Integration of Drone-based Imaging for Coastal Ecosystem Mapping: A Case Study of Shallow Coastal in Phang Nga Bay, Thailand

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Abstract
Efficient management of marine and coastal resources, particularly in shallow areas with sensitive ecosystems such as coral reefs and seagrass meadows, requires continuous and rapid monitoring. These ecosystems, which provide critical habitats, are increasingly vulnerable to climate change, highlighting the need for non-invasive, systematic assessments to support conservation efforts. This study explores the feasibility of using multispectral imaging-equipped unmanned aerial vehicles (UAVs) as an effective alternative to traditional survey methods for evaluating marine resources. Focusing on shallow coastal ecosystems in Phang Nga Bay, Thailand, the study examines methodologies, processes, and data analysis techniques involved in using UAVs for coastal ecosystem mapping. Surveys were conducted in three distinct sub-areas of Phang Nga Bay, each characterized by unique land cover types. The first area, north of Koh Khai Yai, included six land cover types, with underwater rock and coral serving as key indicators of ecological richness. The second region beneath Koh Khai Yai featured seven classifications, depicting both natural and human-influenced elements. The third region, on Koh Khai Nui, consisted of four cover types with distinct rock formations. By comparing UAV-derived data with existing marine resource databases, the study demonstrated the ability of UAV multispectral imaging to deliver high-resolution, detailed data for resource distribution. The results confirm that integrating UAV-based imaging with the ISODATA unsupervised classification method offers a fast, up-to-date, and efficient approach to resource monitoring, reducing ecological disruption and enhancing conservation management for fragile coastal ecosystems.

Keywords: Coastal Ecosystem, Drone, Marine Resources, Remote Sensing, Shallow Coastal Unmanned Aerial Vehicles

1. Introduction

Marine and coastal resources are vital to Thailand's economy but are increasingly vulnerable to anthropogenic pressures, resulting in significant resource degradation. To address this, the Department of Marine and Coastal Resources has initiated an ocean inventory aligned with the System of Environmental-Economic Accounting (SEEA). The SEEA framework integrates environmental data with economic accounts, offering a systematic approach to evaluate the status of marine and coastal resource capital and their utilization across various activities. This initiative aims to provide robust and comprehensive data for informed decision-making and sustainable management of these critical resources [1]. Such an inventory is essential for guiding sustainable economic development in coastal and marine sectors. It will serve as a foundational tool in policy formulation and planning, reducing conflicts over resource use and addressing environmental issues at local, regional, and global scales. Accurate, current, and comprehensive data on both terrestrial and marine resources are crucial for the success of marine resource surveys. To ensure the reliability and relevance of such data, it is imperative that resource databases accurately reflect contemporary conditions.

While up-to-date information is vital, the process of updating marine resource data presents significant challenges, requiring considerable time and financial resources for each survey. Traditional methods, such as underwater diving, have long been used to assess the quantity and condition of marine resources. Divers are able to directly observe and record key metrics, including biodiversity, species abundance, and the health of ecosystems like coral reefs, seagrass beds, and mangroves. While these methods provide highly detailed and firsthand data, they are labor-intensive, costly, and limited in spatial coverage. In addition, underwater diving often requires specialized equipment and training, and the scope of surveys can be constrained by environmental conditions and diver endurance. The limitations of traditional methods in large-scale assessments, emphasizing that while diving remains critical for ground-truthing, its time and resource demands make it less feasible for regular and expansive surveys [2]. Previous research has highlighted the need for complementary tools, such as remote sensing and drone-based technologies, to improve the efficiency and scope of maritime resource monitoring while overcoming the limitations of traditional methods [3]. As a result, while underwater diving continues to provide significant insights into marine ecosystems, it is rapidly being augmented by technologies that enable more comprehensive, faster, and cost-effective data collection methods.

The integration of novel technologies, such as Geographic Information Systems (GIS) and Remote Sensing (RS), provides substantial opportunities to enhance the efficiency and accuracy of maritime resource surveys. An unmanned aerial system (UAS) consists of several interconnected subsystems, including the unmanned aerial vehicle (UAV), launch mechanisms (if appropriate), control stations (terrestrial, marine, or aerial), and sensor payloads [4]. The UAV operates without a human pilot and is equipped with various sensors that capture environmental data, while launch mechanisms facilitate the efficient deployment of the UAV. Control stations manage the UAV's operations, allowing operators to monitor flight paths and data collection. The sensor payloads attached to the UAV, which may include optical cameras, multispectral and hyperspectral sensors, thermal cameras, and LiDAR systems, are critical for capturing data relevant to maritime surveys. The combination of these subsystems enables UAS to operate autonomously or semi-autonomously, allowing for efficient and accurate data collection over large areas that are challenging to survey using traditional methods. Furthermore, the use of GIS in conjunction with UAS data enhances the ability to analyze and visualize complex spatial relationships, enabling researchers to integrate UAV-derived data with existing datasets. This integrated approach significantly improves the capacity for conducting maritime resource surveys, facilitating informed decision-making and supporting sustainable resource management practices. Environmental RS requires regular quick access to current data. Certain applications also require the use of unmanned control, which takes into account safety, accessibility, and adaptability [5]. UAVs have been identified as secure, lightweight, adaptable, and automated systems suited for a variety of applications. As a result, academics are increasingly interested in using Remote sensing and GIS or UAV for a wide range applications, such as weather prediction, precision agriculture [6] and [7], forest management, recovery of forest [8], land use planning [9], infrastructure inspection, disaster management such as landslide [10], identification of oceanic eddies, and marine resources [11]. Another important facet of studying or monitoring marine resources, particularly coral reefs, is monitoring coral health in order to assess the effects of human-caused climate change. Simple survey approaches are strongly desired for coral reef monitoring, with optical surveys standing out as particularly useful tools. These span from basic photography to multispectral satellite imaging, and both are widely used in research. Survey techniques are divided into two categories: in-situ data gathering by divers or robotic equipment directly in the environment, and remote sensing, which collects data above the water's surface through drones, UAVs, or satellites [12]. These technologies have the potential to greatly accelerate data collection, enabling more frequent updates to marine resource databases. Integrating RGB image survey data from UAVs with deep learning algorithms for classification of surface features enhances the accuracy and detail of resource monitoring [13] and [14].

Drone-based imaging has revolutionized the mapping and conservation of coastal ecosystems by offering high-resolution, cost-effective, and adaptable methods for monitoring dynamic environments. Optimal practices for deploying drones in marine and coastal mapping have proven particularly effective for ecosystems such as mangroves, coral reefs, and seagrass beds, where precision and efficiency are critical [15]. Additionally, drones have been instrumental in studying blue carbon habitats, which are vital for climate change mitigation [16].

Advances in semi-automated classification and change detection algorithms further enhance the monitoring of diverse coastal environments, including coral reefs and beaches [17]. Drones also support long-term coastal management by enabling accurate tracking of shoreline changes and vegetation [18], outperforming conventional techniques for shallow coastal mapping [19]. Their ability to integrate high-resolution data into conservation efforts underscores their importance in sustainable coastal ecosystem management [20]. This approach supports the development of more effective policies and resource management strategies, promoting sustainable development and the conservation of marine ecosystems. This study primarily aims to assess the feasibility of the methodologies, processes, and data analysis involved, utilizing multispectral aerial imagery to integrate drone-based imaging for coastal ecosystem conservation mapping. This study focuses on shallow coastal ecosystems in Phang Nga Bay, Thailand, highlighting the innovative application of UAVs in environmental monitoring and conservation efforts.

2. Study Site

UAV flight surveys were done on coral reefs in Phang Nga Bay, Andaman Sea, Thailand. These sites were separated into three distinct survey areas: two near Koh Khai Yai (Sample Area 1 to the north and Sample Area 2 to the south of Koh Khai Yai), and one at Koh Khai Nui (Sample Area 3), as highlighted by red boundaries in Figure 1. Three sample areas for the survey are located in UTM Zone 47, with the following coordinates: Sample Area 1 at X: 446751.287 and Y: 872234.1, Sample Area 2 at X: 446413.849 and Y: 872215.926, and Sample Area 3 at X: 446211.287 and Y: 872974.196. These coordinates mark the specific locations within the zone for data collection and analysis. The study focuses on integrating drone-based imaging for coastal ecosystem conservation mapping in shallow coastal areas of Phang Nga Bay, Thailand. The selected study areas are located near islands with similar water depths and tidal patterns, providing a consistent environment for drone operations under comparable weather and environmental conditions, such as climate and tidal levels. Additionally, the three locations were chosen due to their varying distribution and density of underwater resources, offering a diverse representation of the coastal ecosystem for this research. A thorough investigation of tidal patterns, ocean currents, and sea level variations inspired the selection of these locations, all of which have a significant impact on the usefulness of UAV-based multispectral imaging in marine resource research.

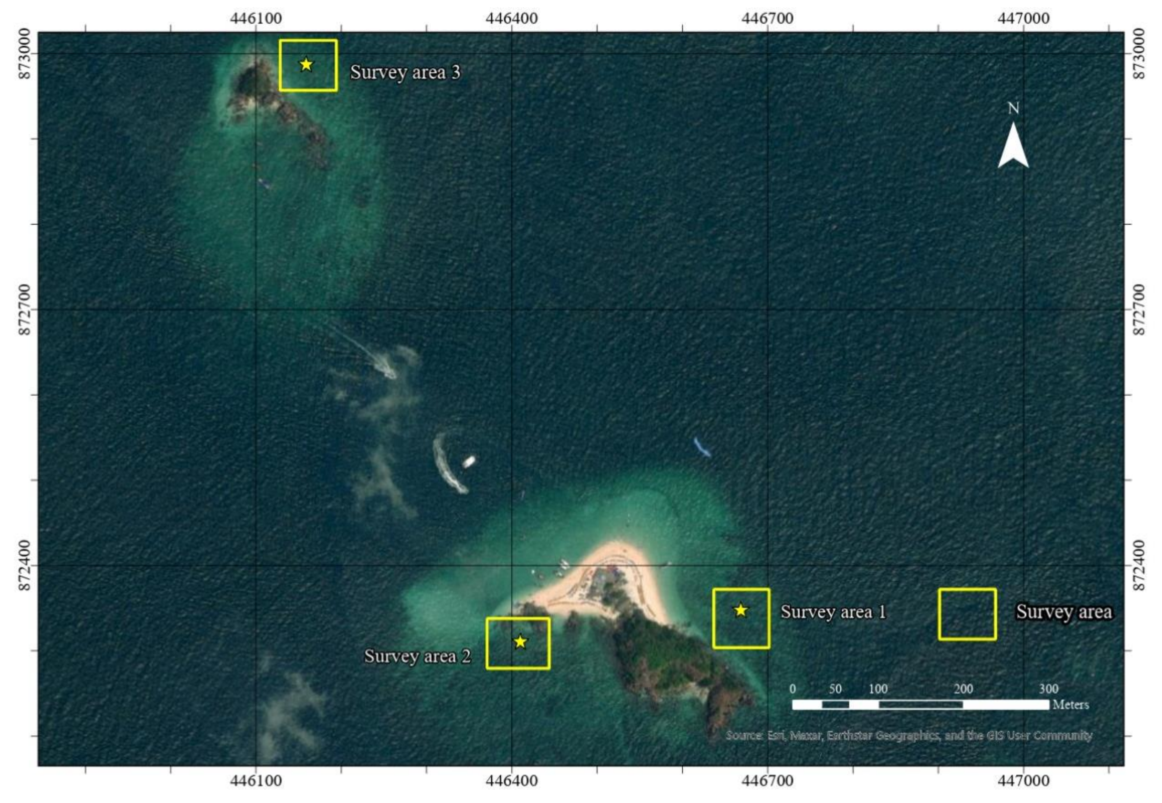

Figure 1: Survey area of Phang Nga Bay, Andaman Sea, Phang Nga Province, Thailand

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3. Methodology

The study procedure was structured into five key processes, beginning with data preparation, where existing geographic data were gathered, UAV flights were planned, and Ground Control Points (GCPs) were established for geospatial accuracy. Field operations followed, involving UAV flights conducted under optimal weather conditions, pre-flight inspections to ensure the suitability of take-off and landing areas, and the placement of GCPs. The next step was data processing, where aerial images were processed using specialized software, integrating GCP data, image stitching, and geo-referencing to produce high-resolution orthophotos. Data quality checking was then performed to validate the geospatial alignment and ensure the outputs met the required resolution and precision standards. Finally, land cover characterization was conducted, analyzing the processed data to classify and assess land cover types within the study areas, providing valuable insights into the condition of marine and coastal resources. The study's steps are explained in detail below.

3.1 The Data Preparation

The data preparation phase involved a comprehensive examination of existing resources relevant to the study area. This included analyzing 1:50,000 scale topographic maps (L7018 series) from the Royal Thai Survey Department and satellite imagery from diverse sources to inform flight planning and identify suitable locations for GCPs. These GCPs were established using coordinates derived from the GNSS system (Satellite Positioning Systems GPS/GLONASS), supported by the GPS network stations of the Department of Public Works and Town & Country Planning or the Department of Lands, with additional Check Points created to verify data accuracy. Subsequently, a detailed flight plan was developed, carefully considering factors such as coverage and area division, which ensured that the survey area was segmented into three sections, each encompassing no less than 100 square meters. Flight planning was conducted using Pix4D and DJI GS Pro software to determine the required ground resolution, or Ground Sample Distance (GSD). GSD refers to the distance on the ground represented by a single pixel in an image, where a lower GSD value indicates higher spatial resolution and greater image detail. The GSD is influenced by factors such as the camera's pixel size, the altitude of the UAV, and the focal length of the camera [21]. For this study, an RGB UAV camera was employed at an altitude of 90 meters, achieving a GSD of 2.45 cm/px. A vertical camera angle was utilized to ensure accurate representation of the terrain's topographical characteristics. To optimize image acquisition, a flight pattern was designed with 75% forward overlap and 60% side overlap, utilizing a Grid Mission approach for mapping purposes. The specific locations for take-off and landing were also adjusted according to real-time operational conditions observed on the day of the survey.

3.2 Field Operations in the Study Area

Field operations involved a series of critical steps to ensure the effective deployment of the UAV. Initially, we assessed weather and visibility prior to each flight to ensure safe flying conditions, thereby minimizing risks to personnel and equipment. To optimize operational efficiency, flights were scheduled between 10:00 and 15:00 hours, when environmental conditions were considered most favorable. Following this, a pre-flight inspection of the take-off and landing zones was conducted on-site to verify their suitability. This inspection included a thorough evaluation of the topography, accounting for variations in terrain elevation and wind direction. Should any unfavorable conditions arise, the flight plan was adjusted accordingly, with flight simulations performed to validate the revised approach. Additionally, Ground Control Points (GCPs) were surveyed, with at least four markers (targets) strategically placed in each sample area to enhance the geospatial accuracy of the UAV imagery. In order to define the border, at least four sea buoys were employed for this procedure. The buoys were strung with ropes, and the GCP was anchored beneath them by tying ropes from the buoys to pins buried in the sea floor's sand. These markers served as essential reference points during the subsequent data processing phase, ensuring reliable integration of the collected data.

3.3 Data Processing Steps

Following the survey of the study area, data were processed through a systematic series of steps designed to ensure accuracy and reliability. First, the preparation of tools and software involved gathering the necessary hardware, including computer systems, and specialized image processing software such as Agi-soft Photo Scan and Pix4Dmapper, specifically developed to handle images captured by UAVs. The second step entailed importing GCP data collected from GNSS measurements, which were converted into horizontal (X, Y) and vertical (Z) coordinate values. These coordinate values served as crucial reference points for ensuring geospatial accuracy throughout the image processing workflow. Next, the starting points of flight photography were meticulously reviewed, utilizing data from the UAV's

Inertial Measurement Unit (IMU) and GNSS sensors to guarantee precise positioning of the digital images.

Automated image processing techniques were then used to improve data handling efficiency. Anchor points were constructed, and the GCP data were merged into image processing software for verification, with stringent checks carried out to verify data accuracy and quality. Following that, aerial photographic data were corrected by stitching individual photos together to form mosaics and aligning them to ensure accurate match with real-world coordinates via a georeferencing method. This included specifying image point density to create a dense point cloud, designing a triangle network for 3D data integration, and modifying image texture to improve visual and spatial quality. The final stage included processing and merging the orthophotos, which resulted in high-quality color images with a spatial resolution of around 3.7 to 4 centimeters per pixel, as measured from the UAV's operational altitude. The completed orthophotos were then exported in Geo-TIFF format, allowing for further geospatial analysis.

3.4 Data Quality Check

This study conducted a thorough quality check on the orthophoto data to identify any differences in data characteristics such as color tones, coordinate systems, or other information that was not included within the project's scope. In cases where inconsistencies were discovered, immediate modifications were made to guarantee that the data fulfilled the requisite requirements while keeping a spatial resolution of no more than 1 meter. Throughout the data quality evaluation procedure, all photos were evaluated with the ArcMap geographic information system software. The ruler tool was used to measure certain parts within the photos, allowing for more accurate and consistent evaluations.

3.5 Land Cover Classification

This study employed remote sensing principles to analyze image data through a GIS program, specifically utilizing an unsupervised classification approach for land cover classification. Given the limited availability of survey data from the actual study area and the researchers' unfamiliarity with the region, this method was deemed appropriate. The approach involves random sampling of the data, which is then categorized into distinct types based on similar spectral characteristics, utilizing a clustering technique known as ISODATA (Iterative Self-Organizing Data Analysis). The decision to use the ISODATA unsupervised classification method was influenced by several factors, with one of the main considerations being the limited availability of training data in the study area. Supervised classification methods, such as Maximum Likelihood or Support Vector Machines (SVM), typically require a substantial amount of ground truth data to generate accurate classifications. This process is often time-consuming and resource-intensive, especially when ground-truthing data is not readily available [22]. In contrast, unsupervised methods like ISODATA do not require training data and can be effectively used to generate an initial classification of the landscape. This initial output can then be refined or validated using field data, making it a practical and efficient choice in data-scarce environments [23].

Additionally, ISODATA is particularly useful in mapping complex, heterogeneous landscapes where there may be no clear prior assumptions about class distribution, allowing for the identification of a broad range of land cover types [24]. While supervised methods may provide higher accuracy when sufficient training data are available, ISODATA serves as a valuable starting point for preliminary classification, especially in areas where obtaining labeled data is challenging. ISODATA method relies on wavelength distances to classify each image point iteratively over multiple rounds. With each iteration, new statistical calculations are performed, allowing for the gradual emergence of distinct patterns in the wavelength distances. The ISODATA algorithm employs the shortest distance criterion to define groups for each image point, commencing with an initial group average predetermined by the user. The process is subsequently repeated, adjusting the average to align with the newly organized data through statistical methods, thus refining the classification accuracy.

4. Result and discussion

4.1 The Survey of Marine Resources in Phang Nga Bay Utilized Current Photographs and High-Angle Still Images Captured by UAV

In this study, UAV-captured current and high-angle still images of marine resources in Phang Nga Bay were processed using the RGB color system and advanced photogrammetric techniques to conduct an automated, image-linked point survey. The methodology involved the application of the image stitching (mosaic) method, which facilitated the enhancement and continuity of aerial photographic data. Key processing steps included aligning photos to ensure consistency across images, followed by geo-referencing to assign real-world coordinates accurately. The technique then included creating a dense cloud in order to identify the density and spatial distribution of picture points, allowing for more detailed spatial representation.

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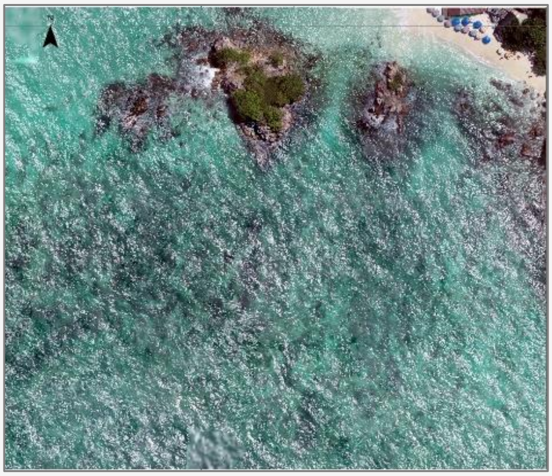
After that, a triangular network (mesh) was built to effectively integrate data into an integrated 3D structure. Texture modifications were made to improve the overall image. The orthophotos were then stitched together to create comprehensive, high-resolution aerial imagery that depicted the examined area in Phang Nga Bay. The outcomes of this process are illustrated in the aerial photograph map and accompanying images, as depicted in Figure 2.

Three aerial photographic maps (Figure 2) of survey areas around Koh Khai. Image (a) shows the survey region north of Koh Khai Yai, in UTM Zone 47, at coordinates X: 446751.287 and Y: 872234.1, with a sea depth of about 2-4 metres. Image (b) shows the survey region south of Koh Khai Yai, at UTM Zone 47 coordinates X: 446413.849 and Y: 872215.926, where the sea depth was around 4-6 meters during the survey. Finally, Image (c) shows the survey region around Koh Khai Nui, at UTM Zone 47 coordinates X: 446211.287 and Y: 872974.196, with a stated sea depth of around 6 meters at the time of the survey. Aerial images produced from UAVs equipped with sensors based on electromagnetic reflection principles allows for effective monitoring of water surfaces and marine resources. These sensors detect light in the red, green, and blue (RGB) channels (centered at around 660 nm, 520 nm, and 450 nm, respectively).

(a)



(b)

(c)

Figure 2: Aerial photograph map three sample areas:
(a) North of Koh Khai Yai, (b) South of Koh Khai Yai, (c) Khai Nui Island area

This provides the basis for imagine capture within the visible spectrum, similar to human visual perception [25]. Water surfaces have different reflectance qualities than other materials, particularly in the infrared spectrum, which allows for more accurate boundary delineation. Reflectance varies greatly according to water conditions such as turbidity, transparency, and the presence of suspended or dissolved particles. Clear water absorbs little light below 0.6 microns and mostly transmits energy at blue and green wavelengths. Water with a high sediment level, on the other hand, reflects more energy, but water containing chlorophyll decreases reflectance in the blue wavelength while increasing it in the green wavelength, due to chlorophyll's unique optical properties. This difference in energy reflection because of water composition provides UAV photography to help in the assessment of water quality and the identification of shallow marine resources, presenting high-resolution data for analysis and classification.

4.2 The Results of the Marine Resource Survey in Phang Nga Bay Utilized Multispectral Band Images Captured by Unmanned Aerial Vehicles (UAVs)

The survey of marine resources in Phang Nga Bay leveraged multispectral imagery from UAVs, highlighting the effectiveness of remote sensing technologies in ecological monitoring and management. The study utilized a multispectral camera to generate detailed aerial photographic maps through photogrammetric techniques that allowed for high-resolution and spatially accurate images. Reference points were integrated with the imagery, facilitating an automated photographic survey approach. The survey then applied a mosaicking method to combine the images (Mosaic), followed by multiple post-processing steps to enhance spatial data quality. These included aligning images for consistency (Align Photos), assigning real-world coordinates (Geo-referencing), and constructing a dense image cloud (Build Dense Cloud) for high detail. Additionally, a triangular mesh (Build Mesh) was created to incorporate topographical information into the dataset, and image texture was refined (Build Texture) for enhanced clarity. The final phases involved processing and stitching the images into orthophotos (Orthophoto) to ensure geometrically accurate representation and conducting unsupervised classification with the ISODATA method to categorize marine resources efficiently. The outcomes of these processes are presented in the form of an aerial photographic map, as illustrated in Figures 3, 4, and 5. The integration of multispectral imaging and UAVs gives significant advantages in monitoring coastal ecosystems, particularly in complex environments such as Phang Nga Bay, where sensitive ecosystems like coral reefs, seagrass beds, and mangroves are affected by both natural changes and human activities [26].

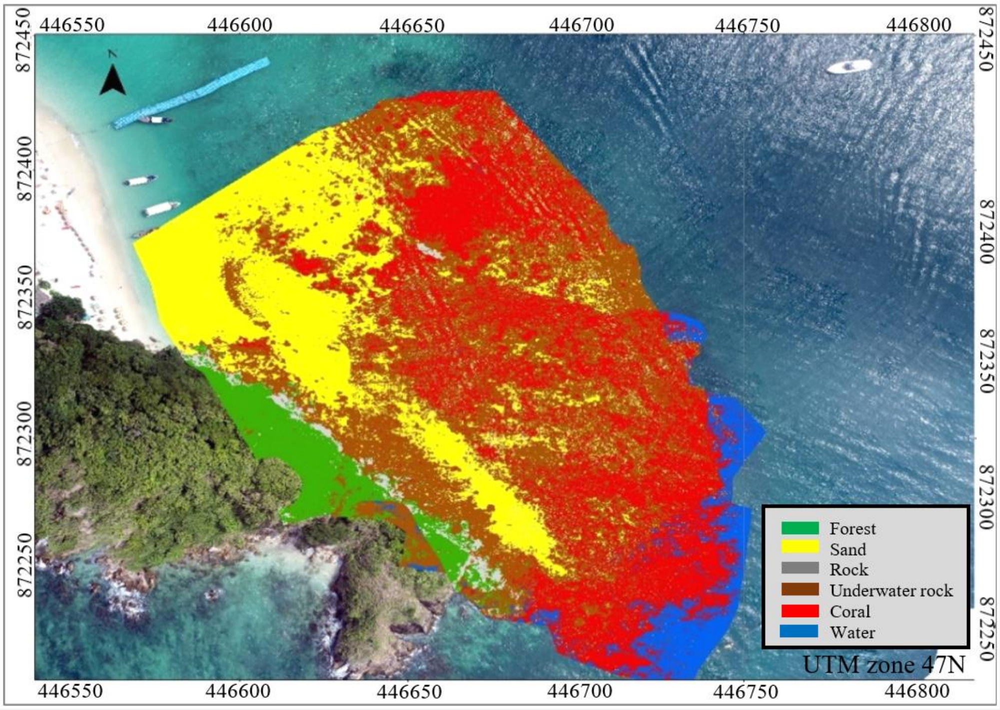


Figure 3: Marine resource classification map using UAV, sample area 1, north of Koh Khai Yai

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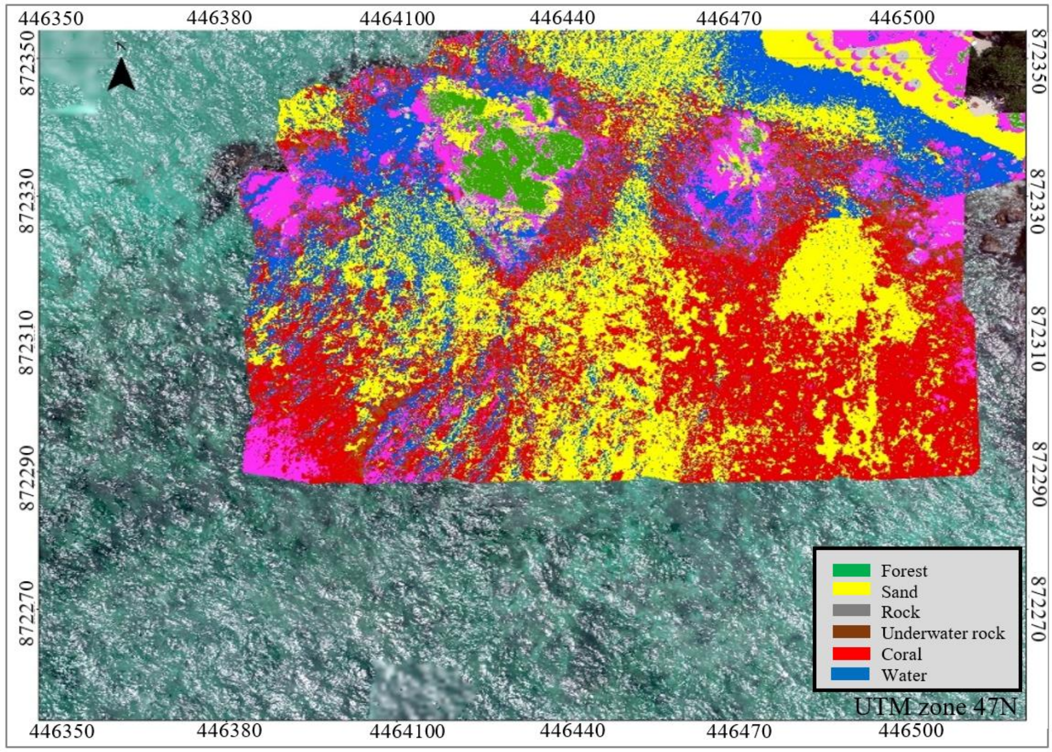

Figure 4: Marine resource classification map using UAV, sample area 2, south of Koh Khai Yai

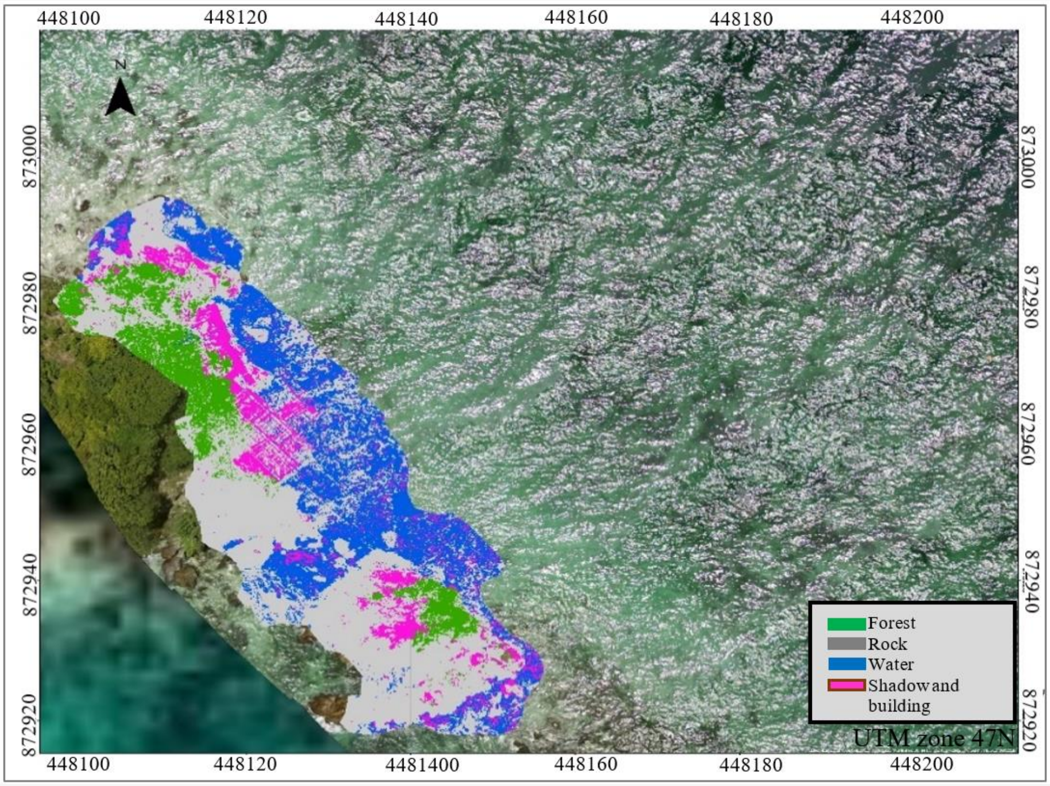

Figure 5: Marine resource classification map using UAV, sample area 3, Khai Nui Island

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Multispectral UAV imaging has great spatial resolution across many spectral bands, which is critical for identifying between habitat types in these ecosystems [26] and [27]. Photogrammetric approaches improve the accuracy of UAV surveys by stitching many photos into high-resolution, coherent maps, allowing for efficient, systematic monitoring without the disturbance produced by ground-based evaluations [28] an [29]. Furthermore, unsupervised classification techniques which include the ISODATA method enable data categorization without previous understanding, which is useful in exploratory research where preliminary spatial pattern analysis can help establish baseline data for continuous evaluation [30] and [31]. These capabilities demonstrate the value of multispectral UAV surveys for long-term, repeatable environmental monitoring, providing an effective method for capturing detailed spatial data required for managing dynamic coastal zones and meeting the demand for accurate environmental assessments [27] and [29].

4.3 Results of the Analysis of the Relationship between Marine Resource Data and Data Obtained from Surveys Using Drone Images, Multispectral Band Images, and the Original Marine Resource Database

The findings of this study indicate that the relationship between marine resource data and the data collected through surveys using drone imagery and multispectral band images varies across the three surveyed areas. These differences are attributed to the distinct physical characteristics of each location. Moreover, the data obtained from these surveys can be effectively compared with the existing marine resource database maintained by the Department of Marine and Coastal Resources, highlighting the utility of drone technology in enhancing marine resource assessments.

Sample Area 1: located north of Koh Khai Yai in Phang Nga Province, comprises six distinct types of land cover, including forest, which occupies an area of 1,429.674 square meters; sand, covering 5,652.777 square meters; rock, with a total area of 728.448 square meters; underwater rock, encompassing 8,923.662 square meters; coral, covering 6,536.707 square meters; and water, which spans 1,383.342 square meters. This classification of land cover types is detailed in Table 1 and visually represented in Figure 6, offering insights into the spatial distribution of various marine and coastal resources within the area.

Sample Area 2: located beneath Koh Khai Yai in Phang Nga Province, features a diverse range of land cover classified into seven distinct types. These include forest, which occupies an area of 322.182 square meters; sand, covering 4,106.778 square meters; rock, with a total area of 245.149 square meters; underwater rock, encompassing 630.682 square meters; coral, spanning 3,585.556 square meters; water, which covers 2,622.099 square meters; and other categories, including shadows and buildings, occupying an area of 1,627.764 square meters. This classification of land cover types is presented in Table 1 and illustrated in Figure 6, providing a comprehensive overview of the spatial distribution of various environmental features in the area.

Sample Area 3: located on Khai Nui Island in Phang Nga Province, consists of four distinct types of land cover. These types include forest, which occupies an area of 210.685 square meters; rock, covering 933.746 square meters; water, spanning 470.978 square meters; and buildings, which encompass an area of 225.274 square meters. This classification of land cover types is detailed in Table 1 and visually represented in Figure 6, providing insights into the spatial distribution of various environmental features on the island.

The comparative analysis of coral reef data from the Marine Resources Database (Figure 6 illustrates coral reef areas in white) across the three examined regions (Areas 1, 2, and 3 in Phang Nga Province) reveals notable differences in land cover types (Table 1). These variations highlight the distinct environmental and physical characteristics unique to each location.

Table 1: Land cover table in the study area

Types of land cover	Sample Area (square meters)		
	Area 1	**Area 2**	**Area 3**
Forest	1,429.674	322.182	210.685
Sand	5,652.777	4,106.778	-
Rock	728.448	245.149	933.746
Underwater rocks	8,923.662	630.682	-
coral	6,536.707	3,585.556	-
Water	1,383.342	2,622.099	470.978
Other	-	1,627.764	-
Buildings	-	-	225.274

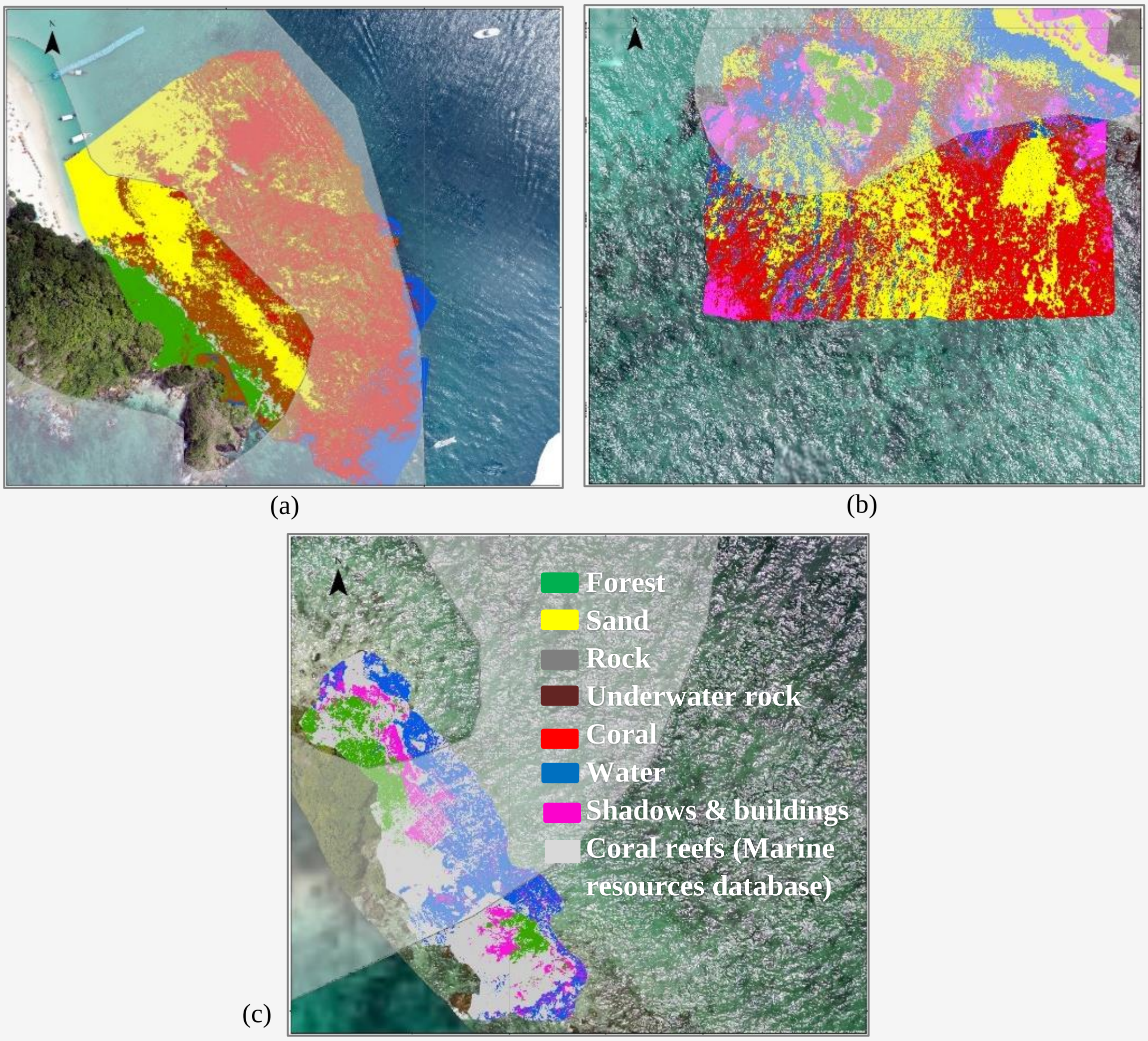

Figure 6: Comparative study of coral reefs (marine resources) in Phang Nga Bay using UAV: (a) area 1 (b) area 2 and (c) area 3

Sample Area 1 (Figure 6(a)), located north of Koh Khai Yai, is the most diverse in terms of land cover types and areas, with six distinct classifications including forest, sand, rock, underwater rock, coral, and water. Notably, underwater rock and coral are predominant, covering 8,923.662 and 6,536.707 square meters, respectively, indicating a rich marine habitat. This area’s composition aligns closely with coral reef ecosystems, likely supporting high biodiversity due to its extensive underwater rock and coral cover. Sample Area 2 (Figure 6(b)), situated beneath Koh Khai Yai, also exhibits substantial diversity in land cover but includes an additional seventh category: "other," which encompasses shadows and buildings and covers 1,627.764 square meters. This area's distribution reveals a notable emphasis on sand (4,106.778 square meters) and coral (3,585.556 square meters), suggesting an active and potentially accessible nearshore environment. The presence of built structures or shadows within this area indicates some level of human activity or modification, which could have implications for conservation and sustainable use practices. The broader range of land cover types here, especially the coral and sand expanses, suggests the area may serve as an accessible and ecologically valuable site for both conservation and tourism. In contrast, Sample Area 3 (Figure 6(c)) on Khai Nui Island contains only four types of land cover: forest, rock, water, and buildings, with minimal coral or sand coverage compared to the other areas. Rock and buildings constitute the largest portions of the land cover, with 933.746 and 225.274 square meters, respectively. The limited variety in land cover types and the absence of significant coral or underwater rock habitats suggest this area may be less diverse in terms of marine resources.

Its more developed profile, with buildings occupying a substantial portion relative to its size, indicates a potential shift towards human-centered use or development, potentially impacting its marine biodiversity and ecosystem functions.

The results of the UAV survey of marine resources in this study revealed relationships between the physical characteristics of each surveyed site and the composition of the associated marine resources. This relationship highlights the effectiveness of multispectral surveys using drones or UAVs in identifying a wide range of land cover types, including underwater objects located 3 to 5 meters below the water surface. The data obtained from this survey method can be effectively utilized for classification purposes, demonstrating high-resolution spatial distribution. Consequently, the findings enable researchers to examine, compare, and manage marine resources more effectively than traditional survey methods, which often lack the spatial resolution necessary for sensitive ecological analyses [26] and [28]. These surveys facilitate the identification of critical habitats, such as coral reefs and seagrass meadows, which are vital for marine biodiversity and ecosystem functioning. By integrating advanced imaging technologies [32], these surveys provide rapid, timely, and context-aware data that do not impact sensitive and fragile resources. Furthermore, aligning the collected data with existing databases of the Department of Marine and Coastal Resources will enhance the potential for targeted conservation initiatives, enabling policy and management strategies to be tailored to the specific ecological characteristics and challenges of each area [27]. This approach is particularly important in regions where human activities are increasingly expanding nearshore, where effective monitoring and management are crucial to sustaining and conserving ecosystems [29] and [33]. Furthermore, drone technology not only enhances the efficiency of data collection but also supports stakeholder engagement in conservation by providing compelling data that can be used for communication and advocacy [26] and [28]. This study highlights the potential of UAVs in monitoring marine resources and coastal changes impacted by climate change [34] and [35]. The insights gained from this survey will significantly contribute to sustainable coastal resource management. This emphasizes the importance of adopting innovative approaches to environmental monitoring [30][31] and [36].

For future work, it is recommended to enhance the accuracy assessment of the classification results by acquiring additional baseline data. This could include obtaining a more comprehensive set of ground-truth data, either through field surveys or high-resolution reference datasets, to serve as a reliable benchmark for validating the results. Ground-truthing is essential for both supervised and unsupervised classification methods, as it enables the comparison of classified images with real-world observations [37]. In addition, employing an integrated approach, such as incorporating time-series data or utilizing other remote sensing technologies (e.g., LiDAR or high-resolution satellite imagery), could provide more robust validation and improve classification accuracy [38]. These steps would allow for a more thorough assessment of the classification performance and ensure the reliability of the results, ultimately contributing to more accurate mapping and resource management.

5. Conclusions

The purpose of this study was to survey marine resources in Phang Nga Bay utilizing UAV-acquired RGB and multispectral imagery, which were combined with photogrammetric algorithms to attain high spatial accuracy and detail. The procedure involves several processes, including imagine alignment and georeferencing, dense cloud formation, mesh building, and texture refinement. The resulting orthophotos served as the foundation for a full analysis of land cover classifications, which was performed using the ISODATA unsupervised classification approach. The data show that land cover varies significantly among sample locations, confirming drone technology's ability to effectively characterize maritime and coastal habitats. Six land cover classifications were detected in Sample Area 1, located north of Koh Khai Yai: forest, sand, rock, underwater rock, coral, and water, with underwater rock and coral being especially prominent, highlighting the area's ecological richness. Sample Area 2: located beneath Koh Khai Yai, featured seven unique types, as well as other elements like as shadows and buildings, indicating human influence on the natural landscape. Sample Area 3: which was located on Khai Nui Island, included four basic land cover classifications, showcasing a simpler distribution with a noticeable presence of rock formations and constructed structures. This study demonstrated that multispectral data collected through UAVs could possibly be efficiently integrated with existing marine resource databases, resulting in an enhanced framework for monitoring coastal ecological changes. UAV-based remote sensing, especially when multispectral sensors are used, provides substantial advantages over traditional field survey approaches, such as high spatial resolution, cost-effectiveness, and simplicity of repeat monitoring.

This study contributes to a stronger understanding of land cover and resource distribution in coastal areas by merging UAV images with photogrammetric techniques such orthophoto generation, dense cloud construction, and unsupervised classification.

The relation between survey data and the Department of Marine and Coastal Resources databases shows the importance of aerial drone technology as a supplement to marine resource management. Integrating this data with established databases allows for continuous monitoring of important ecosystems including coral reefs, mangroves, and seagrasses, which are vulnerable to environmental stresses such as coastal development, climate change, and pollution. Furthermore, the UAV-driven mapping procedures employed here are consistent with spatial theories of environmental ecology and conservation, which highlight the relevance of spatial variation in ecosystem management. UAV spatially explicit data can be examined using GIS to predict biological processes, habitat connectivity, and the effects of environmental change over time. The UAV-based approach used in this study is also applicable to environmental management frameworks such as Integrated Coastal Zone Management, where the spatial and temporal dynamics of resources must be continuously monitored. In this context, UAV multispectral imaging provides critical data to support decision-making processes, guide conservation efforts, and establish thresholds for environmental indicators including as turbidity, vegetation health, and sediment deposition.

In summary, this study supports the use of UAV technology to collect accurate, up-to-date, and complete data. UAV photography and multispectral analysis have the potential to improve coastal and marine ecosystem management approaches. This technology is a crucial tool in adaptive management techniques, since it ensures data-driven responses to quickly changing conditions in vulnerable maritime environments. Future studies have suggestions when conducting surveys of marine resources using unmanned aerial vehicles (UAVs). It is essential to select a time when the water level does not exceed 2 meters. This precaution is necessary because the sunlight reflecting off the water surface can distort the reflection levels of electromagnetic waves, leading to inaccuracies in the assessment of marine resources. Moreover, such reflections significantly impact the mosaic technique and the alignment of aerial photographic data, making it challenging to establish connection points between images. This issue was particularly evident in Sample Area 3, where the use of multispectral cameras posed greater difficulties in image stitching compared to RGB cameras due to their lower image clarity. Therefore, to optimize the effectiveness of studies utilizing multispectral cameras, surveys should be conducted during periods of lowest daily water levels, ideally not exceeding 2 meters, to ensure accurate and reliable results

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