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Research article

Grouping Land Cover Using Orthophoto in Small Islands: An Application of Low-Cost UAV on Mansinam Island

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Abstract

Land cover is crucial for island management, but the lack of accessible and high-resolution remote sensing data has reduced investigations on small islands, including land cover identification. Therefore, this study aimed to investigate land cover using Unmanned Aerial Vehicle (UAV) technology, providing very high-resolution images. Classification and delineation were conducted using automatic segmentation followed by manual reinterpretation and visual verification. The results showed 14 cover classes, consisting of 8 vegetated and six non-vegetated categories. Forest cover on Mansinam island accounted for 75.5% or 302.4 ha, which was evenly distributed. Furthermore, primary forest covered 31.91% or 127.74 ha, and secondary covered 43.63% or 174.68 ha. The classification achieved an overall accuracy of 96% and a kappa coefficient of 0.94. Low-cost UAVs effectively produced high-resolution aerial images of small islands for land cover identification. Therefore, future studies were recommended to consider whether segmentation can reliably distinguish between primary and secondary forests, as well as assess the impact of flight altitude on segmentation accuracy using ground control points. The results were also expected to support spatial planning or sustainable forest and environment management on Mansinam Island.

Keywords: UAV; Land cover; Mansinam; Forest; Small island.

1. Introduction

Indonesia is an archipelagic country with 16771 identified islands in 2020 (KLHK, 2021). Islands spread throughout Sumatra, Kalimantan, Java, Sulawesi, and Papua. Moreover, about 4,514 or 26.9% of the area of this island falls under the administration of West Papua Province (KLHK, 2021). Papua is one of the largest islands in Indonesia, and it has extensive forest cover, making it a significant natural resource. In 2020, Papua recorded a forest cover of 34.3 million hectares (KLHK, 2021). Tropical forests with diverse ecosystems characterize the island (Sothe *et al.*, 2019). It is also among the regions with the richest vegetation in the world (Cámara-Leret *et al.*, 2020).

Rainforest cover in Papua extends evenly from mountainous areas to the coast and even grows on some small islands (Cámara–Leret & Dennehy, 2019). Globally, tropical rainforests are crucial for two main reasons, namely, high biodiversity and an important role in the global carbon cycle. Rainforests are also important for local communities by providing essential products and services such as timber, food, medicine, and clean water (Corlett, 2018; Murdjoko *et al.*, 2021; Sonbait *et al.*, 2021). Papua's tropical rainforests have experienced significant changes, including vegetation dynamics and successional processes that contribute to forest growth (Murdjoko, Brearley, Ungirwalu, Djitmau, & Benu, 2022; Tawer *et al.*, 2021). Effective forest management is essential for maintaining ecosystem services (Yilmaz, Levent, Cigdem, & Oguz, 2017). The first step in forest management is to collect comprehensive and accurate information about the distribution of resources and other ecosystems through land cover identification. Land cover refers to the physical appearance of objects on the earth's surface and helps describe the relationships between natural and social processes (Rahardjo, Aunurrahim, Hayun, & Asri, 2021). It is a critical data point for assessing the condition of an area (Park, Park, Song, & Lee, 2022).

Currently, land cover identification primarily relies on satellite imagery. However, identifying land cover on small islands requires high-resolution satellite images, which are often only available through paid services and are limited in availability. The images can be difficult to obtain quickly and are often affected by fog or clouds (Hyeok and Wan, 2017; Aldyan *et al.*, 2018; Arfan *et al.*, 2021). To address this problem, UAV have been developed to monitor and estimate objects on the earth's surface accurately and efficiently (Sari & Kushardono, 2014). Initially, it was used for aerial photography in the military during the First and Second World Wars, the Korean War, the Vietnam War, and the Cold War (Banu, Borlea, & Banu, 2016; Elkhrachy, 2021; Akturk & Altunel, 2019). In recent years, the technology has been increasingly used to monitor and map objects in agriculture, environmental fields, and forestry (Arham, Sjaf, & Darusman, 2019; Horning *et al.*, 2020; Ramadhani *et al.*, 2015; Torresan *et al.*, 2017; Maria *et al.*, 2017). The rapid development of photogrammetric technology has made UAV practical and relatively low-cost, allowing for quick data collection on the earth's surface (Polat and Kaya, 2021; Umarhadi *et al.*, 2018; Shashkov *et al.*, 2019). Its application for remote sensing offers several benefits, including reduced costs and time, high resolution, and ease of use in various conditions (Zhang, Wu, & Yang, 2019).

Several studies have explored the capability of UAVs in identifying land cover. For example, an investigation on land cover identification at altitudes below 120 m above ground level (AGL) using deep learning methods achieved an overall accuracy rate of 0.82-0.89 (Horning *et al.*, 2020). Moon *et al.* (2017) compared land cover identification based on pixel and object classifications using UAV imagery, producing a kappa accuracy of 0.82. Similarly, Aldyan *et al.* (2018) found that object-based classification outperformed pixel-based methods, producing up to 90% accuracy and a kappa index of 0.88. Jumaat *et al.* (2018) also reported high accuracy for land cover classification from UAV imagery, with a kappa value of 0.92. These results showed the advantages of UAV imagery for recording and analyzing objects on the Earth's surface. However, none of the studies focused on small islands, showing a gap in the investigation on natural resources in small islands of Indonesia, including those in Papua (Ramadhani *et al.*, 2015b). Furthermore, investigations have not been conducted on the use of high-resolution imagery for land cover on small islands in Papua, including Mansinam. Previous studies on Mansinam Islands were limited to biodiversity (Sorondanya, Peday, & Runtuboi, 2021), land cover dynamics using Sentinel-2 with a resolution of 10 m and seven land cover classes (Waromi, 2021), as well as bare land mapping using drones (Raweyai *et al.*, 2023). Therefore, the current study aimed to fill the information gap by providing detailed land cover data for small islands like Mansinam using high-resolution UAV imagery.

Using UAVs to identify land cover in tropical areas such as Indonesia, particularly Papua, is still limited, specifically on small islands. This is due to restricted access and extreme weather conditions, such as strong winds and high waves. Another challenge is ensuring that high-resolution imagery from UAVs can produce precision data. One effective solution is to use segmentation or object-based identification techniques. Classification of spatial information from remote sensing typically uses two methods, namely object-based and pixel-based. Object-based classification (OBIA) not only considers spectral information but also the spatial aspects of the object (Koman, Shofiyal Izza, & Candraningtyas, 2022). The primary function is to divide an image into segments based on its spectral and spatial characteristics (El-Naggar, 2018). A common OBIA technique is multi-resolution segmentation (MRS), which is influenced by parameters such as shape, scale, colour, smoothness, and compactness (Lubis, Rusdi, & Sugianto, 2021). These parameters are well-suited for high-resolution images, like orthophoto from UAV aerial photographs, allowing for clear differentiation between objects. Weih and Riggan (2010) also stated that object-based classification is particularly suitable for high-resolution images.

The current study addressed the question, what is the land cover type of Mansinam Island based on very high-resolution imagery from UAV? The objective was to adopt low-cost UAV technology to identify land cover on small islands using object-based segmentation. The hypothesis is that low-cost UAV technology can provide very high-resolution images that accurately identify land cover on small islands, and segmentation can help properly delineate and classify land cover. The results are expected to provide detailed land cover information that can be used for spatial planning and sustainable forest and environment management on Mansinam Island. The study also aimed to show that low-cost UAVs can be effectively used for mapping small islands.

This article is organized as follows to achieve the study objectives: the next section outlines the acquisition and processing of aerial photographs to identify land cover, which will be presented in the results and discussion section. The final section of this paper will provide the conclusions.

2. Study Methods

2.1. Time and site study

This study was conducted in July and August 2020 on Mansinam Island. Although the data were not current, the results could support studies requiring past land cover data for comparison. The documented conditions might not be applicable currently, making the documentation of past information valuable for future studies. Meanwhile, Mansinam Island holds historical significance for the Papuan people, or "orang asli Pa-pua" (OAP), as it was the first place where evangelists arrived in 1855 (see Figure 1). The island has potential as a religious tourism site, in addition to its panoramic views and beautiful stretches of white sand beaches. Mansinam Island covers an area of ± 400 hectares (ha) and is located in Doreri Bay, Manokwari Barat district, Manokwari Regency, West Papua Province, Indonesia. Geographically, it is situated at coordinates

134°5’16.6” – 134°6’46.2” East Longitude and 0°53’17.1 - 0°55’28.18 South Latitude. The island is approximately 5 km from downtown Manokwari and can be reached in 10-15 minutes by boat. Based on CHIRPS data (https://www.chc.ucsb.edu/data/chirps), the average rainfall in 2023 was 2,192 mm/year, the average wind speed reached 2 meters/second in 2022, and the average temperature of Manokwari (Mansinam Island) was 28°C (BPS, 2023).

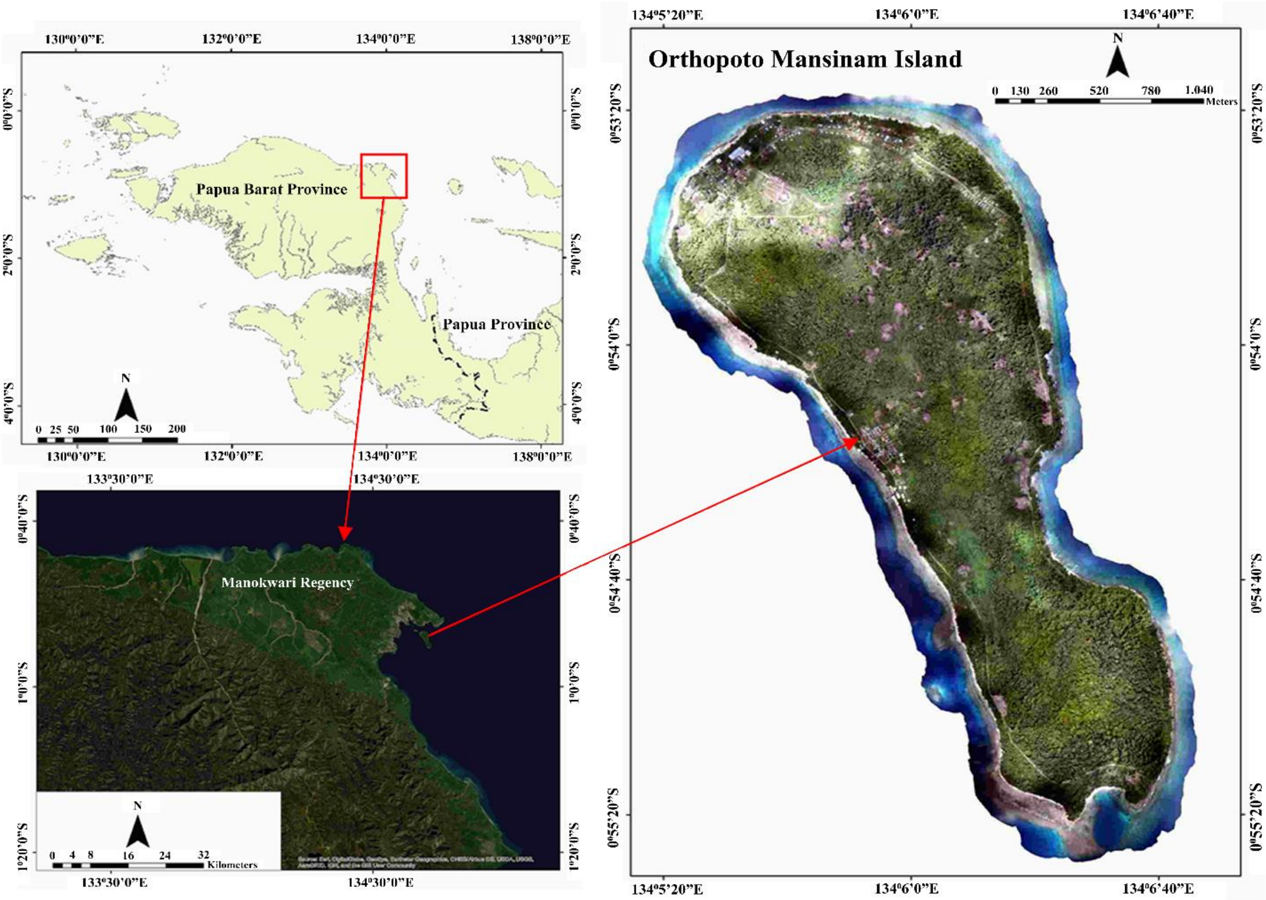

Figure 1. Study site. Map of Mansinam Island (Orthophoto).

2.2. Aerial Photo Acquisition

UAV used in this study was the DJI Phantom 3 Professional, a quadcopter manufactured by DJI (Da Jiang Innovation), a science and technology company based in Shenzen, China. The DJI Phantom 3 Professional, a multicopter UAV equipped with four propellers, ensures stable flight when taking photos and videos (see Figure 2) and can be operated in locations that are difficult to access (Wulan *et al.*, 2016). Although not specifically designed for mapping, UAVs can be used for this purpose with the help of additional software. This software facilitates capturing aerial images automatically and systematically (Wijaya *et al.*, 2019). The DJI Go supported the aerial photography process and Pix4D capture software installed on an IOS-based smartphone device. DJI recommended the IOS platform for its stable connection with UAV.

Figure 2. DJI Phantom 3 Pro equipped with an RGB camera.

Aerial image acquisition was conducted at an altitude of 150 meters (m) or 500 feet AGL during clear, rain-free days. The flight route was planned to cover the island's coastline to ensure complete coverage of the study area in the resulting orthophoto generated from the photogrammetric process. UAV captured images with a 70% front and side overlap, a camera angle of 90°, and at a normal speed for accurate land cover identification.

2.3. Image Processing

Aerial images captured from several flight routes were processed photogrammetrically to obtain a complete orthophoto of the entire island. The images were subsequently resized using the open-source software FastStone Photo Resizer (www.faststone.org) to ensure smooth processing with Agisoft Photoscan Metashape Professional software version 1.6 (Agisoft LLC, St. Petersburg, Russia). The Parameters for the aerial image analysis process included Allign Photos, Build Dense Point Cloud, Build Mesh, Build Texture, Build Tiled Model, and Build Orthomosaic. The processing of aerial images into orthophoto was performed on a computer with the following specifications: Windows 10, Intel Core I7, 16 Gigabyte (GB) RAM, NVIDIA GeForce GTX 1650 3 GB, and 256 GB hard disk Solid-state drive (SSD). The results were exported as images in TIFF (Temporary Instruction File Format). In this study, orthophoto did not use ground control points (GCPs) and relied only on the coordinate information recorded by the global positioning system (GPS) attached to the UAV. While the use of GCPs can improve geometric accuracy (actual location), this investigation only focused on identifying land cover classes and segmentation processes from high-resolution aerial imagery. Therefore, the use of GCPs had a significant impact on the current study.

2.4. Identification of Land Cover Class

The land cover identification process was carried out using a semi-automatic method with the OBIA (object-based image analysis) approach to delineate the boundaries between land cover classes accurately. The principle of OBIA classification relies on the characteristics of each object, such as pixel value, shape, size, area (Harto *et al.*, 2019). One method within OBIA is segmentation, specifically MRS. MRS groups areas with similar adjacent pixel values into objects, where homogeneous areas form larger objects and heterogeneous areas form smaller ones (Purba & Perwira, 2021). Segmentation was performed using eCognition software version 9 (Trimble Germany GmbH, Germany) with parameter values of 200 scale, 0.5 shape, and 0.7 Compactness. Manual reclassification with interpretation was conducted using desktop-based GIS software ArcMap version 10.8 (ESRI, USA). Orthophoto was divided into four different images to facilitate optimal computer performance during the segmentation process. To simplify classification from segmentation results, land cover was divided into seven classes, namely forest cover, bare land, road, agricultural land, built-up land, grass, and shrubs. In general, the characteristics of land cover classes used are as follows: Forest: Located on dry land, dense-medium canopy, with or without logging. Agricultural land: Located on bare land with various agricultural commodities or mixed with shrubs. Shrubs: Coarse texture, generally light green to dark green, and often associated with roads. Built-up land: Irregular object shapes, typically found in settlement areas. Water bodies: Brown to blackish, smooth textured, and located in open areas. Bare land: Slightly blackish-brown, often with white stripes from downed tree trunks. Grass: Smooth texture, generally light to dark green, often associated with buildings or settlements.

Segment classifications are made based on training samples for all predefined land cover classes and distributed to all areas using the nearest neighbour algorithm (NNA) based on the characteristics or properties of each class. Nearest neighbour classification algorithms classify unclassified sample points by finding the nearest sample point from a set of previously classified points (Cover and Hart, 1967). Reclassification for detailing is carried out with manual interpretation of orthophoto and temporary segmentation results based on colour, texture, shape, pattern, and association. When the manual interpretation shows that land cover class can be detailed further, it is adjusted according. Segments that have the same class and are adjacent are merged, while segments with different classes can be split. Reclassification is carried out to improve accuracy (El-Naggar, 2018) and refine land cover classification. The reclassified segmentation results were tested manually through the visual method based on UAV orthophoto using original true colors. To achieve better segmentation results and optimize cover estimation, rule sets were applied through multiple iterative classification trials, with no absolute value parameters (Pasaribu, Aditama, & Setyabudi, 2021).

2.5. Accuracy Test

The accuracy test was conducted using 819 verification points created with ArcGIS software. These points were evenly distributed across Mansinam Island and represented all land cover classes. The accuracy test included both field surveys and visual assessments based on orthophoto. Visual accuracy testing was feasible due to the high image resolution obtained, which was below 10 cm/pixel (Ramadhani, K, & Susanti, 2015a). An analysis was carried out using an error matrix to determine the level of accuracy (Congalton & Green, 1957). Based on the error matrix (Figure 3), the overall accuracy and kappa coefficient were calculated to assess the agreement in the classification evaluation (Kushardono, 2017). This can be seen in Equations 1, 2, and 3.

$$\text{Overall accuracy} = \frac{aA + bB + cC + \ldots}{n} \tag{1}$$

$$\text{Koef Kappa} = (\text{overall accuracy - expected accuracy}) \,/\, (1 - \text{expected accuracy}) \tag{2}$$

$$\text{Expected accuracy} = ((\Sigma a \times \Sigma A)/n + (\Sigma b \times \Sigma B)/n + \ldots + (\Sigma c \times \Sigma C/n)/\, n)/n \tag{3}$$

where:

ΣA : The total value in the column of each class
Σa : The total value in the row of each class
N : Total data
aA : Values in columns that have the same class/ diagonal value

		Field Verification Result Class			Total
		A	B	C	
Class Row Classification Result	a	aA	aB	aC	Σa
	b	bA	bB	bC	Σb
	c	cA	cB	cC	Σc
Total		ΣA	ΣB	ΣC	n

Figure 3. Illustration of land cover accuracy test using error matrix.

2.6. Study Procedure

The procedures and stages of study using low-cost UAVs were tailored to the capabilities of the equipment used. Figure 4 shows the flow of preparation to data analysis used in this study.

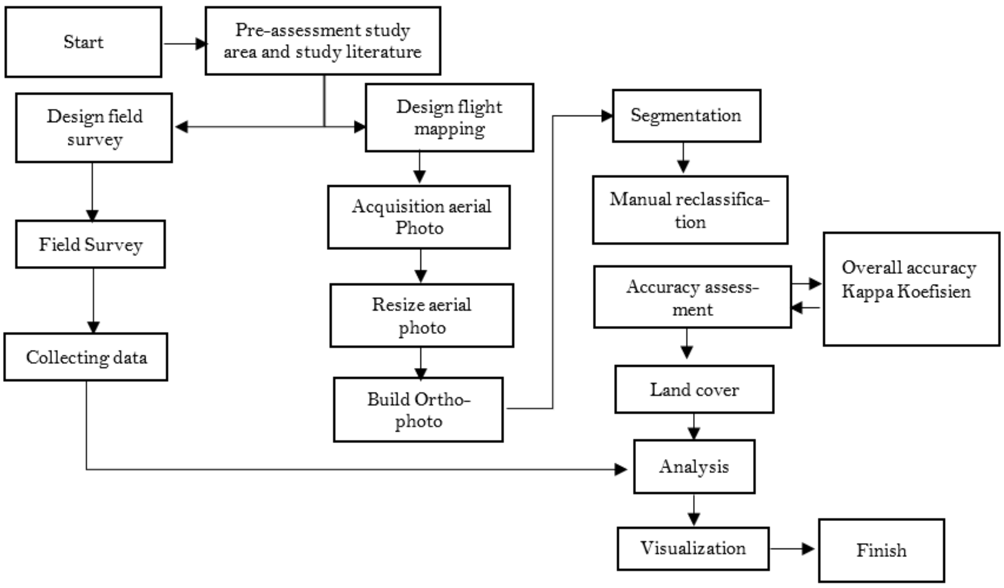

Figure 4. Data processing flow.

3. Results and Discussion

3.1. Orthomosaic

Orthophoto of Mansinam Island was created from 1,972 images recorded using UAV. The photogrammetric analysis showed that orthophoto covered 6.92 km², about 42% more than Mansinam Island. Orthophoto was created with a good photo overlay of >9 images in all areas of the island. The results showed a spatial resolution of 8.7 cm/pixel, with 2.17 m accuracy of camera x error, 2.81 m y error, 6.05 m z error, 3.55 m xy error, and 7.02 m total error. Without ground control points (GCP), the accuracy of the photogrammetric process ranged from 10 to 40 m from the actual position, but the data could still be used for thematic mapping (Nagendran, Tung, & Mohamad Ismail, 2018). This was supported by other studies, showing a measurement accuracy of over 95%, using the DJI Phantom 3 Pro in coastal areas, even without GCP (Wulan *et al.*, 2016). Figure 1 shows the results of the aerial images from UAV, processed into orthophoto.

3.2. Land Cover Classification

The initial classification process identified seven land cover classes, namely forest, buildings, bare land, roads, shrubs, agricultural land, and grass. These results were manually reinterpreted to ensure accuracy, resulting in the identification of 14 classes and the addition of 7 new land cover classes through the reclassification of the segmentation results (Figure 7a or Figure 7b, 7c). The segmentation and manual interpretation of orthophoto showed that various types of vegetation covered Mansinam Island on 93.69%, or 375 ha, of its area, while the remaining 6.31% or 25.27 ha was non-vegetated. This significant proportion showed that Mansinam Island was predominantly covered by vegetation.

Table 1. Land cover class and area of Mansinam Island.

Land Cover Class	Hectare (ha)	Percent (%)
Vegetation	375.05	93.69
Primary Forest	127.74	31.91
Secondary Forest	174.68	43.63
Agricultural land	7.12	1.78
Mixed Agricultural	5.46	1.36
Plantation	6.20	1.55
Grass	11.81	2.95
Shrubs	23.18	5.79
Mixed Plants	18.87	4.71
Non-Vegetation	25.27	6.31
Waterbody	0.27	0.07
Building	4.38	1.09
Road	3.19	0.80
Grave	0.22	0.06
Built-up Land	0.84	0.21
Bare land	16.36	4.09
Grand Total	**400.32**	**100.00**

Table 1 shows that the land cover of Mansinam Island is divided into two main classes, namely vegetation and non-vegetation. The vegetation class was further detailed into eight classes, while the non-vegetation was divided into 6, making a total of 14 land cover classes. The vegetation class was dominated by secondary forest cover (43% or 174 ha), while the non-vegetation was dominated by bare land (4.09% or 16.36 ha). Orthophoto analysis from 2020 showed the presence of 95 new bare land areas on Mansinam Island, totalling 15.2 ha or an average size of 0.15 ha. Further analysis showed that 63.8% or 9.7 ha of the bare land remained unused, while 36.2% or 5.5 ha had been converted into agricultural land (Figure 5b).

The distribution and area of forest cover on Mansinam Island are important results of this study. The classification of orthophoto showed that forest cover accounted for 75.5% or 302.4 ha of the island, with an even distribution. Primary forest covered 31.91% or 127.74 ha, while secondary forest covered 43.63% or 174.68 ha. This showed that the secondary forest area exceeded the primary forest area. Factors contributing to this shift included the demand for sawn timber and land for agriculture, among other reasons requiring further investigation. The primary forest is located mainly in the northern and southern parts of the island, while secondary forests dominate the northern and central regions. The central area, in particular, had varied land cover due to its proximity to settlements, resulting in higher land use interactions. Forests play a crucial role in maintaining ecosystems and significantly impact the environment. Ecosystem services, essential for human life, are influenced by forest cover. Mansinam Island has permanent residents relying on ecosystem services, such as water provisioning, disaster protection, and clean air regulation. Therefore, policymakers need to understand the relationship between humans, nature, and changes in land cover (Vaggela, Sanapala, & Mokka, 2022). The impact of changes in forest cover could affect the availability and function of natural resources. The availability of land supporting natural resources decreases as forest cover conversion increases (Marwa, Sineri, & Hematang, 2020).

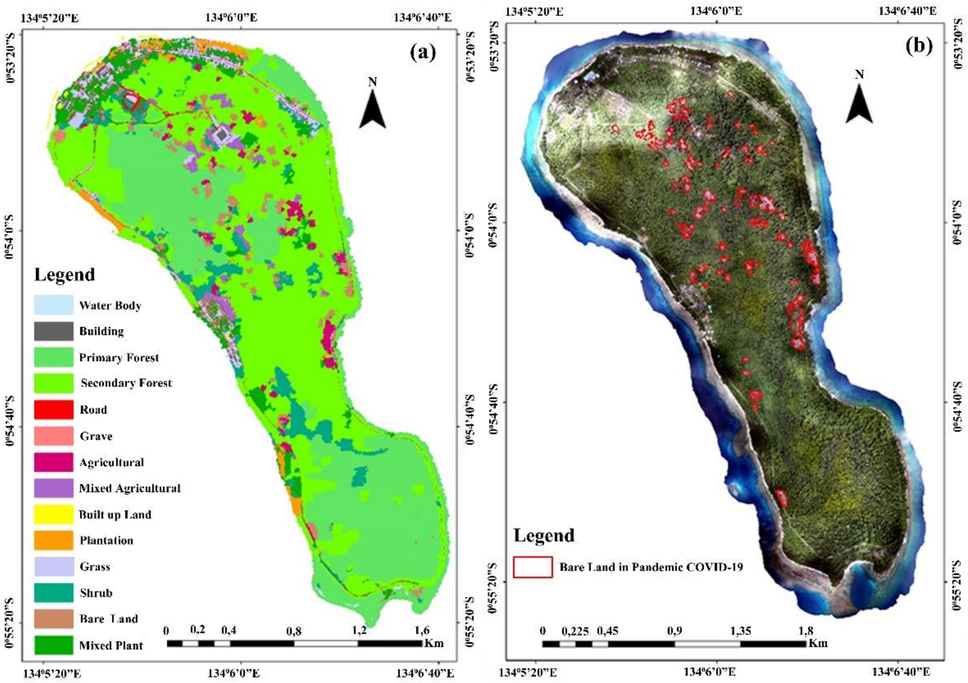

Figure 5. Land cover map of Mansinam Island in 2020: (a) Land cover class, (b) Bare Land**.**

Figure 6. Example of land cover class photo: (a) grass, (b) community agricultural, (c) grave, (d) forest

The interpretation results showed that one cause of the decline in primary forest cover was the conversion of forest by the community into new agricultural land (see Figure 5b). Food is an important priority, specifically during the COVID-19 pandemic. In 2020, while the COVID-19 pandemic was ongoing, the food security index for Manokwari Regency was at level 6 with an index value of 75.42, ranking 218th highest in Indonesia. However, regionally, the West Papua food security index was the second-lowest in Indonesia (BKP, 2020). A high food security index does not guarantee food security for the people living on Mansinam Island. At the beginning of the COVID-19 pandemic, the residents implemented a local lockdown, closing access to and from the island, including access to food. Typically, the residents obtained food from Manokwari, specifically essential items like rice. To ensure food availability during the lockdown, the community created new agricultural land. Consequently, local communities converted forest and other land for agricultural purposes.

Logging trees is one of the factors affecting the primary forest on Mansinam Island. Trees were cut down by the community to be processed into sawn wood, which was generally used for houses and other needs. Therefore, the forest on Mansinam contained several commercial tree species. Studies have also discovered commercial tree species in observation plots, such as *Intsia bijuga* (Colebr) Kuntze, Pometia spp, Dracontomelon dao (Blanco) Merr & Rolfe, Canophyllum inophyllum, and others. Timber harvesting was not only carried out by local communities on Mansinam Island but also by people from Lemon Island and other surrounding areas (Hematang, 2021). Logging trees impacted the distribution of species and the current diversity of tree heights. Other studies showed that the dominant tree height on Mansinam Island was in the range of 19-30 m, with an average tree height of 25 m (Hematang, Murdjoko, Hendri, & Tokede, 2022). This showed there had been intensive logging in the past, making the distribution of tree heights uneven. Logging not based on a good silvicultural system decreased the biodiversity of flora and fauna, increasing the presence of invasive species, one of which is lianas living epiphytically on certain trees. Invasive species like Macaranga spp. were found growing in some areas of Mansinam Island, such as the ring road. This was because, during construction, the areas to the left and right of the road were deforested, allowing invasive species to grow. Bare land or degraded forests no longer used should be replanted or reforested with trees or plants that have economic value, such as fruit trees.

3.3. Land cover accuracy test

The results of the accuracy assessment of land cover classification using the confusion matrix (Table 2) showed that the classification had an overall accuracy of 96% and a kappa coefficient of 94%. The calculation of the overall accuracy and kappa coefficient based on the error matrix is as follows:

$$\text{Overall accuracy} = 100 \text{ x } \left(\frac{1+6+242+\cdots+36}{819}\right) = 96.4\% \text{ or } 0.96$$

$$\text{Expected accuracy} = \frac{\left(\frac{1 \text{ x } 1}{819}\right)+\left(\frac{7 \text{ x } 6}{819}\right)+\left(\frac{243 \text{ x } 258}{819}\right)+\cdots+\left(\frac{38 \text{ x } 38}{819}\right)}{819} = 0.30$$

$$\text{Coefficient kappa} = \frac{0{,}96-0{,}30}{(1-0{,}30)} = 0.94$$

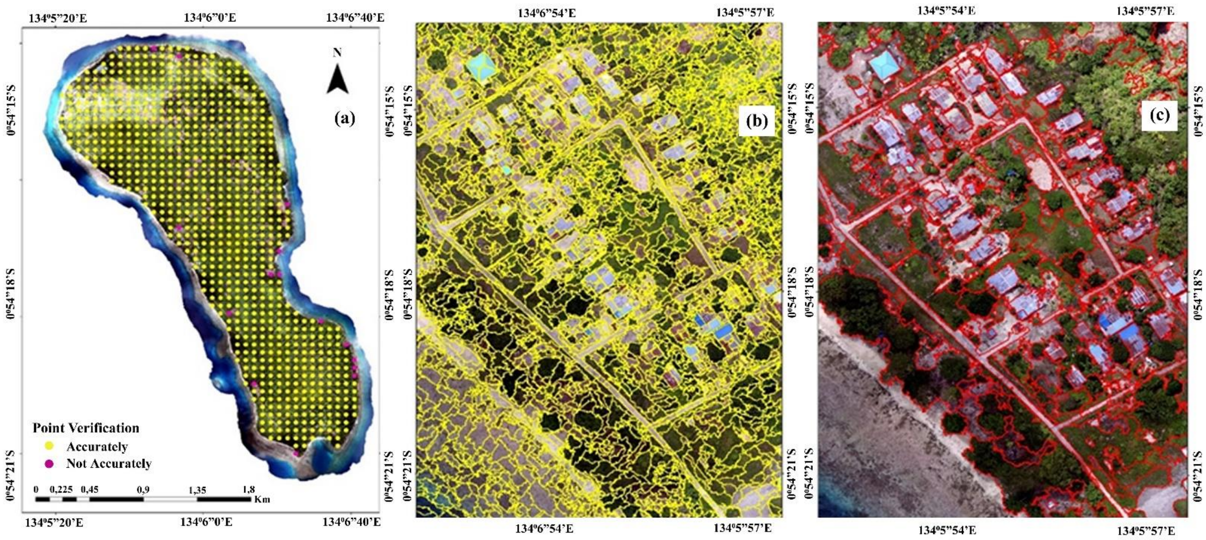

Figure 7. Point verification distribution (a), Segmentation before re-interpretation and re-classification (b), Segmentation after re-interpretation and re-classification (c).

The accuracy test results showed that land cover classification based on the UAV orthophoto of Mansinam Island corresponded with the actual conditions, as evidenced by a kappa coefficient of 0.94, close to 1.0. A kappa coefficient closer to 1.0 showed that orthophoto land cover classification results were nearly identical to the field verification results. This high kappa coefficient value was attributed to the high resolution of 8.7 cm/pixel in the image used to interpret land cover, derived from orthophoto aerial photography. With this resolution, the optimum scale for interpretation was 1:174, according to Tobler's rules. This detailed scale was helpful in distinguishing objects by shape and colour, even with small object sizes. Several other studies supported the accuracy of the high kappa coefficient. For instance, an investigation on land cover mapping of small object-based islands found a kappa coefficient of 0.92 (Ramadhani & Susanti, 2015), while another study achieved a kappa coefficient accuracy of 0.95 in land cover classification using UAV imagery with an OBIA approach (Sitompul *et al.* 2019). Some studies showed that using high-resolution UAV imagery for land cover classification consistently produced high-accuracy results, exceeding other commercial high-resolution images. The current study provided detailed land cover data and accurate information crucial for forest and ecosystem management on Mansinam Island. Moon *et al*. (2017) compared land cover identification based on pixel and object classifications using UAV imagery, achieving a kappa accuracy of 0.82. Object-based land cover identification is highly accurate as it recognizes objects based on shape, colour, size, and pixel values. The overall accuracy (OA) and kappa coefficient results in the current study corresponded with those of recent studies using similar methods and tools. Pasaribu *et al.* (2021) and Miraki *et al.* (2023) reported overall accuracy of 0.81 and 0.98 for mangrove classification using UAV, while another study reported overall accuracy of 0.87 for land cover classification with OBIA from UAV in coastal areas. Object classification parameters are highly suitable for high and very high-resolution images, as all objects can be clearly differentiated. The yellow colour in the results showed consistency between the classification and field verification.

Table 2. Land cover confusion matrix.

Classification	Water Body	Building	Primary Forest	Secondary Forest	Roads	Graveyard	Agricultural Land	Mixed Farmland	Built-up Land	Plantation	Grass	Bush	Open Ground	Mixed Plant	Total Rows
	Verification														
Water Body	1														1
Building		6													6
Primary Forest			242	14								1	1		258
Secondary Forest				364								2			366
Roads					4						1				5
Graveyard						1									1
Agricultural Land							11				1		1		13
Mixed Farmland								10						1	11
Built-up Land									2						2
Plantation										12					12
Grass					1						24			1	26
Bush			1									49			50
Open Ground											2		28		30
Mixed Plant		1										1		36	38
Total Column	1	7	243	378	5	1	11	10	2	12	28	53	30	38	819

3.4. Discussion

Mapping small islands is currently feasible with the advancement of unmanned aircraft technology. This is because UAVs offer various benefits for remote sensing, such as reduced costs, decreased work time, high-resolution imagery, and ease of use in various conditions (Zhang *et al.*, 2019). For instance, capturing and processing aerial images of Mansinam island covering an area of 400 ha into orthophoto took a total of 27 hours. This estimate includes the time required for the UAV to record data according to the flight plan and the processing time for 2002 images using the designated software. However, it does not account for travel to the study location, preparation of UAV, take-off and landing positions, or rest periods during data collection. Another study also showed the estimation of tree diameter in an area of 27.8 ha using low-cost UAVs within 24 hours (Hematang, Murdjoko, & Hendri, 2021). UAV was able to fly and record over an area of 85 ha in 40 minutes with the assistance of 3 people. This contrasted significantly with conventional survey methods, requiring six people to cover an area of 0.25 ha for eight days (Li *et al.*, 2019). For instance, (Otero *et al.*, 2018) found that conducting an inventory in a mangrove forest of 2 ha took approximately 7 hours/day with a team of 3 workers. Němec (2015) also showed that a field survey of 200 ha required 14 workers over 25 days. The cost of acquiring aerial photographs of Mansinam island was IDR 2,450,000, covering workers' salaries, transportation, and other expenses over seven working days. Other DJI series can also be used for land monitoring, such as the DJI Phantom 4 pro with a 1-inch CMOS sensor and 20 million effective pixels, the DJI Mavic Zoom with a 1/2.3-inch CMOS sensor and 12 million effective pixels, and the DJI Mavic 2 Pro with a 1-inch CMOS sensor and 20 million effective pixels (DJI, 2016). With the DJI Phantom 3 pro producing high-resolution aerial images, these newer drone series should provide even higher-quality images.

The current study compared land cover data, specifically forest areas, from various sources. The Ministry of Environment and Forestry, using Landsat imagery with 30 m resolution, determined Mansinam's forest cover (secondary forest) as 256 ha, along with two other land cover classes (KLHK, 2022). Waromi (2021) reported that Mansinam Island had a forest cover of 338 ha based on 10 m resolution Sentinel-2 imagery, with six other cover classes. The current study found 302 ha of forest cover (primary and secondary forest) based on an 8.7 cm resolution orthophoto, identifying 12 other cover classes. The comparison showed that differences in image resolution impacted the optimal scale for interpretation. High image resolution resulted in more accurate land cover classification (number of classes and delineation boundaries). The more accurate land cover classes are identified or delineated, the better the spatial information obtained.

Based on the current study, MRS is an effective algorithm for quickly detecting and delineating object boundaries using high-resolution UAV imagery. The values for scale, shape, and compactness vary depending on the characteristics of each object, such as size, colour, shape, and compactness. Liu and Xia (2010) stated that increasing the segmentation scale decreased segmentation accuracy and increased under-segmentation errors performed on large-scale data. Therefore, selecting appropriate parameter values is crucial for accuracy. Despite using low-cost UAVs with some limitations, the accuracy obtained in the current study was quite good compared to other studies with various methods and UAV development. In addition to MRS and the NNA for classification segmentation, other algorithms like convolutional neural networks (CNN) can also be used. For instance, Akca and Polat (2022) adopted CNN architecture for the semantic segmentation of objects using high-resolution orthophoto from UAV images, achieving an accuracy of 97.2%. Sohl, Mahmood, & Rasheed (2024) used machine learning algorithms like random forest (RF), k-nearest neighbour (KNN), and maximum likelihood classification (MLC) for object classification of high-resolution images from UAV, achieving an overall accuracy of 90% and a kappa coefficient of 0.88. This showed that the accuracy of the results of the current study was comparable to those of other studies using various methods. The reclassification helped distinguish land cover types with similar characteristics, such as forest (primary and secondary) and agricultural land (bare and mixed). Primary and secondary forests are very difficult to distinguish in the segmentation process due to their similar shapes, textures, and colours. The same challenge applies to bare and mixed agricultural lands. In certain cases, bare land may actually be agricultural land with low vegetation, making it difficult to distinguish during segmentation. Therefore, several studies on land cover classification using segmentation from drone aerial photographs focused on easily distinguishable objects based on shape, colour, texture, and compactness. Examples included Sohl *et al.* (2024) and dos Santos and Conti (2022), which classified forest, grass, and shrubs as vegetation, buildings and roads as built-up land. While this approach is common, the current study combined automatic and manual segmentation and classification to obtain detailed and precise land cover data.

Small islands like Mansinam need very high-resolution imagery, such as orthophoto from UAV, for optimal identification of land cover or objects. Orthophoto can detect objects that open-source satellite imagery cannot. In addition, user-set UAV photo acquisition times can be set as desired. In comparison, the best high-resolution open-source satellite imagery, such as Planet, has a resolution of 4-7 m, and the highest resolution commercial satellite imagery is up to 30 cm. While obtaining these commercial images at a desired acquisition time is difficult, using low-cost

UAV is a viable alternative to produce very high-resolution images. This is a significant advantage of UAV imagery for land monitoring. The use of low-cost UAVs, such as the DJI Phantom 3 pro, has some disadvantages, including passive sensors, limited flight range, and a larger aircraft body compared to the Mavic series. However, the advantages of UAVs include aerial photographs with very high resolution, usability in areas with limited landing and takeoff space, and the ability to produce digital elevation models (DEM). Low-cost UAVs can also be used to estimate tree diameter and height (Hematang, Murdjoko, Hendri, & Tokede, 2022; Hematang, Murdjoko, & Hendri, 2021), coastal land monitoring (Bispo dos Santos & Conti, 2022), above-ground biomass estimation (Zhao *et al.*, 2023), and flood mitigation (Rohman and Prasetya, 2019). The limitations of low-cost UAVs, specifically in terms of coverage, make it challenging to extract data over large areas for land and environmental monitoring or natural disaster management. Alternatives include using a combination of satellite imagery and aerial photography to analyze land cover dynamics (Diack *et al.*, 2024) and water quality (Rahul *et al.*, 2023; Wasehun *et al.*, 2024). Cloud-based platforms like Google Earth Engine (GEE) can also be used for monitoring land cover (Ghosh, Kumar, & Kumari, 2022), flooding (Ghosh *et al.*, 2022; Uddin & Matin, 2021), soil erosion (Jodhani, Patel, Madhavan, & Singh, 2023), while aerial images can serve as sample data. Therefore, the use of UAV technology, specifically low-cost UAV, for identifying land cover and phenomena on the earth's surface through aerial photo analysis is a novel tool applicable to spatial planning, forestry, and environmental science for small islands. UAV is particularly useful for providing high-resolution images free of clouds and fog because image acquisition is carried out at a certain altitude during sunny weather. Despite the several functions in providing information about the earth's surface, UAV prices vary widely from low to high costs.

The risk to UAV is significant, including potential loss of contact during flight, limited flying areas and altitude, and flight parameters affected by wind, weather, and fog. The advantage of the DJI Phantom series for mapping small islands is the ability to withstand windy conditions, even though the tolerance limit specified by the manufacturer is 10 m/s (DJI, 2016). Similarly, a study using DJI Phantom 4 to capture aerial images of mangrove forest in coastal areas adhered to a wind speed limit of 15 knots, or 7.7 m/s (Navarro *et al.*, 2020). Radiofrequency from the remote control to the aircraft is another crucial parameter. Airborne monitoring on small islands often faces challenges related to land accessibility. Pilots tend to operate in narrow open spaces (obstructed by buildings or tree canopies) with limited altitude, causing radio frequency interference since DJI products are designed for open areas where radio frequencies can operate normally. Despite these challenges, the current study showed that the DJI Phantom 3 Pro, a low-cost UAV, can successfully capture aerial images of small islands. The choice of UAV depends significantly on the purpose and the type of data needed. Low-cost UAVs can be used to obtain high-resolution images.

The use of UAVs for data collection in the field has been proven to reduce both time and cost. UAVs can move more freely in the air compared to the ground, and the ability to fly at various altitudes improves the capacity to capture ground objects over larger areas. Based on the current study, low-cost UAVs are particularly beneficial for identifying land cover on small islands. Orthophoto generated from aerial photogrammetry provides up-to-date imagery essential for monitoring natural resources on small islands. However, MRS segmentation has limitations, such as under-segmentation and over-segmentation. Under-segmentation occurs when a larger object segment covers a smaller image object, while over-segmentation occurs when an image object is divided into separate segments (Chen *et al.*, 2021; El-Naggar, 2018; Liu and Xia, 2010). These limitations can be mitigated by manually classifying aerial images using the merge and split method, ensuring the calcification results have high accuracy. Orthophoto error values are not only influenced by the number and distribution of GCPs, but also by other factors such as sensor type (RGB or multispectral), sensor resolution, flight altitude, and image overlaps (Deliry & Avdan, 2021). In the context of land cover, not using GCPs generally affects the geometric accuracy of orthophoto, leading to inaccurate positioning of objects. However, the advantage of using orthophoto from UAVs without GCPs is that the resolution allows for more detailed object identification and classification than satellite imagery. Satellite imagery with similar resolution is typically commercial, and the current study aimed to explore alternatives for obtaining high-resolution imagery. Future studies could consider evaluating segmentation in distinguishing between primary and secondary forest cover, as well as the impact of flight altitude and the use of GCPs.

4. Conclusion

In conclusion, low-cost UAV like the DJI Phantom 3 Pro could fly at an altitude of 150 m AGL on small islands and produce very high-resolution images at 8.7 cm/pix. This high image resolution facilitated land cover classification, resulting in high accuracy with an overall accuracy of 96% and a kappa coefficient value of 0.94. Another important result from orthophoto was that forest cover on Mansinam Island comprised 75.5% or 302.4 ha of the total area, distributed across the northern and southern parts of the island. Primary forest covered 31.91% or 127.74 ha, while secondary forest covered 43.63% or 174.68 ha. Furthermore, in 2020, there were 95 new deforestation areas on Mansinam Island, covering 15.2 ha, with 64% or 9.7 ha being bare land and 36% or 5.5 ha being bare land converted into agricultural land. Classification and delineation using automatic segmentation combined with manual reinterpretation proved effective in producing accurate and precise land cover information from UAV imagery. Low-cost UAVs could also be used for future investigations on small islands, such as coastal land mapping (mangroves, seagrass, coral reefs), disaster management (coastline, floods, landslides), and biodiversity assessments of flora and fauna. Land cover information could facilitate sustainable forest and environmental management by all stakeholders. Therefore, future studies were recommended to focus more on exploring changes in island cover, specifically deforestation and degradation, as well as improving accuracy through the use of ground control points.

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Conflict of interest

All authors declare that they have no conflicts of interest.

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References

Akca, S., & Polat, N. (2022). Semantic segmentation and quantification of trees in an orchard using UAV orthophoto. *Earth Science Informatics*, 15(4), 2265–2274. doi: 10.1007/s12145-022-00871-y

Akturk, E., & Altunel, A. O. (2019). Accuracy assesment of a low-cost UAV derived digital elevation model (DEM) in a highly broken and vegetated terrain. *Measurement: Journal of the International Measurement Confederation*, 136, 382–386. doi: 10.1016/j.measurement.2018.12.101

Aldyan, F., Hernawati, R., Minarno, P., Afif, H., & Solikhin, A. (2018). Kajian Tutupan Lahan Berbasis Obyek Menggunakan Data Uav Trimble Ux5 (Wilayah Studi: Desa Pagak, Kab. Purworejo Jawa Tengah). *Seminar Nasional Geomatika*, 2, 517. doi: 10.24895/sng.2017.2-0.449

Arfan, A., Nyompa, S., Maru, R., Nurdin, S., & Juanda, M. F. (2021). Mapping Analysis of Mangrove Areas using Unmanned Aerial Vehicle (UAV) Method in Maros District South Sulawesi. *Journal of Physics: Conference Series*, 2123(1). doi: 10.1088/1742-6596/2123/1/012010

Arham, I., Sjaf, S., & Darusman, D. (2019). Strategi Pembangunan Pertanian Berkelanjutan di Pedesaan Berbasis Citra Drone (Studi Kasus Desa Sukadamai Kabupaten Bogor). *Jurnal Ilmu Lingkungan*, 17(2), 245. doi: 10.14710/jil.17.2.245-255

Banu, T. P., Borlea, G. F., & Banu, C. (2016). The Use of Drones in Forestry. *Journal of Environmental Science and Engineering B*, 5(11), 557–562. doi: 10.17265/2162-5263/2016.11.007

Bispo dos Santos, G. A., & Conti, L. A. (2022). Coastal land cover mapping using UAV imaging on the southeast coast of Brazil. Journal of Coastal Conservation, 26(5). https://doi.org/10.1007/s11852-022-00886-z

BKP. (2020). Indeks Ketahanan Pangan 2020. In Badan Ketahanan Pangan (Vol. 0). Retrieved from http://bkp.pertanian.go.id/storage/app/media/2021/ikp-2020-20210120fix.pdf

BPS. (2023). Papua Barat Province In Figures 2023. Manokwari: Statistics Agency of Papua Barat Province.

Cámara-Leret, R., Frodin, D. G., Adema, F., Anderson, C., Appelhans, M. S., Argent, G., … van Welzen, P. C. (2020). New Guinea has the world's richest island flora. *Nature*, 584(7822), 579–583. doi: 10.1038/s41586-020-2549-5

Cámara–Leret, R., & Dennehy, Z. (2019). Indigenous Knowledge of New Guinea's Useful Plants: A Review. *Economic Botany*, 73(3), 405–415. doi: 10.1007/s12231-019-09464-1

Chen, Y., Chen, Q., & Jing, C. (2021). Multi-resolution segmentation parameters optimization and evaluation for VHR remote sensing image based on meanNSQI and discrepancy measure. *Journal of Spatial Science*, 66(2), 253–278. doi: 10.1080/14498596.2019.1615011

Congalton, R., & Green, K. (1957). Assessing the Accuracy of Remotely Sensed Data: Principles and Practices. I*n The Photogrammetric Record*, 25(130), 204-205. doi: 10.1111/j.1477-9730.2010.00574_2.x

Corlett, R. T. (2018). Tropical Rainforests and Climate Change. In Encyclopedia of the Anthropocene (1st ed.). *Elsevier Inc*, 2, 25-29. doi: 10.1016/B978-0-12-809665-9.09501-X

Cover, T. M., & Hart, P. E. (1967). Nearest Neighbor Pattern Classification. IEEE Transactions on Information Theory, 13(1), 21–27. doi: 10.1109/TIT.1967.1053964

Deliry, S. I., & Avdan, U. (2021). Accuracy of Unmanned Aerial Systems Photogrammetry and Structure from Motion in Surveying and Mapping: A Review. *Journal of the Indian Society of Remote Sensing*, 49(8), 1997–2017. doi: 10.1007/s12524-021-01366-x

Diack, I., Diene, S. M., Louise, L., Aziz, D. A., Benjamin, H., Olivier, R., … Moussa, D. (2024). Combining UAV and Sentinel-2 Imagery for Estimating Millet FCover in a Heterogeneous Agricultural Landscape of Senegal. I*EEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 17, 7305–7322. doi: 10.1109/JSTARS.2024.3373508

DJI. (2016). Phantom 3 Profesional : User Manual. 3–6. Retrieved From https://dl.djicdn.com/downloads/phantom_3/User Manual/Phantom_3_Professional_User_Manual_v1.8_en.pdf

DJI. (2024). Mavic Pro Specs. Retrieved May 29, 2024, Retrived From https://www.dji.com/id/mavic/info

El-naggar, A. M. (2018). Determination of optimum segmentation parameter values for extracting building from remote sensing images. *Alexandria Engineering Journal*, 57(4), 3089–3097. doi: 10.1016/j.aej.2018.10.001

Elkhrachy, I. (2021). Accuracy Assessment of Low-Cost Unmanned Aerial Vehicle (UAV) Photogrammetry. *Alexandria Engineering Journal*, 60(6), 5579–5590. doi: 10.1016/j.aej.2021.04.011

Ghosh, S., Kumar, D., & Kumari, R. (2022). Cloud-based large-scale data retrieval, mapping, and analysis for land monitoring applications with Google Earth Engine (GEE). *Environmental Challenges*, 9, 100605. doi: 10.1016/j.envc.2022.100605

Harto, A. B., Prastiwi, P. A. D., Ariadji, F. N., Suwardhi, D., Dwivany, F. M., Nuarsa, I. W., & Wikantika, K. (2019). Identification of banana plants from unmanned aerial vehicles (UAV) photos using object based image analysis (OBIA) method (a case study in Sayang Village, Jatinangor District, West Java). *HAYATI Journal of Biosciences*, 26(1), 7–14. doi: 10.4308/hjb.26.1.7

Hematang, F. (2021). Pendugaan dimensi tegakan hutan di pulau mansinam kabupaten manokwari : pendekatan aplikasi uav (unmanned aerial vehicle) (Unpublished thesis). Papua University.

Hematang, F., Murdjoko, A., & Hendri. (2021). Model Pendugaan Diameter Pohon Berbasis Citra Unmanned Aerial Vehicle (Uav) Pada Hutan Hujan Tropis Papua: Studi Di Pulau Mansinam Papua Barat. *Jurnal Penelitian Kehutanan Faloak*, 5, 16–30.

Hematang, F., Murdjoko, A., Hendri, H., & Tokede, M. (2022). Application of Unmanned Aerial Vehicle (UAV) For Estimation of Tree Height in Heterogeneous Forest. *Biosaintifika: Journal of Biology & Biology Education*, 14(2), 168–179.

Horning, N., Fleishman, E., Ersts, P. J., Fogarty, F. A., & Wohlfeil, M. (2020). Mapping of land cover with open-source software and ultra-high-resolution imagery acquired with unmanned aerial vehicles. *Remote Sensing in Ecology and Conservation*, 6(4), 487–497. doi: 10.1002/rse2.144

Hyeok, K. G., & Wan, C. J. (2017). Land cover classifcation with high spatial resolution using orthoimage and DSM based on fixed-wing UAV. *Journal of the Korean Society of Surveying, Geodesy, Photogrammetry and Cartography*, 35(1), 1–10. doi: 10.7848/ksgpc.2017.35.1.1

Jodhani, K. H., Patel, D., Madhavan, N., & Singh, S. K. (2023). Soil Erosion Assessment by RUSLE, Google Earth Engine, and Geospatial Techniques over Rel River Watershed, Gujarat, India. *Water Conservation Science and Engineering*, 8(1). doi: 10.1007/s41101-023-00223-x

Jumaat, N. F. H., Ahmad, B., & Dutsenwai, H. S. (2018). Land cover change mapping using high resolution satellites and unmanned aerial vehicle. *IOP Conference Series: Earth and Environmental Science*, 169(1). doi: 10.1088/1755-1315/169/1/012076

KLHK. (2021). Statistik Bidang Planalogi Kehutanan dan Tata Lingkungan Tahun 2020. Kementerian Lingkungan Hidup Dan Kehutanan, 2013–2015.

KLHK. (2022). Sistem Informasi Geospasial KLHK. Retrieved May 27, 2024, Retrived From https://geoportal.menlhk.go.id/Interaktif2/

Koman, W. A. F., Shofiyal Izza, N., & Candraningtyas, D. (2022). Perbandingan parameter segmentasi OBIA dalam klasifikasi tutupan lahan. *Jurnal Paradigma: Jurnal Multidisipliner Mahasiswa Pascasarjana Indonesia*, 3(2), 104–113.

Kushardono, D. (2017). Klasifikasi Digital Pada Penginderaan Jauh. In IPB Press (Vol. 1).

Li, Z., Zan, Q., Yang, Q., Zhu, D., Chen, Y., & Yu, S. (2019). Remote estimation of mangrove aboveground carbon stock at the species level using a low-cost unmanned aerial vehicle system. *Remote Sensing*, 11(9). doi: 10.3390/rs11091018

Liu, D., & Xia, F. (2010). Assessing object-based classification: Advantages and limitations. *Remote Sensing Letters*, 1(4), 187–194. doi: 10.1080/01431161003743173

Lubis, K. A., Rusdi, M., & Sugianto, S. (2021). Proses Segmentasi Citra Satelit Untuk Pemetaan Tutupan Lahan. *Jurnal Ilmiah Mahasiswa Pertanian*, 6(4), 691–698. doi: 10.17969/jimfp.v6i4.18414

Marwa, J., Sineri, A. S., & Hematang, F. (2020). Biecological Carrying Capacity of Forest and Land in Manokwari Regency, West Papua Province. *Jurnal Sylva Lestar*i, 8(2), 197. doi: 10.23960/jsl28197-206

Miraki, M., Sohrabi, H., & Immitzer, M. (2023). Tree Species Mapping in Mangrove Ecosystems Using UAV-RGB Imagery and Object-Based Image Classification. *Journal of the Indian Society of Remote Sensing*, 51(10), 2095–2103. doi: 10.1007/s12524-023-01752-7

Moon, H.-G., Lee, S.-M., & Cha, J.-G. (2017). Land cover classification using UAV imagery and object-based image analysis-focusing on the Maseo-Myeon, Seocheon-Gun, Chungcheongnam-Do. *Journal of the Korean Association of Geographic Information Studies*, 20(1), 1–14.

Murdjoko, A., Brearley, F. Q., Ungirwalu, A., Djitmau, D. A., & Benu, N. M. H. (2022). Secondary Succession after Slash-and-Burn Cultivation in Papuan Lowland Forest, Indonesia. *Forests*, 13(3), 1–14.

Murdjoko, A., Ungirwalu, A., Mardiyadi, Z., Tokede, M. J., Djitmau, D. A., & Benu, N. M. H. (2021). Floristic Composition of Buah Hitam Habitats in Lowland Tropical Mixed Forest of West Papua, Indonesia. *Floresta e Ambiente*, 28(3). doi: 10.1590/2179-8087-FLORAM-2021-0042

Nagendran, S. K., Tung, W. Y., & Mohamad Ismail, M. A. (2018). Accuracy assessment on low altitude UAV-borne photogrammetry outputs influenced by ground control point at different altitude. *IOP Conference Series: Earth and Environmental Science*, 169(1). doi: 10.1088/1755-1315/169/1/012031

Navarro, A., Young, M., Allan, B., Carnell, P., Macreadie, P., & Ierodiaconou, D. (2020). The application of Unmanned Aerial Vehicles (UAVs) to estimate above-ground biomass of mangrove ecosystems. *Remote Sensing of Environment*, 242, 111747. doi: 10.1016/j.rse.2020.111747

Němec, P. (2015). Comparison of modern forest inventory method with the common method for management of tropical rainforest in the Peruvian Amazon. *Journal of Tropical Forest Science*, 27(1), 80–91.

Otero, V., Van De Kerchove, R., Satyanarayana, B., Martínez-Espinosa, C., Fisol, M. A. Bin, Ibrahim, M. R. Bin, … Dahdouh-Guebas, F. (2018). Managing mangrove forests from the sky: Forest inventory using field data and Unmanned Aerial Vehicle (UAV) imagery in the Matang Mangrove Forest Reserve, peninsular Malaysia. *Forest Ecology and Management*, 411, 35–45. doi: 10.1016/j.foreco.2017.12.049

Park, G., Park, K., Song, B., & Lee, H. (2022). Analyzing Impact of Types of UAV-Derived Images on the Object-Based Classification of Land Cover in an Urban Area. *Drones*, 6(3). doi: 10.3390/drones6030071

Pasaribu, R. A., Aditama, F. A., & Setyabudi, P. (2021). Object-based image analysis (OBIA) for mapping mangrove using Unmanned Aerial Vehicle (UAV) on Tidung Kecil Island, Kepulauan Seribu, DKI Jakarta Province. *IOP Conference Series: Earth and Environmental Science*, 944(1). doi: 10.1088/1755-1315/944/1/012037

Polat, N., & Kaya, Y. (2021). Investigation of the Performance of Different Pixel-Based Classification Methods in Land Use/Land Cover (LULC) Determination. *Türkiye İnsansız Hava Araçları Dergisi*, 3(1), 1–6. doi: 10.51534/tiha.829656

Purba, H. A., & Perwira. (2021). Penggunaan Teknologi Uav Pada Pemetaan Pantai Dengan Pendekatan Berbasis Objek Geografis. 2(2), 6.

Rahardjo, N., Aunurrahim, A., Hayun, G., & Asri, M. (2021). Unmanned Aerial Vehicle (UAV) Data as a Land Cover Data Renewal in Pandanrejo Village, Kaligesing Sub-District, Purworejo. *International Journal of Sciences: Basic and Applied Research (IJSBAR) International Journal of Sciences: Basic and Applied Research*, 55(1), 247–261. Retrieved from http://gssrr.org/index.php?journal=JournalOfBasicAndApplied

Rahul, T. S., Brema, J., & Wessley, G. J. J. (2023). Evaluation of surface water quality of Ukkadam lake in Coimbatore using UAV and Sentinel-2 multispectral data. *International Journal of Environmental Science and Technology*, 20(3), 3205–3220. doi: 10.1007/s13762-022-04029-7

Ramadhani, Y. H., K, A. P., & Susanti, R. (2015a). Pemetaan Pulau Kecil dengan Pendekatan Berbasis Objek Menggunakan Data Unmanned Aerial Vehicle (UAV) Studi Kasus di Pulau Pramuka , Kepulauan Seribu. *Majalah Ilmiah Globe*, 17(2), 125–134.

Ramadhani, Y. H., K, A. P., & Susanti, R. (2015b). Pemetaan Pulau Kecil dengan Pendekatan Berbasis Objek Menggunakan Data Unmanned Aerial Vehicle (UAV) Studi Kasus di Pulau Pramuka , Kepulauan Seribu. *Majalah Ilmiah Globe*, 17(2), 125–134.

Raweyai, J., Sadsoeitoeboen, B., Tokede, M., Kesaulija, F., Mentansan, G., & Mardiyadi, Z. (2023). Rekognisi MBKM bentuk free form dalam riset tematik pemanfaatan lahan oleh masyarakat di Pulau Mansinam. *IGKOJEI: Jurnal Pengabdian Masyarakat*, 4(1), 50–60. doi: 10.46549/igkojei.v4i1.358

Rohman, A., & Prasetya, D. B. (2019). Rapid Mapping for Simple Flood Mitigation Using Commercial Drone at Way Galih Village, Lampung, Indonesia. *Forum Geografi*, 33(1), 101–113. doi: 10.23917/forgeo.v33i1.8421

Sari, N. M., & Kushardono, D. (2014). Klasifikasi Penutup Lahan Berbasis Obyek Pada Data Foto Uav Untuk Mendukung Penyediaan Informasi Penginderaan Jauh Skala Rinci (Object Based Classification Of Land Cover On Uav Photo Data To Support The Provision Of Detailed-Scale. *Remote Sensing Informat*, 11(2), 114–127.

Shashkov, M., Ivanova, N., Shanin, V., & Grabarnik, P. (2019). Ground Surveys Versus UAV Photography: The Comparison of Two Tree Crown Mapping Techniques. In Springer Proceedings in Earth and Environmental Science. *Springer International Publishing*, 2, 48–56. doi: 10.1007/978-3-030-11720-7_8

Sitompul, J. R., Ruswanti, C. D., Sukandar, H., & Ganesa, A. S. (2019). Klasifikasi Vegetasi dan Tutupan Lahan Pada Citra UAV Menggunakan Metode Object-Based Image Analysis di Segara Anakan , Kabupaten Cilacap Classification of Vegetation and Land Cover in UAV Images Using the Object-Based Image Analysis Method in Segara Anak. *Researcgate*, 2, 504–511.

Sohl, M. A., Mahmood, S. A., & Rasheed, M. U. (2024). Comparative performance of four machine learning models for land cover classification in a low-cost UAV ultra-high-resolution RGB-only orthomosaic. *Earth Science Informatics*, (0123456789). doi: 10.1007/s12145-024-01318-2

Sonbait, L. Y., Manik, H., Warmetan, H., Lina, Y., Wambrauw, D., Sagrim, M., … Murdjoko, A. (2021). The natural resource management to support tourism : A traditional knowledge approach in Pegunungan Arfak Nature Reserve, West Papua, Indonesia. *Biodiversitas*, 22(10), 4466–4474. doi: 10.13057/biodiv/d221040

Sorondanya, N., Peday, H., & Runtuboi, Y. (2021). Type and Distribution of Forest Ecosystems in Mansinam Island, Manokwari. *Jurnal manajemen Hutan Tropica*, 7(1), 99–120.

Sothe, C., Dalponte, M., de Almeida, C. M., Schimalski, M. B., Lima, C. L., Liesenberg, V., … Tommaselli, A. M. G. (2019). Tree species classification in a highly diverse subtropical forest integrating UAV-based photogrammetric point cloud and hyperspectral data. *Remote Sensing*, 11(11). doi: 10.3390/rs11111338

Tawer, P., Maturbongs, R., Murdjoko, A., Jitmau, M., Djitmau, D., Siburian, R., … Tambing, J. (2021). Vegetation dynamic post-disturbance in tropical rain forest of bird's head peninsula of west papua, indonesia. *Annals of Silvicultural Research*, 46(1), 48–58. doi: 10.12899/ASR-2145

Torresan, C., Berton, A., Carotenuto, F., Di Gennaro, S. F., Gioli, B., Matese, A., … Wallace, L. (2017). Forestry applications of UAVs in Europe: a review. *International Journal of Remote Sensing*, 38(8–10), 2427–2447. doi: 10.1080/01431161.2016.1252477

Uddin, K., & Matin, M. A. (2021). Potential flood hazard zonation and flood shelter suitability mapping for disaster risk mitigation in Bangladesh using geospatial technology. *Progress in Disaster Science*, 11(3), 100185. doi: 10.1016/j.pdisas.2021.100185

Umarhadi, D. A., Danoedoro, P., Wicaksono, P., Widayani, P., Nurbandi, W., & Juniansah, A. (2018). The Comparison of Canopy Density Measurement Using UAV and Hemispherical Photography for Remote Sensing Based Mapping. *Proceedings - 2018 4th International Conference on Science and Technology, ICST 2018*, 2–6. doi: 10.1109/ICSTC.2018.8528670

Vaggela, A., Sanapala, H., & Mokka, J. R. (2022). Monitoring Land Use and Land Cover Changes Prospects Using Remote Sensing and GIS for Mahanadi River Delta, Orissa, India. *Geoplanning*, 9(1), 47–60. doi: 10.14710/geoplanning.9.1.47-60

Waromi, J. (2021). *Dinamika Perubahan Tutupan Hutan Dan Pemanfaatan Lahan Pulau Mansinam*. Universitas Papua.

Wasehun, E. T., Hashemi Beni, L., & Di Vittorio, C. A. (2024). UAV and satellite remote sensing for inland water quality assessments: a literature review. *Environmental Monitoring and Assessment*, 196(3). doi: 10.1007/s10661-024-12342-6

Weih, R. C., & Riggan, N. D. (2010). Object-based classification vs. pixel-based classification: Comparitive importance of multi-resolution imagery. T*he International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XXXVIII, 1–6.

Wijaya, M. S., Ramadhani, Y. H., Rudiastuti, A. W., Nurteisa, Y. T., Rahadian, A., Pujawati, I., & Hartini, S. (2019). Kajian Wahana Udara Nir-Awak Untuk Akuisisi Data Survei Parameter Biofisik Vegetasi Mangrove. *Seminar Nasional Geomatika 2018 :Penggunaan Dan Pengembangan Produk Informasi Geospasial Mendukung Daya Saing Nasional*, 3, 947. doi: 10.24895/sng.2018.3-0.1061

Wulan, R. T., Ambarwulan, W., Putra, A. S., Maulana, E., Maulia, N., Putra, M. D., … Raharjo, T. (2016). Uji Akurasi Data Uav (Unmanned Aerial Vehicle) di KAwasan Pantai Pelangi, Parangtritis, Kretek, Kabupaten Bantul. *Prosiding Seminar Nasional Kelautan, (September)*, 232–240. doi: 10.13140/RG.2.2.23481.57448

Yilmaz, V., Levent, T., Cigdem, Y., & Oguz, G. (2017). Determination of Tree Crown Diameters with Segmentation of a UAS-Based Canopy Height Determination of Tree Crown Diameters with Segmentation of a UAS-Based Canopy Height Model. *IPSI BgD Transactions on Internet Research*, 13(7), 63–67.

Zhang, Y., Wu, H., & Yang, W. (2019). Forests Growth Monitoring Based on Tree Canopy 3D Reconstruction Using UAV Aerial Photogrammetry. *Forests*, 10(12), 1–16. doi: 10.3390/f10121052

Zhao, Y., Zhou, L., Chen, C., Li, X., Du, H., Yu, J., … Song, M. (2023). Urban Forest Above-Ground Biomass Estimation Based on UAV 3D Real Scene. *Drones*, 7(7). doi: 10.3390/drones7070455