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Assessments of Nipa Forest Using Landsat Imagery Enhanced with Unmanned Aerial Vehicle Photography

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Abstract

Nipa palms are exposed by the transformation of land use and land cover changes (LULCC) due to changes to aquaculture and orchards. Modern remote sensing for environmental monitoring of LULCC has been made easier by the use of high spatial resolution images, innovative image processing and Geographic Information Systems (GIS). The expense of high-resolution satellite imagery has resulted in investigators moving to open sources (e.g., Landsat), therefore, the interpretation of images at a medium resolution can be classified simply as LULCC classes and are constrained by the detection of small-scale disturbances. This research applied Landsat imagery with very high-resolution imagery from Unmanned Aerial Vehicles (UAVs). In order to be useful for real-world applications, the accuracy of remote sensing data must be validated using proven ground-based methods. UAVs equipped with multispectral sensors were flown over the Nipa palms at the Prasae River, Rayong Province, Thailand. The main advantage of UAV-based remote sensing is that it reduces costs and immediate availability of high-resolution data. The UAV imagery was expensed as "drone truthing data" to train image classification algorithms. These results show that UAV data can be used effectively to support and categorize similar land-cover/use classes (aquaculture vs. mangrove forest vs. nipa forest) with consistently high identification of over 87.6% on the generated thematic map, where the mangrove forest detection rate was as high as 86%. For that reason, UAVs are engaged successively in management and conservation tasks, which can be used for regional or local scale studies to compare the achieved accuracy to a general regional land cover map. This approach can be used for the variability of plants to rectify land-cover classification. Therefore, UAV images are a very useful tool to fill the gap between remote sensing information and expensive ground field campaigns.

Keywords: Nipa forest; Unmanned Aerial Vehicle imagery; Landsat imagery

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Introduction

The rapid enlargement and evolution of drones as a remote sensing platform for environmental monitoring have resulted in an increased uptake in forest management [1]. The land use classification system in Thailand was developed from the Department of Mineral Resources United States of America (USGS). Level 1 is categorized into 5 types of land-use: community and construction (U), agricultural (A), forest (F), water body (W) and miscellaneous land-use (M). Continuous monitoring of land-use/land-cover (LULCC) types intended to follow where transformation (and how fast) is conducted in order to identify conservation priorities and to plan actions [2].

The capability of highest resolution, fly on-demand at a critical stage identified Unmanned Aerial Vehicles (UAVs) or simply "Drones", as an advantage machine. Recently, much work on remote sensing in forests integrated drones for remote sensing to increase the efficiency of data acquisition.

Nypa fruticans (nipa palms) are important sources of sustenance to people living in riparian and coastal zones. Local people have traditionally managed the nipa palm to produce food and construction materials. Nipa palm forests in Thailand have been removed for various reasons ranging from the expansion of aquaculture, road construction and the use of nipa palm for various purposes. There is a positive correlation between the size and age of the villages and occurrence of Nipa. This is probably through the mechanism of selective harvesting of Nipa palm for domestic use [3]. In terms of ecological service, *Nypa fruticans* protect coastal areas from erosion and are habitats for breeding and nursing of aquatic animals. Dense Nipa stands are also associated with areas where domestic waste is discharged. These areas have the highest nutrient content (nitrogen and phosphorus). All seem to stress and afford opportunity for Nipa palms to establish. It is also probable that fluctuations in climate change will affect the survival of this species. Although there is deterioration in many areas, this species is listed as Least Concern.

Previous and ongoing researchers have applied UAVs to classify forest types with either a thermal imaging system or NDVI computation [4]. Descriptions were acquired by near infrared to derive the different vegetation indices [5] which increased the feasibility of corrections in wetlands surveying at high resolution to stop the habitat changes. The prevalence of studies highlights supervised object-based classification as the best method to classify land use types in a wetland environment [6].

On-the-ground surveys could authorize a highly correct classification, nevertheless, timewasting, laborious, and expensive costs are problematic, which creates remote sensing as an obvious and preferred alternative. Undoubtedly, a compromise between the purpose and the costs of satellite imagery makes monitoring LULC changes by remote sensing extremely challenging, as the situation efficiency depends on spatial and temporal resolution of the accessible data [2].

Medium spatial resolution data, such as Landsat, are appropriate for land cover or regional vegetation mapping at a local scale [7]. For example, Landsat 8 OLI, Landsat 7 ETM+, and Landsat 5 TM have been successfully used for large-scale forest classification [8] however, resolution (30 m) limited to specify the classification, frequently prominent to the presence of non-natural forests into a standard 'forest' class, and creating unfortunate LULC maps [9–10].

Distinguishing wetland types using Google Earth Engine with 88% accuracy [11], and expending image texture to enhance multispectral imagery to distinguish land use cover with up to 78% accuracy [12]. The success of UAV/Drone requirements for extensive application: (1) the highest resolution satellites are expensive, and disapprove consistent reconsideration without government or commercial tasking; (2) hyper-spectral imagery is encouraging and accumulative in availability with confined coverage; and (3) satellite classification contains general field work for training and validation [6]. Nowadays, UAVs/Drones are extremely flexible technology that are continuously varying in innovative techniques to greater effectiveness. The evolution of UAV/Drone based remote sensing to innumerable fields of study has attracted decision makers to extend its potential as an alternative for training and corroboration of satellite imagery. The medium spatial resolution-classification required Unmanned Aerial Vehicles (UAVs) to capture high quality images to replace on-the-ground verification of land cover [2]. UAVs presented an extraordinary prospective to escalate the efficiency and condense the cost of surveys and LULC change assessments.

The propose of this study is to stimulate UAV-derived images validating how to support a supervised classification method of Landsat imagery focusing on the Nipa habitat. In addition, refining the value and effectiveness of the Landsat consequent LULC maps, this approach creates the potential to reasonably enhance the details of land-cover classes. Therefore, sustainable Nipa forests can be a good source of supplementary income or constitute an alternative source of livelihood in rural areas and at the same time provide ecological and environmental benefits. There are no conservation measures specific to this species. Thus, continued monitoring and research is required information for conservation and management of Nipa utilization. The chances of this research are to critically examine the present status of Nipa areas in order to maintain an acceptable balance between conservation and utilization.

Material and methods

1) Study area

The study area covers 2,067.25 km^2 of the East Coast of the Gulf of Thailand. The Prasae River originated from Klong Phai canals that are located in the Koa-Chamoa mountain ranges in the eastern sub-region covering Rayong Province (Figure 1). The mean annual precipitation is around 2,400 mm and the mean annual runoff is around 29 m^3 s^{-1}. The Prasae River length is approximately 26 km, with a variety of ecosystems such as freshwater brackish and the marine ecosystem. The riparian zone and coastal zone are potential areas for agriculture and aquaculture. However, the problem of land utilization is a lack of soil maintenance, The Nipa habitat is a major riparian zone with diverse utilization in the local community. Forest disturbance causes a lack of moisture and reduces the ability to slow down the water. Soil erosion is increasing. Sludge is deposited in waterways, resulting in shallow water sources, with wastewater from agricultural areas, decay of natural water sources, and deterioration of quality [13].

2) Satellite imagery preprocessing and classification

This study used Landsat 8 OLI imagery engaged on 17 February 2016 available at: http://earthexplorer.usgs.gov. The study area covered by Landsat images was path 128/row 51. The multispectral bands contain spatial resolution at 30×30 meters and the panchromatic band has a spatial resolution of 15×15 m. The scene preprocessed together with geo-referencing to sub-pixel accuracy and spectral normalization. Based on this, the spectral values were corrected by applying a ‘forest normalization’ algorithm, where all spectral bands (values) were adjusted based on acquisition dates and reference data collected from evergreen forest cover by applying a linear shift. Although the imagery had less than 10% cloud cover, the images masked out clouds during the pre-processing. Landsat imagery parameters (band-specific multiplicative rescaling factor, band-specific additive rescaling factor, quantized and calibrated standard product pixel values, recording date/time, and local solar zenith angle) were gathered from the imagery metadata [2].

Following the preprocessing, random forest supervised classifier algorithms [14] were used to discriminate land-cover classes with ArcGIS 9.1. Individual decisions expanded a random subset of selected independent variables and the final classification categorized by relating a majority vote condition to all the decision trees in the collective. Samples prevented from tree generation were used to rank variables as stated by their importance (in terms of predictive power) and to evaluate model accuracy [15] To train the RF logarithm, this research used UAV collected data to discriminate six different LULCC classes, which are (1) mangrove forest, (2) nipa forest, (3) swamp, (4), community, (5) aquaculture and (6) water, as shown in Figure 2.

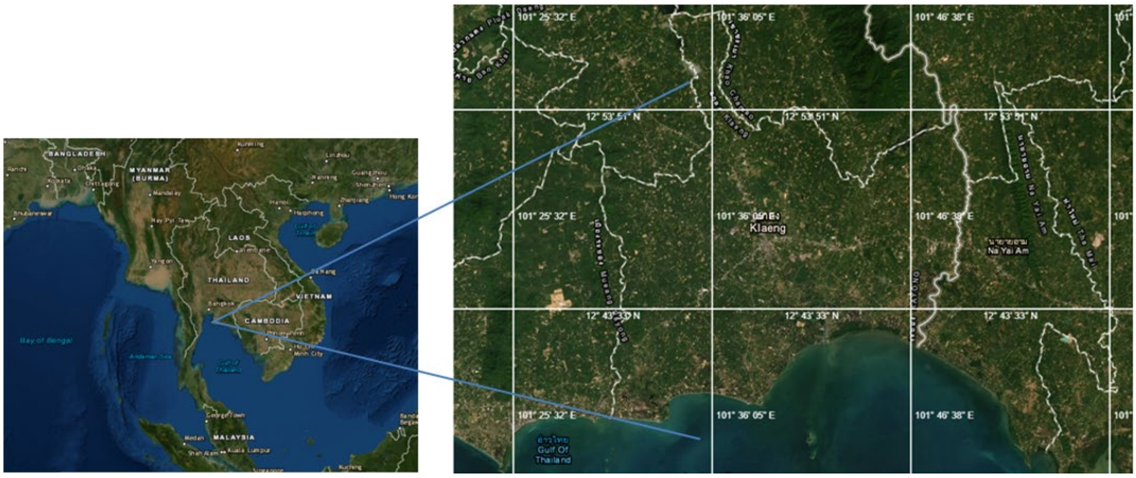

Figure 1 Study area location, Prasae sub-watershed, Thailand.
Source: Earth Explorer (2020)

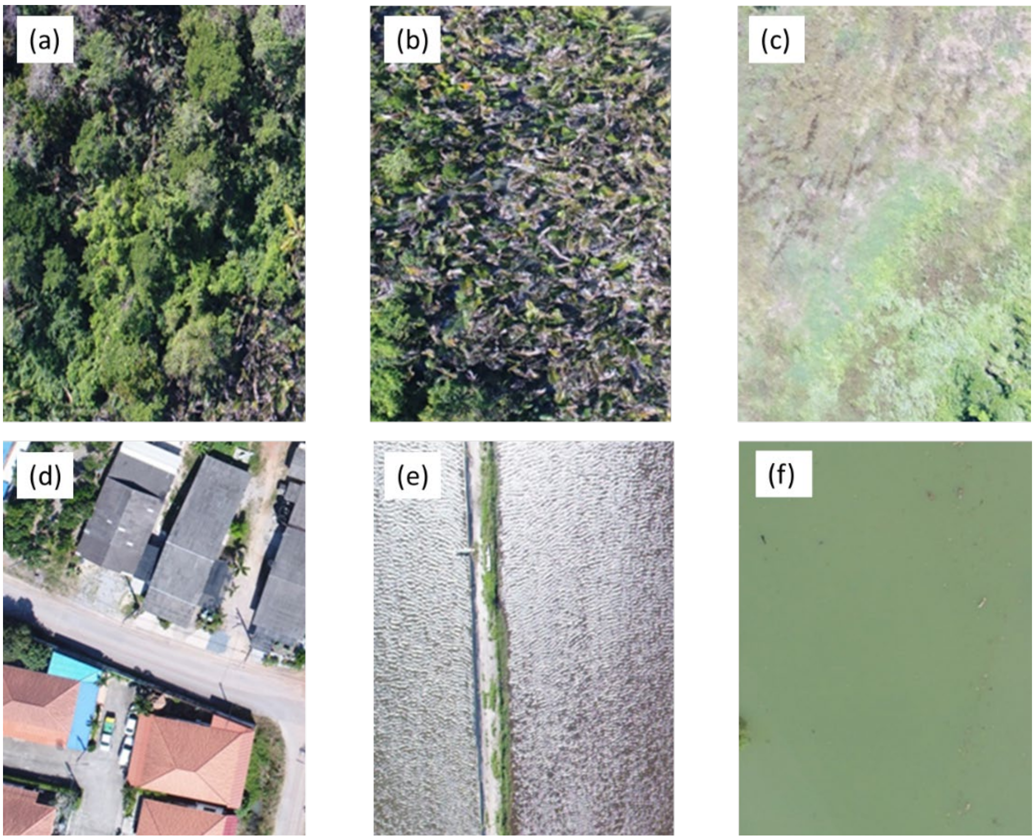

Figure 2 Training data captured from UAV imagery: (a) mangrove forest, (b) Nipa forest, (c) swamp, (d) community, (e) aquaculture, and (f) water.

3) UAV imagery collection and processing

A commercial light quad-copter (1160 g) Phantom 4, with a built-in camera (Phantom vision FC6310_8.8_5472x3648) was used on the platform with a high definition RGB camera (12.4 MP), a 1/2.3" sensor, a lens with a focal length of 20 mm (35 mm format equivalent) f/2.8 focus at ∞ and three possible fields of view (FOV) at 94 degrees. Although the aircraft flies using a preprogrammed flight plan stored on a PIX 4D, it was under the supervision of a pilot.

Regulations for UAV flights in Thailand have been recently adopted, these were not in place at the time of this study. Nevertheless, we were authorized to operate flights by the American Society for Photogrammetry and Remote Sensing 2014 (ASPRS 2014) [16].

UAV flight missions have approximately a 70% forward overlap and a 30% side overlap between photographs to generate geo-referenced mosaics. Four flights were made within the perimeter of the Nipa palm forest (Figure 3) in easily accessible areas. Flights took place between 12:00 and 14:00 h, in optimal atmospheric conditions in terms of lighting and wind on all four flights. The average altitude of the four flights was 90 m with an average speed of 10 m s^{-1}. The flights were set on automatic mode to fly linear transects, using the Pix4D capture mapper application, with the camera angle 90° to the ground. This could be attributed to the possibility that the image overlapping was good for the post-processing of the image. The data acquisition was done on 17 December 2016, and in total, 310 pictures were used to derive the results. Data processing of automatically taken images was synchronized with an SD card, from the UAV, to the Pix4D application and downloaded to a personal computer after each data collection. The uploaded pictures were input to Pix4D to generate 2D maps. The Average Ground Sampling Distance (GSD) was 3.94 cm./1.55 in.

Images were geo-tagged by the internal GPS. The photogrammetry software (Pix4D) optimized the positions of the camera and increased the overall ground accuracy of the GPS locations (Figure 3). This made it possible to superimpose satellite images and orthomosaic photographs, since the UAV-based image collecting period related to the Landsat data.

4) Ground inventory

To survey the features and spatial distribution of land utilization in the study site, plot-based field investigations were carried out in June-July 2016, on the study area. A handheld GPS device (Garmin 64s) was used to record the precise locations of the Nipa samples, and the locations were verified with UAV and Landsat data.

The plot-based (10*10 m^2) dimensions were attained from Nipa forest (from the riverside to the terrestrial edge), and the existing land-use/cover (e.g., mangrove, aquaculture, community and swamp) was collected with a camera and GPS. Altogether, 50 mangrove plots and 60 Nipa plots in 250 ground verification points were explored from the wetland area, as shown in Figure 4.

Results

The error matrix of the total samples was calculated and the total accuracy of the classification was 88% (Table 1). This was obtained from the error matrix by using different approximate weights that were determined by random sampling. The land-cover and land-use classes strongly aligned with the Nipa presence/absence showing a high consistent accuracy (91.6%). Mangrove was classified with a producer's accuracy of 86%, while aquaculture was categorized with a high rate (80%) and has a major significance in observing Nipa habitat destruction.

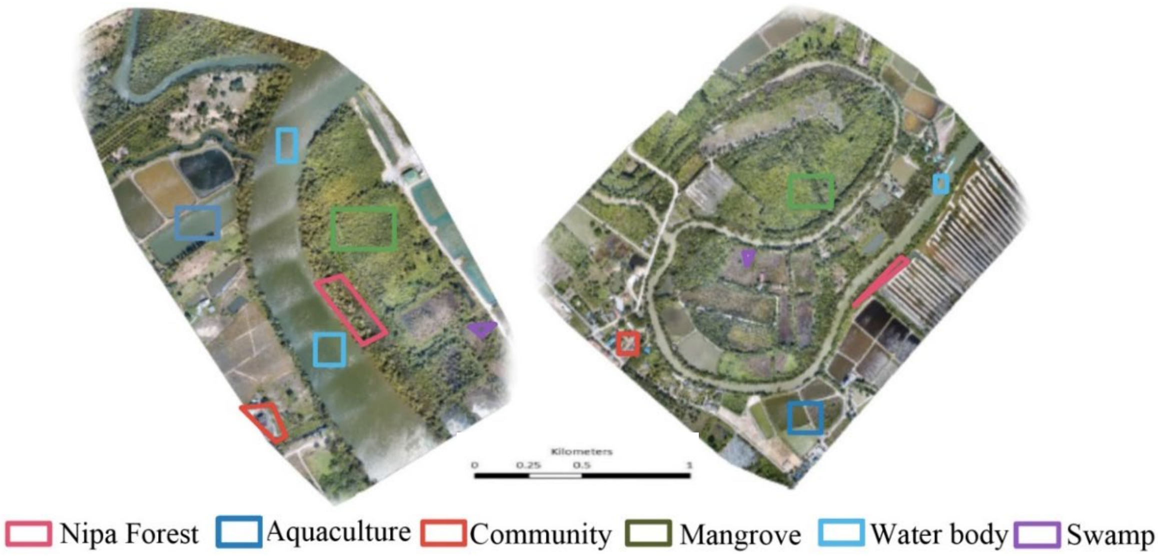

Figure 3 Geo-referenced mosaics of the UAV and corresponding training data polygons.

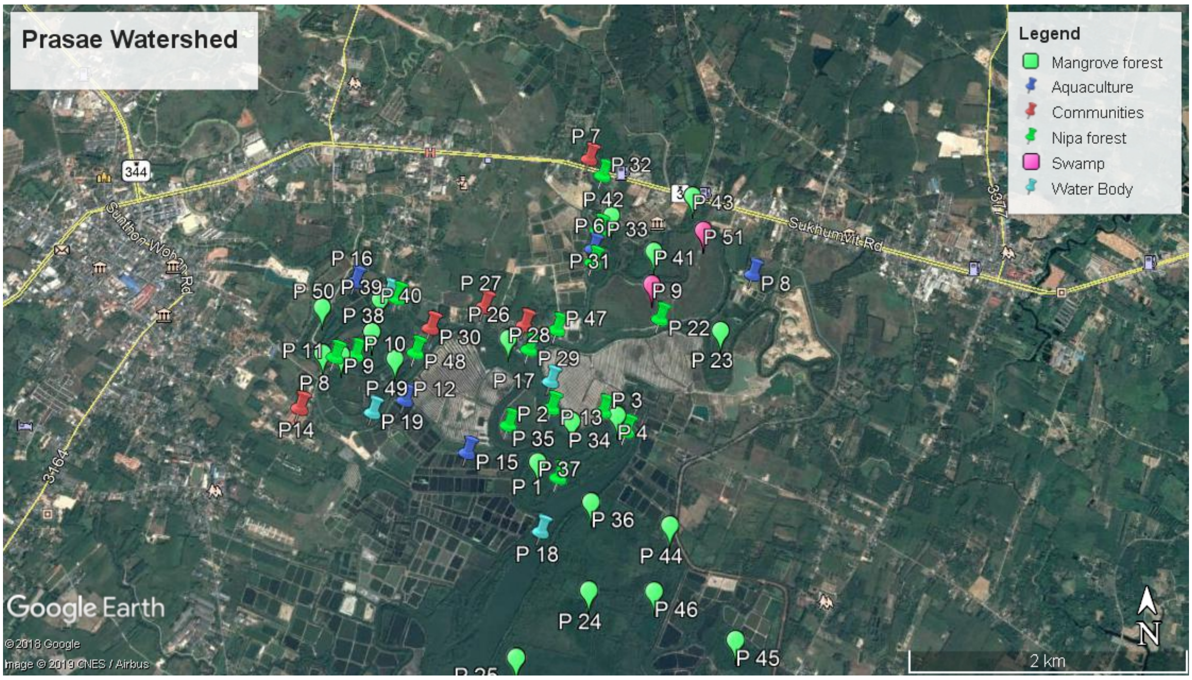

Figure 4 Testing points in various LULC of the Prasae sub-watershed.
Source: Google Earth (2020)

The community area was discovered (96% accuracy) and had a very small demonstration on the ground. Additional classes, such as aquaculture, were recognized with an accuracy of approximately 80%, and water bodies such as streams or canals were identified (85% accuracy) on the map (Figure 5). Basic principles for the interpretation of the shape and distribution of trees were established by the plant boundary of the coastal and mangrove areas using color saturation and color, size, shape, texture, height and shadow. It was found that nypa fruticans leaves are dark green if mature which is completely different from the nearby mangrove forest. Nipa leaves sprout from the middle of the trunk and are easily detected when compared to neighboring plants.

When quantified, the spatial coverage of various LULCC types within the predicted Nipa distribution range account for the corresponding detection accuracy of the thematic map (Table 2). The range of the Nipa distribution is approximately 807.52 km^2 for the Prasae sub-watershed and approximately 0.02 km^2 within the watershed. This result is similar to the information of the Land Development Department that classified agriculture (807.52 km^2) as the principal LULCC type of the study area covering around 4/5 of the total. Additionally, the supervised classification identified the area covered by 109.13 km^2 of forest, 29.1 km^2 of aquaculture and 40.27 km^2 of water bodies.

Discussion

Utilization of very high-resolution images has become a new trend in forest management, particularly in the detection and identification of forest stand variables. Support Vector Machine (SVM) classification process was used to extract Nipa (*Nypa fructicans*) with a high accuracy (95%) in inland areas by using the available LiDAR data [17].

A hybrid of a pixel-based maximum likelihood classifier and an object-based segmentation approach was applied on unmanned aerial vehicle (UAV) images to measure crown closure of Nipa palms [18]. The best combination of segmentation parameters was of the spatial radius (hr), range radius (hr), and minimum region size, with the overall accuracy of 76.6% and kappa accuracy of 55.7%.

Table 1 Accuracy assessment between different land-use types of the Prasae sub-watershed

Lu type	Mangrove	Nipa	Swamp	Community	Aquaculture	Water body	Total
Mangrove	43	1	1	0	4	0	49
Nipa	3	55	1	1	3	1	64
Swamp	1	1	45	0	1	1	49
Community	1	0	0	19	0	0	20
Aquaculture	1	2	1	0	40	1	45
Water body	1	1	2	0	2	17	23
Total	50	60	50	20	50	20	250

Overall accuracy = (43 + 55 +45 +19 + 40 + 17)/250 * 100 = 87.6 %
Kappa index = (250 * 219) – 11,850 / 2502 – 11,850 = 84.7

Table 2 Area coverage of each Land-Use and Land-Cover (LULC) in the Prasae sub-watershed

Lu type	Total area (Rai)	Total area (km^2)	Percentage of total	Producer's accuracy	User's accuracy
Mangrove	10,315.00	6.45	1	86	87.7
Nipa	40.6	0.02	0.003	91.6	85.9
Swamp	501.4	0.31	0.028	90	91.8
Community	129,329	80.83	10	96	95.0
Agricultural	1,025,363	640.85	79	N.A.	N.A.
Aquaculture	46,554	29.10	4	80	88.8
Water body	64,429	40.27	5	85	73.9
Total	1,292,031	807.52	100		

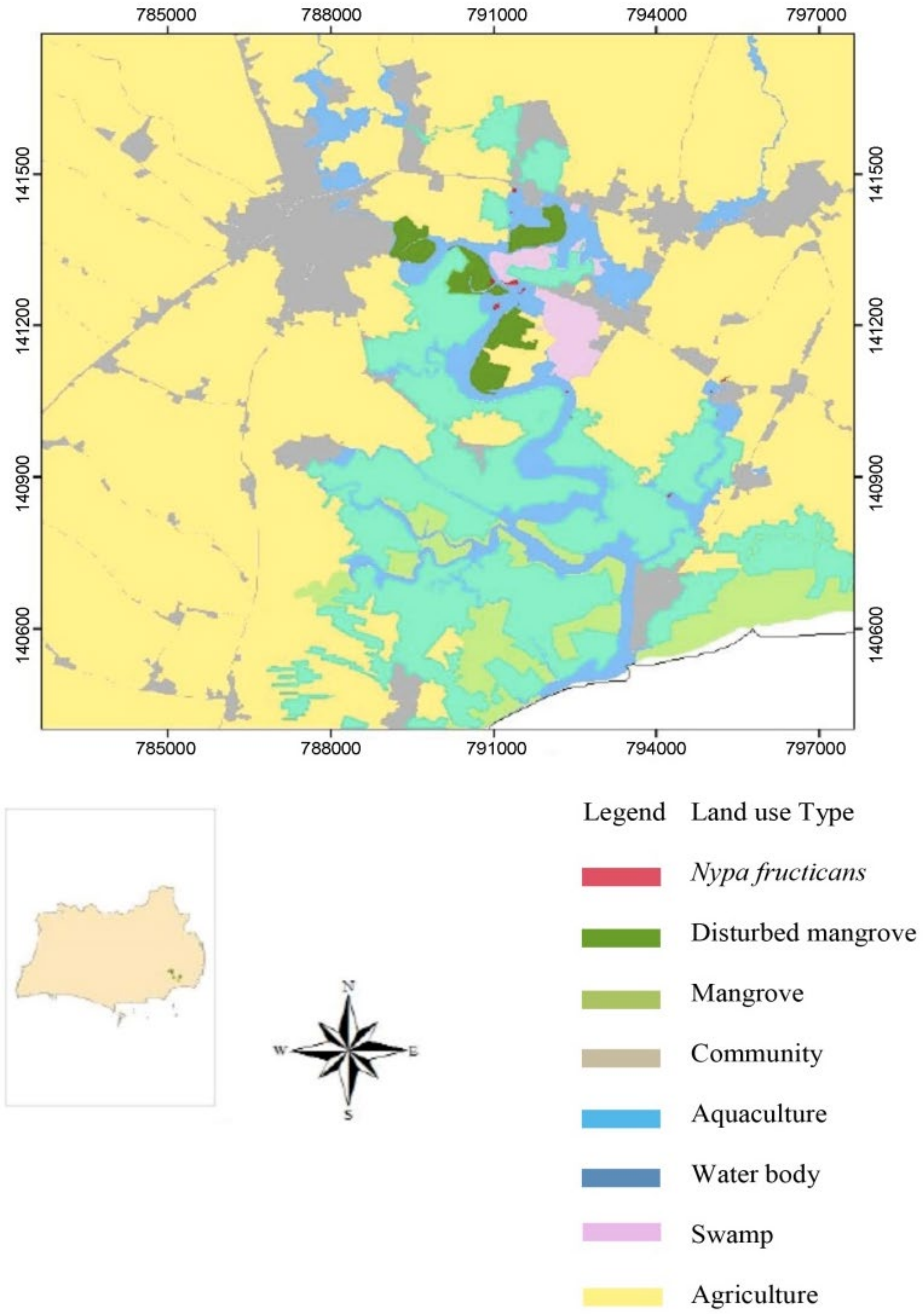

Figure 5 LULC and Nipa forest distribution map of the Prasae sub-watershed.

This paper demonstrates that with the support of UAVs it is probable to define a Nipa forest with data from Landsat images. High-resolution UAVs provide precise information close to that engaged in the study area, which can be used to validate satellite platform information. The demand for regular information on the evolution of plant cover is necessary and remote sensing provides wide, regular and easily accessible images, and this data is important to validate and make sense of land management. This work demonstrates the suitability of UAV platforms to calibrate and validate satellite information without resorting to the terrain.

The pre-processing of UAV images was used with algorithms for the generation of orthomosaics (incorporated in Pix4D software) which greatly facilitated the cost of processing high-resolution images and offered optimal results to achieve the objectives. The possibility of photos interpreting the severity of a phenomenon through the visible spectrum at intermediate scales has confirmed the possibility of using these images in calibration and validation processes.

Observation of the Nipa habitat is fundamental to the operation of conservation approaches. Nevertheless, to be active, monitoring strategies should be dependent on procedures accomplished between LULC types with a high level of accuracy to ensure that the changes are discovered. These results present how satellite imagery at moderate spatial resolution, such as Landsat 8 and UAV images, can be developed to create precise LULC maps containing classes with high applicability for Nipa conservation.

The training data relied on UAV imagery which was arranged with a supervised machine learning classifier [19–20] and the overall accuracy was suitable for this approach. More importantly, the three key classes that are difficult to recognize and explain with Landsat 8 imagery alone (i.e., mangrove forest, reforested areas and Nipa forest) were accurately categorized by this approach.

The main benefits of this approach are the cost-effectiveness, which creates a capable tool for rapid monitoring of LULC classes, such as natural resources conservation. An additional advantage is the timing as the UAVs can be effective at any time depending on the weather. Despite an inexpensive budget, the method certifies the classification of multiple classes of conservation.

It is imperative to categorize forest areas overlapping the Nipa distribution for conservation because research has specified that behavior and densities differ between mangrove and Nipa forest. Most of the previous work used UAVs intensively in areas where specific plants were collected. This study confirmed that UAV images can replace ground truth data to achieve better categorization (i.e., thematic map) than that supplied by automated algorithms. This technique is valuable for time saving and decreases the use of ground truthing.

The limitations of this approach are (1) medium-resolution satellite images should be collected at similar time frames with the UAV ground data to discharge the potential biases and (2) classification should be regularly methodized based on accessible medium-resolution satellite imagery (such as Landsat 8 and Sentinel 2).

Conclusions

This paper demonstrates that it is possible to define Nipa forest data from Landsat and UAV images. Steps have been identified where the modeling process can be improved, and the proposed methodology can be simulated to classify each area associated with more intense fieldwork. Thus, the methodology can also be adapted to spatial and spectral resolution sensors other than those of Landsat satellites. The major advantage of UAVs is the capability to rapidly deliver high temporal and spatial resolution image information. Not only can UAVs be used in studying Nipa forest, which is an improvement on the previous use of classified LULC. UAVs can also be used to study the impact of urbanization and pollution, as well as to develop carbon stock and biodiversity data. Future studies should consider the use of UAVs to study allometry and wider areas of mangroves forest to determine the impact of salinity, hydrocarbon pollution and urbanization.

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