Improving the Accuracy of RPA Image Classification in Vegetation Mapping of Magsaysay, Occidental Mindoro using RGB Indices, Canopy Heights, and Feature Importance Weighting

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Abstract

Mapping vegetation cover is an important step in generating baseline data for various purposes such as smart agriculture, disaster and hazard monitoring, as well as risk assessment and planning. For this purpose, the use of Remotely Piloted Aircraft (RPA) has become prevalent in recent years as an efficient and cost-effective way of obtaining very-high-resolution images. However, it is limited by its lack of spectral bands used for discriminating between land cover classes, especially vegetation. An object-based approach was used due to its suitability with high-resolution input datasets, as it can recognize complex shapes and patterns aside from spectral characteristics. The drone images were segmented using optimal parameters to produce image objects which were subsequently classified through supervised learning using the Random Forest (RF) algorithm. This study incorporated non-conventional spectral indices that use RGB bands only, such as Triangular Greenness Index (TGI), Excess Green (ExG), and Tree-Grass Differentiation Index (TGDI), as well as the canopy height data derived from RPA photogrammetry to improve classification accuracy. To further improve model performance, appropriate band weights for segmentation were determined by running a RF classifier to obtain band importance values. Accuracy assessments reveal that using additional indices and heights improved the accuracy resulting in a 20% increase in the average f1-score, with the vegetation classes improving by a 25% increase in their f1-scores (8-41% improvement per class). Using the integration of band importance values as weights to the object-based segmentation slightly decreased accuracy values for the vegetation classes by an average of 0.04 in the f-1 score. The methods developed to improve the accuracy of RPA image classification make it more suitable for mapping vegetation.

1. Introduction

With climate change exacerbating the intensity and occurence of natural hazards, there has been an increasing need to improve ways of monitoring the natural landscape for disaster risk reduction and management. Land cover information is significant for hazard and risk mapping, geographical and environmental analysis, socio-economic activities, and spatial planning approaches. Thus, it is important to generate accurate land cover maps which include reliable vegetation classes. These vegetation classes can be primarily used for but not limited to agriculture monitoring, soil erosion monitoring, sustainable forest management, reforestation efforts, monitoring of flora and fauna, and grassland encroachment. It can also be used to determine the potential loss of crops caused by natural disasters and its effect on the economy.

Land cover mapping will also enhance the capacity building of the local government units for developing their land use plans for policy-making, risk assessments, and disaster preparedness and mitigation. Therefore, the availability of reliable and up-to-date vegetation cover plays a vital role for effective monitoring, planning, and management approaches.

Over the years, remote sensing has a wide range of methods to effectively map land cover and land use. Various techniques have been introduced for land cover classification. Among these include pixel-based image classification and object-based (OB) image classification. A pixel-based supervised image classification analyzes the spectral properties of every pixel within the area of interest, without considering the spatial or contextual information related to the pixel of interest (Weih and Riggan, 2010). One of the most widely used pixel-based supervised classification methods is the Random Forest (RF) algorithm. According to Phan et al. (as cited in Mahdianpari et al., 2017 and Xia et al., 2017) (2020), RF receives considerable interest because it is good in handling outliers and noisier datasets. It provides higher accuracy than other popular classifiers. And it increases the processing speed by determining and selecting important features. However, applying pixel-based methods to high-resolution images often results in a "salt and pepper" effect (Feng et al., 2015) which contributed to the inaccuracy of the classification. Furthermore, when mapping imagery with pixel sizes less than 5m, greater spectral variability within land cover classes frequently results in inconsistency in pixel classification (Whiteside et al., 2011).

On the contrary, OB image classification involves aggregation of image pixels into spectrally homogenous image objects using an image segmentation algorithm and then classifies the generated individual objects (Liu and Xia, 2010). The homogeneity of the segmented objects is based on either spectral or spatial characteristics. These objects have attributed geographical/geometrical features such as shape and length, and topological properties which provides significantly more information than that for individual pixels (Whiteside et al., 2011 as cited in Baatz et al., 2004). The relationships of this information as parameters of which are assigned a certain weighing and it may provide a powerful tool for improving classification based on studies (Shahadan et al., 2022). The development of strong object-based image analysis (OBIA) methods that are capable of classifying satellite images with medium (10-30 m pixel size) to high (2-10 m pixel size) spatial resolution is a reliable alternative to the 'traditional' pixel-based (PB) methods of analyzing and categorizing remotely sensed data (Whiteside et al., 2011; Baatz et al., 2004; Benz et al., 2004). OBIA requires image segmentation, however, despite the

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numerous techniques that are currently available for image segmentation, the key challenge is to select optimal parameters and algorithms that can general image objects matching with the meaningful geographic objects (Hossain and Chen, 2019) for accurate vegetation classification. Therefore, the possible solution is to use feature importance for setting the weights for OBIA to improve the classification performance.

Remotely Piloted Aircraft (RPA) otherwise referred to as Unmanned Aerial Vehicle (UAV) has been extensively used for remote sensing and aerial photogrammetry. It is more readily and regularly deployed for quick monitoring, assessment and mapping of natural resources at a user-specific spatio-temporal scale in comparison with satellite images. It also provides a cost-effective way for data collection. In addition, RPA can fly at lower altitude than other piloted aircraft, resulting in incomparable spatial resolution (Feng et al., 2015). Hence, RPA images are often used as validation data for satellite image classification. Pixel-based image classification and OBIA can utilize high resolution images derived from RPA for classification. However, the former treats each pixel as independent and can no longer capture the characteristics of high-resolution images required for classification, whereas the latter considered the spatial characteristics of the neighboring pixels rather than as single one (Feng et al., 2015). Therefore, this study will use the OB image classification to capture the characteristics of RPA images.

The overall objective of this study is to improve the land cover classification of RPA images. More specifically, this study aims to determine the level of importance of input features and assess its reliability; to identify the effective indices using RGB bands for classification of vegetation; and to improve the OBIA techniques by integrating feature importance from RF, indices, and heights for classification.

2. Study Area and Methods

2.1 Study Area

The area of the study is in the municipality of Magsaysay in Occidental Mindoro. Five sites (Figure 1) were selected from the land cover mapping survey using RPA with an average of 0.16 square kilometers per site: CAG-01-01, CAG-01-02, POB-02-01, POB-02-02, and POB-03-01. Two sites are located in Barangay Caguray and the rest are in Barangay Poblacion. The diversity of the land cover classes present in the municipality made it a good research study for land cover classification.

2.2 Methods

The general workflow of the study is shown in Figure 2. Photos taken by the RPA are processed to generate orthomosaics, spectral indices, and canopy height models (CHMs). Both pixel-based and object-based methods will be used for classification. In improving the initial RGB bands available from the RPA images, the addition of the indices, heights and the incorporation of feature importance from random forest as weights will be tested. Lastly, comparison of accuracy assessment for every method will be done.

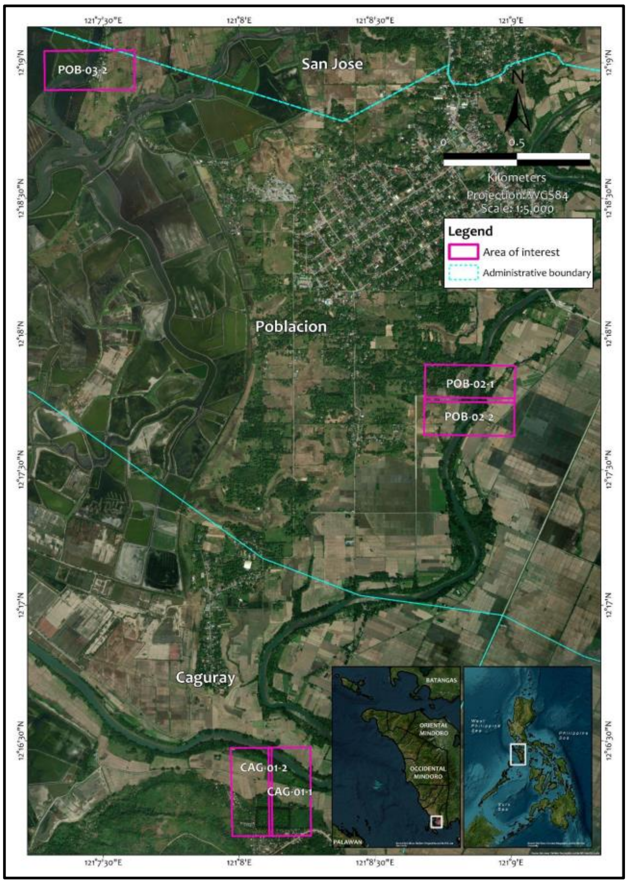

Figure 1. Location map of the study area.

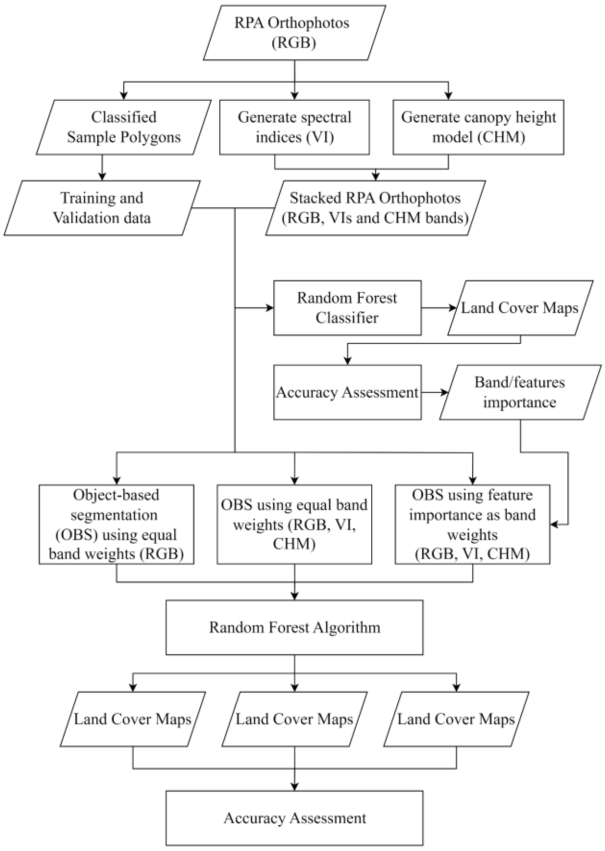

Figure 2. Flowchart of Methodology.

2.2.1 Data Acquisition and Pre-processing: The images were acquired using a small RPA called DJI Phantom 4 RTK. It weighs 1.40 kg and has a built-in camera with 20 MP 1-inch CMOS Sensor that acquires RGB images. The flight altitude was 100 m resulting in an average of 0.34 m pixel size. During the flight mission planning, the horizontal and vertical overlap was set to 70% and 80%, respectively.

Preprocessing of images was done using Agisoft Metashape Pro. The images were ortho mosaicked and georeferenced. Digital Surface Model (DSM) and Digital Terrain Model (DTM) were also generated to produce CHM that were considered as a parameter for classification as shown in Figure 3.

Images were captured at different times; thus, cloud shadows and inconsistent brightness were observed. Hence, for this study, images with minimal cloud shadows and with consistent brightness were utilized based on the optical inspection. However, different illumination conditions and terrains were not considered in this study.

Aside from the RGB bands of the RPA images, additional features were also integrated into the datasets for land cover classification, namely: elevation through a canopy height model, three spectral indices, specifically the (1) Triangular Greenness Index (TGI), (2) Excess Green Index (ExG), and the (3) Tree-Grass Differentiation Index (TGDI), as well as the canopy heights. The generation of the additional features are discussed in the following subsections.

2.2.2 Generation of Spectral Indices: Three spectral indices were integrated into the dataset for classification: (1) TGI, (2) ExG, and the (3) TGDI (Equations 1-3), as these indices only require the red, green, and blue bands (Hunt et al., 2011; Qian et al., 2020; Woebbecke et al., 1995). The equations are shown below:

$$TGI = [(650 - 450)(R - G) - (650 - 560)(R - B)] \div 2 \quad (1)$$

$$ExG = 2 * (G - R - B) \div (G + R + B) \quad (2)$$

$$TGDI = -log10(Canny\ values) * (R + G + B) \div 3, \quad (3)$$

where R, G, B are the red, green, and blue bands of the RPA images and 650, 450, and 560 are the respective wavelengths of the red, green, and blue bands.

As shown in Figure 4b, the TGI highlights differences between green vegetation and bare land and is highest in bright green vegetation (Hunt et al., 2011). Meanwhile, the ExG also uses the RGB bands to increase contrast between vegetation and non-vegetation classes (Woebbecke et al., 1995). Compared to TGI, ExG shows a higher contrast between vegetation and non-vegetation pixels; higher values were also correlated with darker green vegetation, specifically perennial crops and tall shrubs, while negative values were observed in non-vegetation pixels (Figure 4c).

The TGDI considers the texture and spectral characteristics of vegetation classes and has been shown to reduce misclassification between trees and grass. For the TGDI, the green band was used as the basis for the computation of the Canny edges and brightness. The Canny values were computed by getting the Canny edges of the image using skimage's feature.canny function and then getting the percentage of edge pixels within a 33 x 33 sliding window per pixel. Parameters for the Canny edges and the brightness values were based on Qian et al. (2020). TGDI also highlighted differences between vegetation and non-vegetation pixels, although not as well as the previously discussed ExG. Since all edges were included in the index computation, many texture features in the original green band were still observed in the TGDI values (Figure 4d).

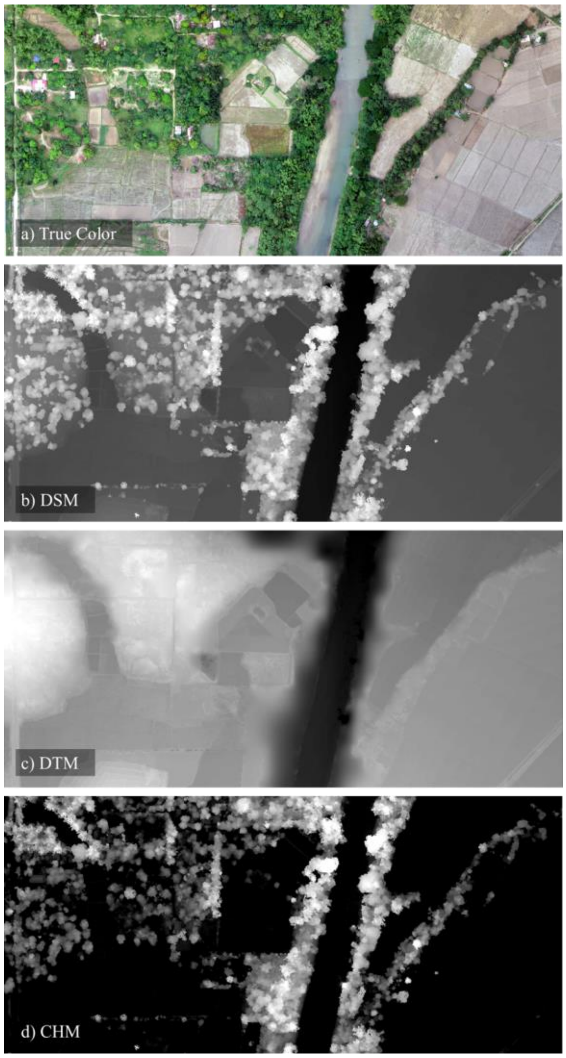

Figure 3. Generated DSM, DTM, and CHM for POB-02-01.

2.2.3 Selection of Training and Validation Data: Seven classes were used for the land cover classification: (1) grass, (2) crops, (3) trees, (4) brush, (5) bare soil. (6) built-up, and (7) water. The classes were based on the relevant land cover types monitored during disaster risk reduction and management. Built-up areas are used to denote populated areas and different types of vegetation (crops and trees) also indicate different agricultural practices. Apart from the monitoring aspect, vegetation land covers were also separated into three classes since they are difficult to distinguish from each other (Ayhan & Kwan, 2020; Qian et al., 2020). Trees were not divided into forests and perennial crops since the forests are not present in the selected AOIs. Training and testing data were first obtained from each AOI using stratified random sampling, with each land cover class having 15 3m x 3m samples. They were distributed to the whole area of each image, ensuring that each class varies in representation. This was done to ensure that training for each land cover class was adequately populated. The labeled data was then rasterized so that it could be used in the classifier.

2.2.4 Pixel-based Image Classification: The random forest classifier has been shown to have the highest accuracy among other machine learning methods for land cover classification (Talukdar et al., 2020). It also shows the importance of each band in the dataset in determining the class of each pixel, making the resulting feature importance a good baseline for the weights each band should have in other classification techniques. The random forest (RF) function from the scikit-learn module was used, with the number of trees set to 175 and the max depth to 20 (Holden, 2017). Optimization of the RF parameters was done by comparing incremental improvements of the out-of-bag prediction of accuracy. Acceptable overall accuracy values were set to 77% to 90% (Pelletier et al, 2016). Land cover maps for each AOI were then generated by exporting the predicted land cover for the entire image as a raster. Feature importance was also derived from the RF classification results.

2.2.5 Object-Based Image Classification: Multi-resolution segmentation was conducted for the prepared RPA imagery with stacked indices using Trimble eCognition. For the initial analysis, all bands were assigned a weight of 1. The general parameters used for the segmentation are: 150 for the scale, 0.3 for the shape, and 0.7 for compactness. The scale parameter was determined through trial and error until the segments were deemed sufficiently homogeneous and representative of the selected classes. A considerably low value was used for the shape criterion in order to prioritize the color parameter which corresponds to the band values in segmentation. A high value was assigned to the compactness parameter in order to ensure that neighboring objects have comparable sizes as well as avoid the generation of objects with convoluted shapes.

After segmentation, sampling was conducted by first creating a class hierarchy similar to the one used in the RF model, depicting the possible classes that can be identified in the image. The training data was then imported in shapefile format and intersected with the produced image objects. Image objects that overlap with training polygons were assigned to the latter’s land cover class. These samples were then used in a Random Forest model in order to train and classify the image. These were then exported as raster data for accuracy assessment.

2.2.6 Integration of Feature Importance: The band importance derived from the initial RF algorithm was integrated into the OBIA workflow by incorporating the values as weights during the segmentation of the images into image objects. Higher weights were subsequently assigned to bands considered more important in order to prioritize their values when grouping pixels into objects. The same workflow in the initial OBIA approach was used for the creation of samples and classification of land cover classes.

2.2.7 Accuracy Assessment: Testing data was separated from the training data by sampling 20% of the labeled tiles. Assessment of the RF classifier was done by inspecting the confusion matrix of each AOI’s land cover classes. The overall accuracy scores as well as the classification report containing the precision, recall, and f1-score were also generated for each AOI. These metrics were all computed using the scikit-learn module.

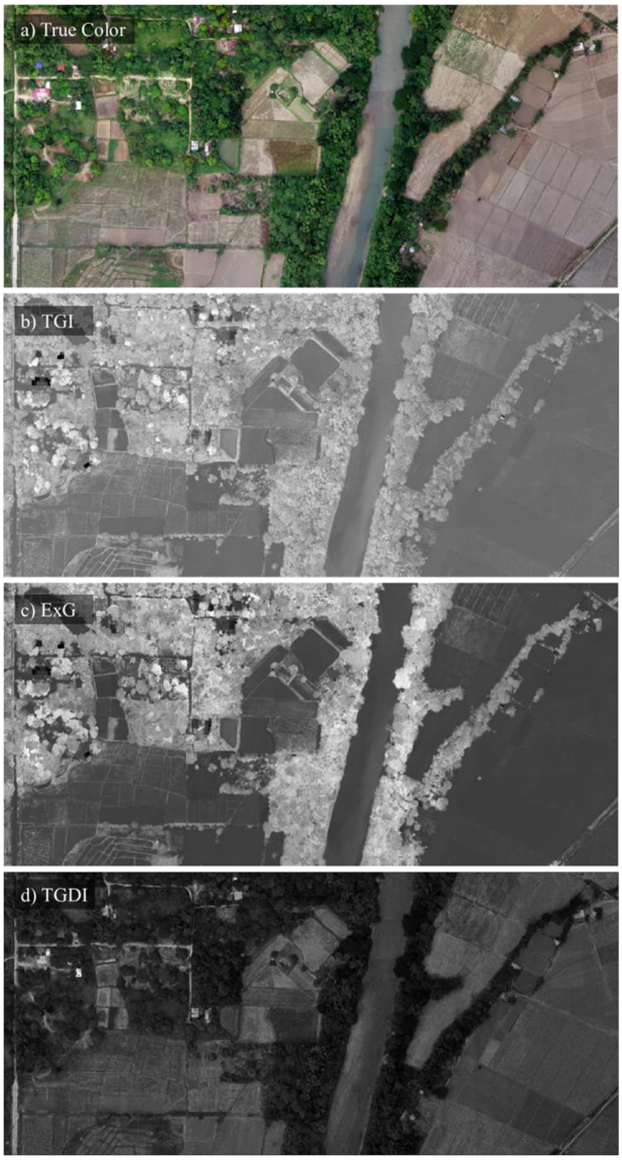

Figure 4. Vegetation indices of POB-02-01.

3. Results and Discussion

3.1 Accuracy Assessment of RF LC Classification: Classification of all five AOIs using the dataset with vegetation indices and canopy heights had overall accuracies ranging from 70% to 82%. The bare, built-up, and water classes consistently had high f1-scores, with an average of 0.89. In the vegetation classes, trees had the highest f1-scores (0.73 average) while brush had the lowest (0.59 average), with the crops and grass generally in the middle. These outputs were remarkably better than when only the RGB bands were used, which had overall accuracy values ranging from only 65% to 79%.

AOI	Band						
	R	G	B	TGI	ExG	TGDI	CHM
CAG-01-01	0.13	0.08	0.18	0.15	0.17	0.08	0.20
CAG-01-02	0.15	0.07	0.17	0.13	0.15	0.09	0.24
POB-02-01	0.11	0.06	0.14	0.16	0.19	0.08	0.26
POB-02-02	0.12	0.07	0.21	0.13	0.16	0.10	0.20
POB-03-01	0.11	0.06	0.14	0.19	0.19	0.08	0.23

Table 1. RF feature importance per AOI.

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Based on the confusion matrices, the brush class had the highest incidence of misclassification with the other vegetation classes while trees had only minimal confusion with brush and grass. There was also some confusion between grass and crops. Heights made a large contribution in the classification among vegetation classes, greatly influencing the differentiation of trees from brush and grass. In primarily brush areas, pixels classified as trees had a significant height difference from the surrounding pixels and vice versa. For vegetation classes with similar heights, visual color affected the classification, as classified crop pixels tended to be lighter in color (e.g. yellow, light green) while classified grass pixels tended to be darker (e.g. brown, dark green).

The ratio of the feature importance was also consistent for all images, with the canopy heights having the highest importance and the ExG having the highest importance among the indices. The green band had the lowest contribution although this may be due to the inclusion of the excess green and triangular greenness indices, making spectral differences more distinct than in the green band. Resulting feature importance of an RF classification indicates which bands or features had the highest contribution in the resulting classification, making them a good basis for weights when implementing OBIA (Saarela & Jauhiainen, 2021). Since all AOIs had acceptable accuracy values, the ratios of each band based on the evaluated feature importance may be used for further analysis.

3.2 Object-based LC Classification using RGB bands: Object-based segmentation was conducted on orthophotos with only RGB bands. Equal weights were assigned to each band while the general segmentation parameters were used. Generated objects showed a broad grouping for spectrally heterogeneous areas such as crops and trees. This was also the case for built-up areas, occasionally including adjacent bare areas in the objects. Grouping was heavily influenced by brightness levels, resulting in multiple objects within the same class.

Accuracy assessment was conducted for land cover maps generated using the OBIA workflow on RGB bands. The results depicted relatively low overall accuracies for the study areas ranging from 57% to 71%. The model found it particularly difficult to differentiate between the various vegetation classes. This is highlighted by the low mean f-scores, with 0.39 for grass, 0.47 for trees, and 0.62 for brushes.

The model performed well in classifying water and crops classes, likely due to their homogeneous spectral characteristics. Classification of vegetation classes such as grasslands, brushes, and trees were inconsistent due to the differences in green values from varying brightness levels. Bare areas showed mediocre to relatively good classification accuracies. This is largely affected by the wide range of spectral values between different built-up objects such as roofs and roads.

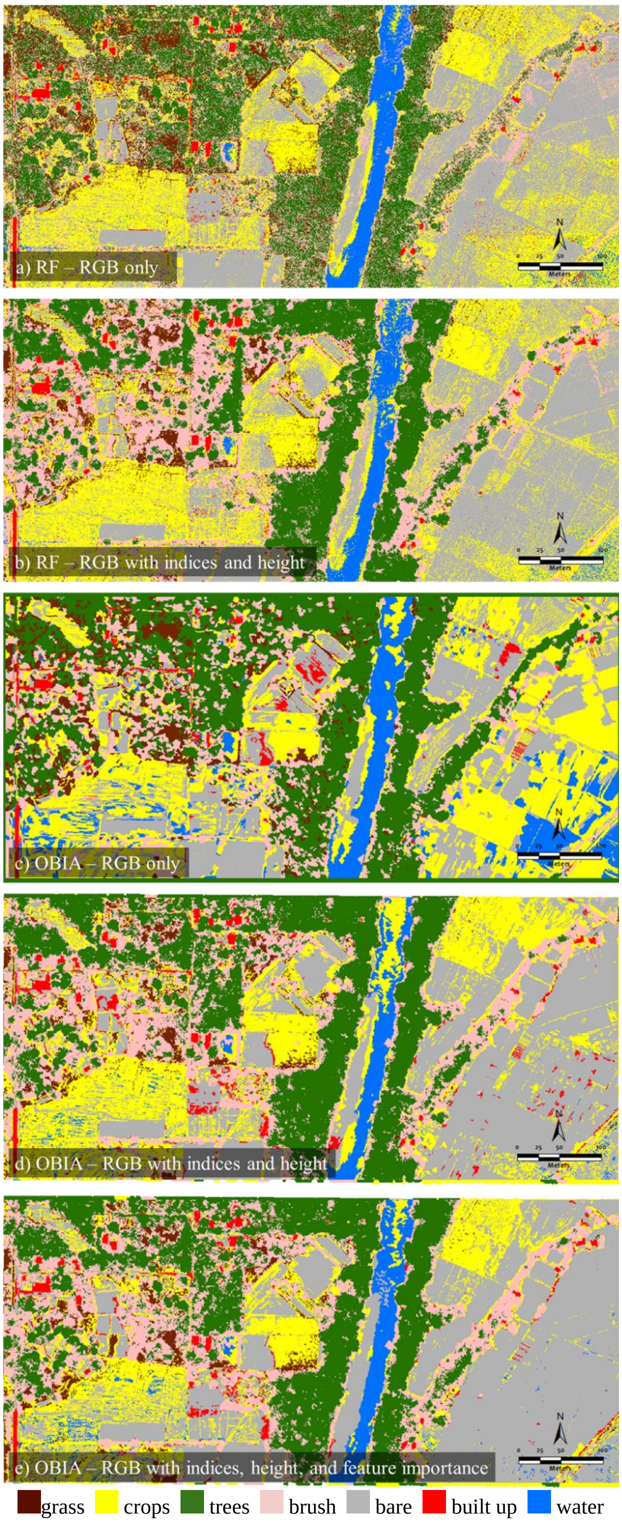

Figure 5. Land Cover Maps for POB-02-01.

3.3 Object-based LC Classification using RGB with Vegetation Indices and Height: The orthophotos stacked with additional vegetation indices and height map were segmented using OBIA. Equal weights and parameters were used similar to the previous workflow. Segmentation yielded more objects of smaller scales, likely due to the increased number of bands for consideration. Heterogeneous classes such as trees and crops were segmented more precisely, resulting in less variation within image objects. Built-up areas were also well-defined.

Land cover classification using the OBIA workflow on the images with stacked vegetation indices and height maps yielded good accuracies, with a mean overall value measured at 84%. The model was particularly good in classifying water, built-up areas, and bare, as shown by the high mean f1-scores of 0.93, 0.92, and 0.91, respectively. The classification of vegetation showed improved consistency compared to the RGB-only model.

Upon visual inspection, some cases of misclassification occurred between built-up areas and bare soil due to comparable values between sections of roads and roofs, with light-colored bare areas such as fallow lands and dirt and sand/gravel roads. Misclassification was also observed in inland waters as sections of rivers were sometimes classified as crops or forms of vegetation such as trees or shrubs. This is likely due to the wide range of spectral values in inland waters resulting from differences in water depth, composition, and other environmental factors.

Errors in classification are suspected to have stemmed from the sampling phase of the workflow. The datasets used to train the RF model were also used in the OBIA workflow to ensure comparability between the two algorithms. In the case of OBIA however, each square polygon of the training shapefiles contained multiple objects with distinct spectral values. This resulted in the assignment of similar classes to image objects with varying mean spectral values which may have led to misrepresentation of land cover classes.

Overall, this method of using object-based classification with vegetation indices and heights showed significant improvements in accuracy from the previous method of using RGB bands only due to the additional bands which helped distinguish between classes which have similar aspects of spectral values. This is especially apparent in the differentiation between the vegetation classes as height and greenness were taken into consideration.

3.4 Object-based LC Classification using RGB with Vegetation Indices, Height, and Feature Importance: For the integration of feature importance derived from the Random Forest Classification, the input data and workflow followed was like the previous, with the difference being the use of the feature importance values as weights for the corresponding bands. A large number of objects were produced and were significantly finer in size, similar to the results of the previous segmentation progress.

The use of band importance as weights in the segmentation phase of the OBIA workflow showed an overall accuracy of 82% minor decrease in classification accuracy compared to only using default weights. F1-score slightly dipped for all classes compared to the previous model, most notably for the grass and crop classes which went from 0.77 to 0.68, and 0.83 to 0.67 mean f-1 score, yet still performed significantly better than the RGB-only workflow. The slight decrease in performance may be related to the shape and color parameters, as the pixel values were prioritized during segmentation when feature importance was incorporated in order to maximize the use of the additional indices.

Misclassification can be observed between water, bare soil, and crop areas. This likely originates from their similarity in some spectral aspects, as bare soil, crop, and some sections of the water area exhibit comparable RGB values and low height profiles.

3.5 Comparison between different OBIA workflows:

The resultant objects from multi-resolution segmentation were compared between the different workflows. The objects produced from the raw orthophotos were significantly larger and undersegmented, with several objects containing multiple classes. In contrast, the two workflows that used stacked orthophotos for segmentation produced finer objects that were able to precisely delineate boundaries between different classes. This was largely due to the additional bands for the latter workflows that assisted in further distinguishing between land cover types.

The accuracies were likewise compared between the three OBIA workflows. The most consistent and accurate of the three conducted workflows was the second method which used orthophotos stacked with vegetation indices and height map without integrating feature importance. The least accurate model was with only the raw RGB bands as input for classification.

For the land cover classes, the bare soil, built-up, and water classes were consistently classified well for all workflows. This is due to their homogeneity and relatively constant spectral characteristics. The vegetation classes showed considerable improvement when incorporating vegetation indices and heights, with an f1-score improvement ranging from 0.12 to 0.42.

Classification Type	Mean Overall Accuracy	Class	Mean Precision	Mean Recall	Mean f-1 score
OBIA-RGB	0.65	Grass	0.59	0.56	0.39
		Crops	0.67	0.65	0.75
		Trees	0.58	0.54	0.47
		Brush	0.46	0.50	0.62
		Bare	0.74	0.65	0.67
		Built-up	0.81	0.70	0.73
		Water	0.93	0.95	0.93
OBIA-RGB, VIs, CHM	0.84	Grass	0.83	0.73	0.77
		Crops	0.88	0.81	0.83
		Trees	0.85	0.93	0.88
		Brush	0.68	0.81	0.74
		Bare	0.99	0.85	0.91
		Built-up	0.94	0.91	0.92
		Water	0.93	0.94	0.93
OBIA-RGB, VIs, CHM w. FI	0.82	Grass	0.71	0.67	0.68
		Crops	0.76	0.61	0.67
		Trees	0.85	0.95	0.89
		Brush	0.69	0.81	0.74
		Bare	0.90	0.87	0.88
		Built-up	0.94	0.91	0.92
		Water	0.92	0.92	0.92

Table 2. Comparison of accuracy metrics per classification method.

4. Conclusion and Recommendations

4.1 Conclusion

The study attempted to improve the land cover classification of RPA imagery using vegetation indices and canopy heights, as well as the integration of RF feature importance as weights in object-based classification. Feature importance from RF revealed that canopy heights had the highest contribution in the final classification. It was followed by the ExG, which amongst the vegetation classes showed the greatest visual contrast between vegetation classes.

Object-based image analysis proved to be an effective approach for land cover classification with RPA orthophotos when supplemented with additional vegetation indices and height data to assist in distinguishing between cover types. Incorporating the additional bands resulted in a noticeable increase in classification accuracy compared to only using the default RGB bands from the drone imagery. This is most noticeable in the f1-scores for the vegetation classes. For the integration of RF feature importance as band weights for segmentation, the results showed a minor decrease in classification accuracy compared to using equal band weights. This may have stemmed from the prioritization of pixel values of the image for segmentation and giving less weight to the shape parameter.

4.2 Recommendations

Improvements can be made to the general OBIA workflow by adjusting in the sampling phase. More appropriate training data dimensions should be selected to avoid misassignment of classes to samples, which may result in overlaps between the spectral values of different classes. Adjustments in segmentation parameters can also improve the model performance, particularly with regards to the shape and color, as well as the smoothness and compactness parameters. The use of texture features could also be explored. For classification, other algorithms for object segmentation can also be tested for classifying land cover types.

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