitra V., Nualchawee K., Buranapratheprat A. 2018. Multi-temporal mapping of seagrass distribution by using integrated remote sensing data in Kung Kraben Bay (KKB), Chanthaburi province, Thailand. International Journal of Agricultural Technology, 14(2), 161-170.
5. Congalton R.G., Green K. 2008. Assessing the accuracy of remotely sensed data: principles and practices. 2nd edition. CRC Press. https://doi.org/10.1201/9780429052729
6. Congalton R.G., Green K. 2019. Assessing the accuracy of remotely sensed data: principles and practices. 3rd edition. CRC Press, Boca Raton.
7. Dekker A., Brando V., Anstee J., Fyfe S., Malthus T., Karpouzli, E. 2006. Remote sensing of seagrass ecosystems: use of spaceborne and airborne sensors. Seagrasses: Biology, Ecology and Conservation, 347-359.
8. Duarte C.M. Cebrián J. 1996. The fate of marine autotrophic production. Limnology and oceanography, 41(8), 1758-1766.
9. Doukari M., Katsanevakis S., Soulakellis N., Topouzelis K. 2021. The Effect of Environmental Conditions on the Quality of UAS Orthophoto-Maps in the Coastal Environment. ISPRS Int. J. Geo-Inf, 10(18), https://doi.org/10.3390/ijgi10010018.
10. Ginting D.N.B., Wicaksono P., Farda N.M. 2023. Mapping Benthic Habitat from WORLDVIEW-3 Image Using Random Forest Case Study: Nusa Lembongan, Bali, Indonesia. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 48, 123-129.
11. Glasby T.M., West G. 2018. Dragging the chain: Quantifying continued losses of seagrasses from boat moorings. Aquatic Conservation: Marine and Freshwater Ecosystems, 28(2), 383-394.
12. Hallac D.E., Sadle J., Pearlstine L., Herling F., Shinde D. 2012. Boating impacts to seagrass in Florida Bay, Everglades National Park, Florida, USA: links with physical and visitor-use factors and implications for management. Marine and Freshwater Research, 63(11), 1117-1128.
13. Indayani A.B., Danoedoro P., Wicaksono P., Winarso G., Setiawan K.T. 2020. Analisis spektral dari serapan dan pantulan daun lamun menggunakan spektroradiometer trios-ramses di Nusa Lembongan dan Pemuteran, Bali. Jurnal Penginderaan Jauh dan Pengolahan Data Citra Digital, 17(2).
14. Joyce K.E., Duce S., Leahy S.M., Leon J., Maier S.W. 2018. Principles and practice of acquiring drone-based image data in marine environments. Marine and Freshwater Research, 70(7), 952-963.
15. Karang I.W.G.A., Dharma I.G.B.S, Astaman I.D.M.K.P. 2022. Mapping of shallow-water benthic habitats in Nusa Lembongan, Bali using Sentinel-2B and Landsat 8 satellite data. AACL Bioflux, 15(3).
16. Karang I.W.G.A., Nagendra I.W.M.D., Astaman I.D.M.K.P., Hendrawan I.G. 2019. Pemetaan Habitat Perairan Dangkal di Kawasan Padat Wisata Tanjung Benoa Bali Menggunakan Data Remote Sensing. ECOTROPHIC : Jurnal Ilmu Lingkungan (Journal

Of Environmental Science), 13(2), 227-237.

17. Khairunnisa, Setyobudiandi I., Boer, M. 2021. Seagrass distribution in the east coast of Bintan. IOP Conference Series: Earth and Environmental Science, 782(4), 042001.
18. Knudby A., Nordlund L. 2011. Remote sensing of seagrasses in a patchy multi-species environment. International Journal of Remote Sensing, 32(8), 2227-2244.
19. Kumara I.S.W. 2018. Pemetaan sepsies lamun melalui integrasi citra multispektral dan pola respon spectral di Nusa Lembongan, Bali. Thesis, Universitas Ghajah Mada. Yogyakarta, Indonesia.
20. Lazuardi W., Ardiyanto R., Marfai M.A., Mutaqin B.W., Kusuma D.W. 2021. Coastal Reef and Seagrass Monitoring for Coastal Ecosystem Management. International Journal of Sustainable Development & Planning.
21. Li, S. 2018. Seagrass Mapping and Human Impact Evaluation Using Remote Sensing Imagery at Core Banks, North Carolina.
22. LIPI, 2014. Technical guide for mapping bottom habitat of shallow marine waters. Pusat Penelitian Oseanografi Lembaga Ilmu Pengetahuan Indonesia, 300, Jakarta, Indonesia.
23. Lyons M., Phinn S., Roelfsema C. 2011. Integrating Quickbird multi-spectral satellite and field data: Mapping bathymetry, seagrass cover, seagrass species and change in Moreton Bay, Australia in 2004 and 2007. Remote Sensing, 3(1), 42-64.
24. Nababan B., Mastu L.O.K., Idris N.H., Panjaitan J.P. 2021. Shallow-water benthic habitat mapping using drone with object based image analyses. Remote Sensing, 13(21), 4452.
25. Nahirnick N.K., Reshitnyk L., Campbell M., Hessing-Lewis M., Costa M., Yakimishyn J., Lee L. 2019. Mapping with confidence; delineating seagrass habitats using Unoccupied Aerial Systems (UAS). Remote Sensing in Ecology and Conservation, 5(2), 121-135.
26. Oguslu E., Islam K., Perez D., Hill V.J., Bissett W.P., Zimmerman R.C., Li J. 2018. Detection of seagrass scars using sparse coding and morphological filter. Remote Sensing of Environment, 213, 92-103.
27. O’Neill J.D., Costa M. 2013. Mapping eelgrass (Zostera marina) in the Gulf Islands National Park Reserve of Canada using high spatial resolution satellite and airborne imagery. Remote Sensing of Environment, 133, 152-167.
28. Phinn S., Roelfsema C., Dekker A., Brando V., Anstee J. 2008. Mapping seagrass species, cover and biomass in shallow waters: An assessment of satellite multi-spectral and airborne hyper-spectral imaging systems in Moreton Bay (Australia). Remote sensing of Environment, 112(8), 3413-3425.
29. Riani E., Djuwita I., Budiharsono S., Purbayanto A., Asmus H. 2012. Challenging for seagrass management in Indonesia. Journal of Coastal Development, 15(3), 234-242.
30. Riniatsih I., Ambariyanto A., Yudiati E., Redjeki S., Hartati R., Triaji M.J.R., Siagian H. 2021, April. Spatial assessment of seagrass ecosystem using the Unmanned Aerial Vehicle (UAV) in Teluk Awur, Coastal Water of Jepara. IOP Conference Series: Earth and Environmental Science, 744(1), 012063.
31. Roelfsema C.M., Lyons M., Kovacs E.M., Maxwell P., Saunders M.I., Samper-Villarreal J., Phinn S. R. 2014. Multi-temporal mapping of seagrass cover, species and biomass: A semi-automated object based image analysis approach. Remote Sensing of Environment, 150, 172-187.
32. Román A., Tovar-Sánchez A., Olivé I., Navarro G. 2021. Using a UAV-Mounted Multispectral Camera for the Monitoring of Marine Macrophytes. Frontiers in Marine Science, 1225.
33. Rosalina D., Irwan K.H R., Jamil K., Surachmat A., Utami E. 2022. Diversity, Ecological Index, and Distribution Pattern of Seagrass in Coastal Waters of North Bali. Journal of Hunan University Natural Sciences, 49(9).
34. Sari K.A.P., Pertami N.D., Pratiwi M.A. 2023. Keanekaragaman dan Asosiasi Antarspesies Lamun di Perairan Pantai Samuh, Nusa Dua, Bali. Current Trends in Aquatic Science, V(1), 64-73.
35. Sondak C.F.A., Kaligis E.Y. 2022. Assessing the seagrasses meadows status and condition: A case study of Wori Seagrass Meadows, North Sulawesi, Indonesia. Biodiversitas Journal of Biological Diversity, 23(4).
36. Sudiarta I.K., Sudiarta I.G. 2011. Status kondisi dan identifikasi permasalahan kerusakan padang lamun di Bali. Jurnal Mitra Bahari, 5(2), 104-126.
37. Suteja Y., Atmadipoera A.S., Riani E., Nurjaya I.W., Nugroho D., Cordova M.R. 2021. Spatial and temporal distribution of microplastic in surface water of tropical estuary: Case study in Benoa Bay, Bali, Indonesia. Marine Pollution Bulletin, 163, 111979.
38. Tahara S., Sudo K., Yamakita T., Nakaoka M. 2022. Species level mapping of a seagrass bed using an unmanned aerial vehicle and deep learning technique. PeerJ, 10, e14017.
39. Théau J. 2008. Temporal Resolution. In: Shekhar, S., Xiong, H. (eds) Encyclopedia of GIS. Springer, Boston, MA.
40. Wang L., Zhao G., Li Y., Zhang Y., Yu W. 2021. Multi-source remote sensing image registration with feature-based method. International Journal of Remote Sensing, 42(7), 2616-2635.
41. Watiniasih N.L., Nuarsa I.W., Merdana I.M., Budiarsa I.N., Dharma A., Antara I.N.G., Poborini M. W. 2019. Organism Associated with Cymodocea

Serulata in Different Habitats near Urban Coastal Area. IOP Conference Series: Earth and Environmental Science, 396(1), 012006.

42. Wicaksono P., Hafizt M. 2013. Mapping seagrass from space: Addressing the complexity of seagrass LAI mapping. European Journal of Remote Sensing, 46(1), 18-39.
43. Wicaksono P., Fauzan M.A., Kumara I.S.W., Yogyantoro R.N., Lazuardi W., Zhafarina Z. 2019. Analysis of reflectance spectra of tropical seagrass species and their value for mapping using multispectral satellite images. International Journal of Remote Sensing, 40(23), 8955-8978.
44. Wijantara I.G.A., Karang I.W.G.A., Indrawan G.S. 2022. Pemetaan Distribusi Lamun di Selat Ceningan Menggunakan Drone Komersial. Journal of Marine and Aquatic Sciences, 8(2), 279-287.
45. Yang B., Hawthorne T.L., Hessing-Lewis M., Duffy E. J., Reshitnyk L.Y., Feinman M., Searson H. 2020. Developing an introductory UAV/drone mapping training program for seagrass monitoring and research. Drones, 4(4), 70.
46. Yang D., Huang, D. 2011. Impacts of typhoons Tianying and Dawei on seagrass distribution in Xincun Bay, Hainan province, China. Acta Oceanologica Sinica, 30(1), 32.
47. Zhang C., Xie Z. 2013. Object-based vegetation mapping in the Kissimmee River watershed using HyMap data and machine learning techniques. Wetlands, 33, 233-244.
48. Zhang X., Liu J., Zhang X. 2018. Multi-source remote sensing image registration based on feature extraction and cross correlation coefficient. International Journal of Remote Sensing, 39(12), 3852-3871.