COMPARISON OF OBJECT-BASED IMAGE CLASSIFICATION OF WORLDVIEW-2 AND SMALL FORMAT AERIAL PHOTOGRAPHY IMAGES FOR VEGETATION MAPPING

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ABSTRACT: High-spatial resolution remote sensing images play an important role in discriminating and mapping vegetation and non-vegetation objects in coastal areas. The advancement of remote sensing sensors and commercially available unmanned aerial vehicle (UAV) offered opportunities for detailed mapping and monitoring vegetation objects. This study aims to compare the utility of a pan-sharpened WorldView-2 (WV-2, 0.5 m pixel size) and Small Format Aerial Photograph (SFAP, 0.32 m pixel size) images in discriminating and mapping vegetation and non-vegetation objects in Perancak Estuary, Bali, Indonesia. An object-based image classification was selected to perform the classification process. This method is well-suited for high-spatial resolution image data where there is high value of heterogeneity of pixel values within a single object on the image. A multi-resolution segmentation was applied to segment both images into object candidates. To select the most relevant segmentation parameters, a systematic simulation between scale parameters, color, and shape of the segments was performed. In the classification stage, a rule-based classification was applied to classify the object candidates into meaningful land-cover with two classes, including vegetation and non-vegetation. The method emphasizes the use of vegetation index transformation in the visible bands to distinguish vegetation and non-vegetation classes. Vegetation index transformation includes Green Red Vegetation Index (GRVI), Kawashima Index (IKAW), Red Green Ratio Index (RGRI), Visible Atmospheric Resistance Index (VARI), and Green Leaf Index (GLI). The accuracy of object-based image classification mapping used visual interpretation. The results of this study show that optimum rule-based segmentation and classification parameters depend on the image used for classification, and Green Leaf Index (GLI) produced highest vegetation class accuracy for both WV-2 and SFAP images.

1. INTRODUCTION

Remote sensing imagery is very efficient data to be used for vegetation identification and mapping. It provides synoptic overview of the targeted area, able to monitor vegetation at different time and scale, and able to distinguish type of vegetation through their spectral reflectance. As technology develops, the appearance of high spatial resolution satellite imagery can improve accuracy in vegetation mapping. One of the high-spatial resolution satellite imagery available is WorldView-2 (WV-2), which was launched on October 8, 2009 at the Vandenberg airbase, California (Digital Globe, 2010). WV-2 image has a spatial resolution of 0.46 m - 0.5 m for panchromatic images and 1.84 m for multispectral images. This image has eight multispectral bands with different wavelengths, which supports the needs of vegetation analysis. These bands are coastal band (400 - 450 nm), blue band (450 - 510 nm), green band (510 - 585 nm), yellow band (585 - 625 nm), red band (625 - 705 nm), red-edge band (705 - 745 nm), NIR 1 band (745 - 860 nm), and NIR 2 band (860 - 1040 nm). The remote sensing photographic system also experienced very rapid development with the advent of Small Format Aerial Photograph (SFAP) using unmanned aerial vehicles (UAV). This system offers a problem-solving in terms of operational cost of conventional imaging systems (Warner et al., 1996). SFAP produces images with higher spatial resolution (which is around 0 - 0.5 m) compared to other remote sensing images. SFAP imagery is very useful in the field of remote sensing because it is economical, high time flexibility and is suitable for detailed scale mapping.

The use of object-based classification methods or Geographic Object-Based Image Analysis (GEOBIA) for high spatial resolution images is still a hot topic in the field of remote sensing (Blaschke et al., 2010). The development of remote sensing technology has changed the classification paradigm from pixel-based to object-based for high-spatial resolution images. The main paradigm shift was concerning the pixel of an image which can represent the object in the field with different pixel values. In pixel-based classification, the smallest mapping unit is a pixel that only shows a value that can be different even in the same object field. In GEOBIA the smallest mapping unit is a segment of objects composed of several homogeneous neighboring pixels. The concept of objects in GEOBIA has been seen as representing real objects on the surface of the earth than using only pixel values in a pixel-based approach (Blaschke & Strobl, 2001). The advantages of GEOBIA over pixel-based approach are: it is more appropriate for high spatial resolution images, it eliminate salt and pepper effects, able to incorporate multiple scales, consistent and repeatable method, better mimics human perception of objects, and able of integrating attributes important to landscape analysis (tone, shape , size, texture, context; Morgan et al. 2010).

This study aims to compare the utility of a pan-sharpened WV-2 (0.5 m pixel size) and SFAP (0.32 m pixel size) images in discriminating and mapping vegetation and non-vegetation objects. This research utilizes object-based classification method to distinguish vegetation and non-vegetation objects through vegetation index applied to both images. The first focus of this research is to compare the results of segmentation of the visible bands in the two images. Image segmentation is an important step in object-based methods (GEOBIA). This process groups image pixels into object candidates based on their homogeneity according to specified criteria. Several factors affect the conditions and conditions of segmentation, namely scale, shape and compactness (Trimble, 2011). The second focus is to use a vegetation index transformation in distinguishing vegetation and non-vegetation objects in the two images. Vegetation index states the value of a phenomenon associated with vegetation characteristics (Jensen, 2005). In this context, SFAP has limited bands, i.e. only visible channels. Therefore, the comparison between the two remote sensing images uses several transformations of vegetation index that incorporating visible bands (Saberioon & Gholizadeh, 2016). The vegetation index transformations used in this study are Green Red Vegetation Index (GRVI), Kawashima Index (IKAW), Red Green Ratio Index (RGRI), Visible Atmospheric Resistance Index (VARI), and Green Leaf Index (GLI).

2. METHODS

2.1 Research Site

The location of this study is in Perancak Mangrove, a part of Budeng Village, Jembrana District, Jembrana Regency, Bali Province (Figure 1). The mangrove vegetation in some of Perancak area is managed by the Institute for Marine Research and Observation, Ministry of Maritime Affairs and Fisheries. The absolute location of the study area is centered at 114^{o} 37 ’42" E and 8^{o} 23 ’35" S. This location was chosen because of the uniqueness of vegetation included mangrove, non-mangrove and grass.

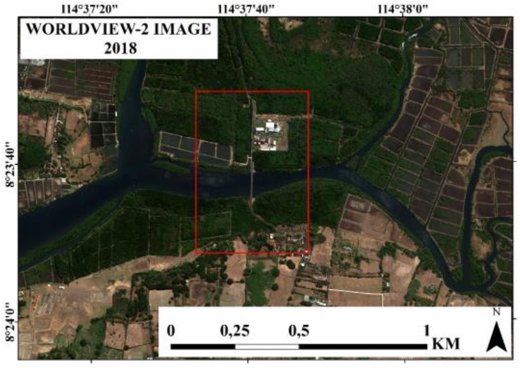


Figure 1. Research site at Perancak mangroves, Bali, Indonesia.

2.2 Geometric and Radiometric Correction of Aerial Photography Mosaic

First step was planning the field survey before image acquisition to produce high quality images. This included the design of flight paths, time of acquisition, and selection of Ground Control Points (GCPs) in the field. We used DJI Phantom 4 rotary wings drone to capture the study site, with camera system was set to default setting. The geometric correction is carried out for the SFAP images to combine several aerial photos into to produce a mosaic image. Several GCPs was set in the field and their precise positions were measured using a geodetic global positioning system (GPS) receiver as the position reference for geometric correction. The geometric correction process was carried out with Agisoft Software by applying the georeferenced image matching method (Purwanto, 2017). The resampling method used was the nearest neighbor which is expected to preserve the pixel value of the overlaying areas of the image. For radiometric correction we applied the Radiometric Normalization method developed by Clemens (2012), which divides the radiometric correction process into 3 steps: brightness correction, white panel correction, and image reflection correction. Radiometric correction was performed using white reflectance calibration (92%) which was photographed before and after aerial photo flight surveys. The result was SFAP image mosaic with radiometric value ranging from 0-1 (representing 0% to 100% of spectral reflectance).

2.3 Geometric and Radiometric Correction of WorldView-2 Image

The WV-2 image was obtained in an ortho-rectified format, corrected at Level 3X (LV3X), therefore, no further geometric correction required. Radiometric correction is the process of improving the pixel value from any interference that occurs due to the systematic influence of the image acquisition process. So, the pixel values represent the actual reflectance energy recorded by the sensor. Radiometric correction of WV-2 images was done by following the guidelines from Digital Globe by using image characteristic data from image metadata as input variable. This correction changes the pixel value of the digital number to at-sensor radiance (W/m2.sr.µm). The following correction was atmospheric correction, using the dark object subtraction (DOS) method. This correction was aimed to convert the at-sensor radiance value to at-sensor reflectance (% reflectance) values between 0-1 (representing 0% to 100% of spectral reflectance).

2.4 Vegetation Map Reference

The reference map in this study is used for object-based classification data validation tools for both images. Reference maps are made through visual interpretation of WV-2 and SFAP images that contain two classes, namely vegetation and non-vegetation objects. This visual interpretation process is implemented through screen digitation using ArcGIS 10.5 software. During the screen digitation process, it is necessary to pay attention to the scale of each image so that the zooming process can be adjusted to the pixel size at spatial resolution. The results of this reference map will be compared with the results of the GEOBIA classification to assess the accuracy of the delineation of vegetation and non-vegetation objects in the study area.

2.5 Image Segmentation

Image segmentation subdivides the image into groups of contiguous pixels called objects or segments that correspond to targets in the field (Blaschke & Stroble, 2001). This process is based on the spectral information and local pattern or textural information of the neighbouring pixels (Oruc et al., 2004; Mathieu et al., 2007). The segmentation process uses eCognition Developer 9.0 with multiresolution segmentation method which has advantages in forming segmentation parameters. These parameters include color, shape, smoothness, compactness, and scale of segmentation (Trimble, 2011). The assignment of weights to each parameter is a process that influences each other so that segmentation will proceed by oversegmentation or undersegmentation on the final accuracy results. Determination of the weight value of each parameter is done flexibly by the operator or researcher.

2.6 Object-based Classification

The results of the segmentation process are still in the form of polygons which are thought to be a particular object so that further classification is needed to explain more specifically, especially to distinguish vegetation and non-vegetation using vegetation index transformation. Transformation of vegetation index functions to increase or classify the value of an image so that it highlights vegetation objects. Table 1 shows the equations of vegetation indices incorporating the visible bands, namely the Green Red Vegetation Index (GRVI), Kawashima Index (IKAW), Red Green Ratio Index (RGRI), Visible Atmospheric Resistance Index (VARI), and Green Leaf Index (GLI). The use of rule-based classification methods is done by researchers through a trial and error process to produce the optimum class between vegetation and non-vegetation. This method uses specific rules for each class of objects based on information available on the results of segmentation. This classification is considered complicated and requires a long time compared to sample-based classification of segments.

Table 1. Vegetation indices using visible bands.

Vegetation Index	Equation	Equation number
Green Red Vegetation Index (GRVI)	$\frac{(G-R)}{(G+R)}$	(1)
Kawashima Index (IKAW)	$\frac{(R-B)}{(R+B)}$	(2)
Red Green Ratio Index (RGRI)	$\frac{R}{G}$	(3)
Visible Atmospherical Resistance Index (VARI)	$\frac{(G-R)}{(G+R-B)}$	(4)
Green Leaf Index (GLI)	$\frac{(2G-R-B)}{(2G+R+B)}$	(5)

Source: Saberioon & Gholizadeh (2016)

2.7 Area-based Accuracy Assessment

The calculation of the value of mapping accuracy applies the area-based accuracy assessment approach conducted by Zhan et al (2005), Whiteside et al (2010) and Kamal (2017). This research uses area-based accuracy so it needs reference data and data to be tested. Reference data uses classification through visual interpretation while data that is tested uses object-based classification. Vegetation index transformations used in object-based classification will be compared to produce the best index transformation for vegetation between two remote sensing images. Aspects considered in object-based accuracy calculations include overall quality (OQ), user's accuracy (UA), producer's accuracy (PA) and overall accuracy (OA). The following equation is used by previous researchers in calculating GEOBIA accuracy.

$$OQ = \frac{C \cap R}{(\neg C \cap R)+(C \cap \neg R)+(C \cap R)} \quad (6)$$

$$UA = \frac{C \cap R}{C} \quad (7)$$

$$PA = \frac{C \cap R}{R} \quad (8)$$

$$OA = \frac{C \cap R}{C \cup R} \quad (9)$$

The letter C is an object-based classification area and R is the result of the reference data classification. C ∩ R is the area between R and C, ¬C ∩ R is R that is not covered by C, C ∩ ¬R is C that is not covered by R, and C U R is a joint area between object-based data and reference data. Reference data goes through a field test process so that the object class created has good accuracy.

3. RESULTS AND DISCUSSION

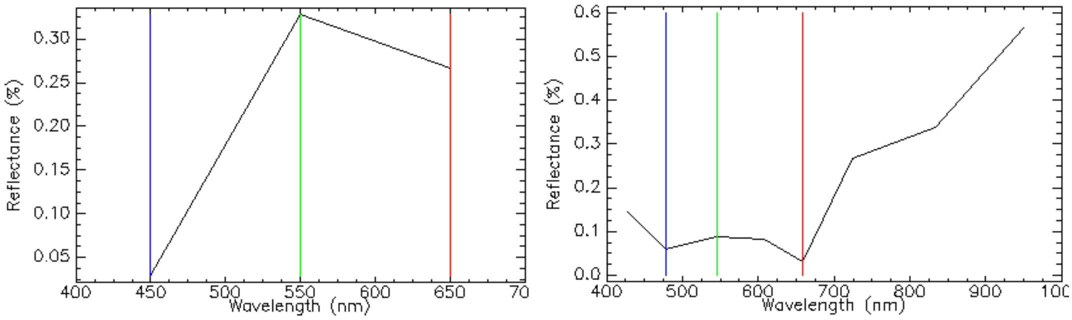
3.1 Spectral Reflectance Correction of SFAP and WV-2

Radiometric correction is an important step to carry out in object-based classification analysis. The spectral value of the two images is the raw value of the recording results. Spectral value correction is needed to represent the reflection value of the real object in the field. SFAP image correction uses the method developed by Clemens (2012) through brightness correction, white panel correction, and image reflection correction stages. White reflection as a radiometric correction parameter uses white material with 92% reflection. The function of white reflection is as a standard to correct each band reflections due to the influence of sunlight. The SFAP image correction results show a number from the range 0-1 (representing 0% to 100% of spectral reflectance). For WV-2 image the correction process was carried out in several stages of correction. Stages of correction include the top of the atmosphere spectral radar to be at surface reflectance to get the value of the object's reflection. Correction at surface reflectance uses the dark object subtraction (DOS) method by using the darkest objects such as water or cloud shadows on remote sensing images. The final correction result of the reflection value of WV-2 image object produces a range between 0-1 (representing 0% to 100% of spectral reflectance). Table 2 shows the results of the correction between the FUFK image and the WV-2 image.

Table 2. Comparison of image radiometric/atmospheric correction results

No.	Image	Band	Min	Max	Mean	Stdev
1	SFAP Mosaic	Band 1 (Blue)	0	0.920	0.218	0.159
		Band 2 (Green)	0	0.920	0.365	0.133
		Band 3 (Red)	0	0.920	0.339	0.143
2	WV-2	Band 1 (Coastal)	0	0.881	0.146	0.037
		Band 2 (Blue)	0	0.668	0.067	0.019
		Band 3 (Green)	0	0.695	0.084	0.031
		Band 4 (Yellow)	0	0.757	0.085	0.040
		Band 5 (Red)	0	0.840	0.042	0.025
		Band 6 (Red-edge)	0	0.982	0.143	0.087
		Band 7 (NIR 1)	0	1.239	0.162	0.120
		Band 8 (NIR 2)	0	1.588	0.298	0.219

For example, vegetation objects form a curve that shows high spectral reflectance at green band and low spectral reflectance at the blue and red bands. The pattern is in accordance with the spectral response characteristics of vegetation, which has high reflectance on the green wavelength, and high absorption at the blue and red wavelengths for photosynthesis process. To enable direct comparison between SFAP and WV-2, we focused on the visible bands of the image. The spectral reflectance on WV-2 images on vegetation objects show a similar pattern to the results of SFAP radiometric correction in visible bands (Figure 2a, b). This indicates that the image radiometric/atmospheric correction was performed successfully. In addition, the spectral reflectance curve of vegetation objects increases sharply in the near infrared channel due to reflectance from the internal structure of the leaves.

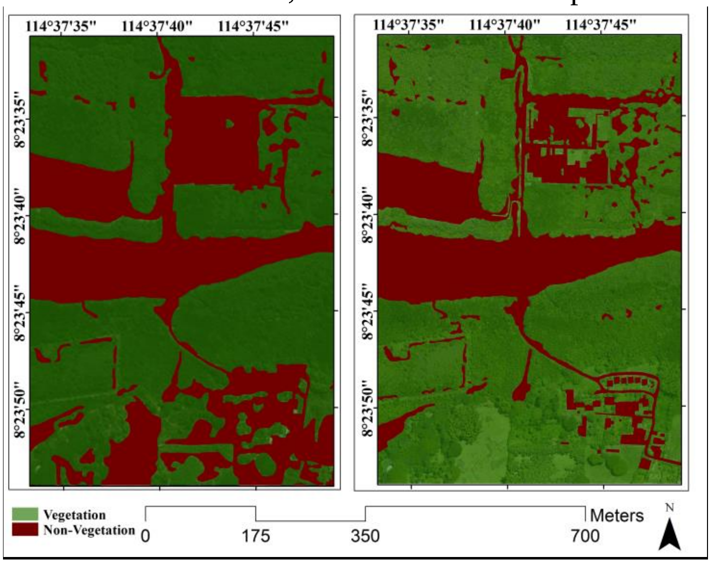


(a) (b)

Figure 2. Spectral reflectance curve difference of (a) SFAP; (b) WV-2 image. The visible bands are indicated by vertical colored lines.

3.2 Visual Interpretation Result

Image classification using visual interpretation method was used for the validation of the WV-2 image and SFAP classification results from the GEOBIA method. Data used for the process of visual interpretation using each image was WV-2 in 2018 and FUFK in 2019. The results of the classification of visual interpretation produced two classes of objects, namely vegetation and non-vegetation. The class adjusts the research objective to compare two different remote sensing images with the transformation of vegetation index in visible bands. The process of visual interpretation takes into account the scale of the map output of 1: 2,500 which is included in large-scale mapping. The results of the classification of visual interpretation through qualitative field testing stages to produce object information with good accuracy. The results of the interpretation consist of vegetation objects including mangrove vegetation, non-mangrove vegetation and grass vegetation. Grass objects change in a period of a year, which was originally bare land object on WV-2 (Figure 3a) turned into grass object in SFAP (Figure 3b). Non-vegetation objects consist of water bodies, bare land and built-up areas.

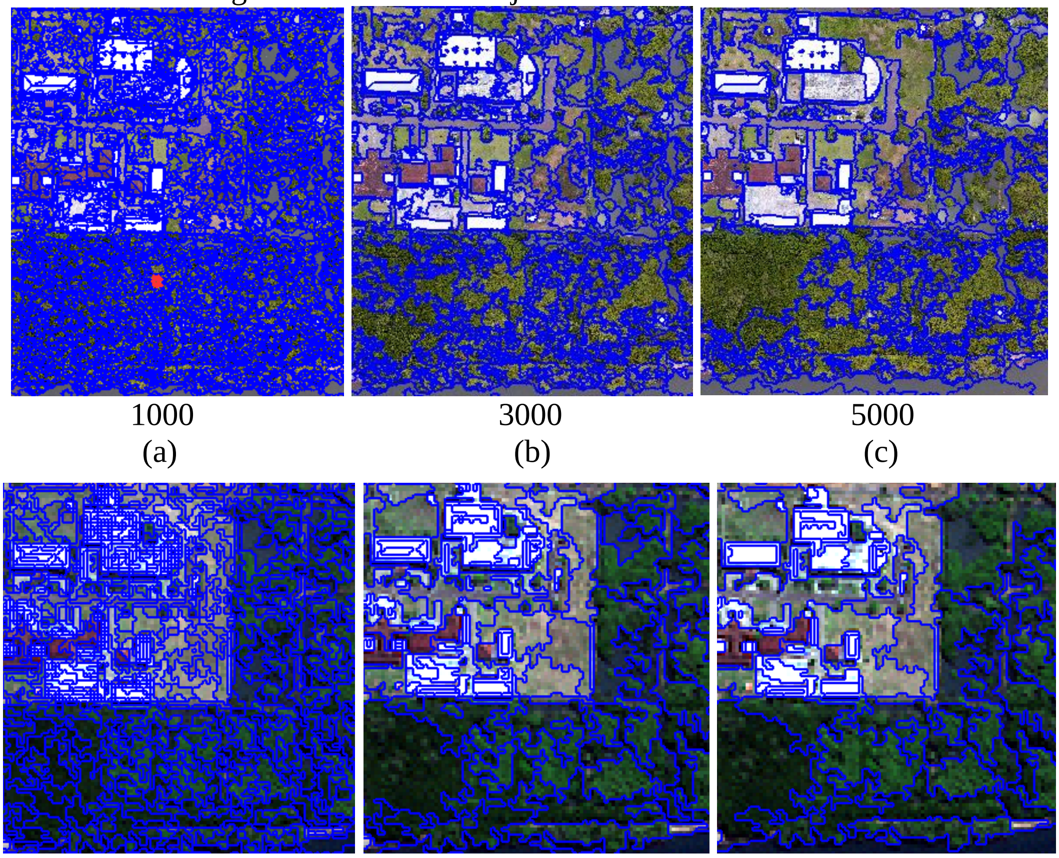


(a) (b)

Figure 3. Visual interpretation difference of (a) WV-2 image; (b) SFAP.

3.3 Image Segmentation Results

A multiresolution segmentation method was implemented in this study to segment the two images. This segmentation method has several segment-forming parameters including scale, color, shape, compactness, and smoothness. Each parameter has its own role in forming the segments. The parameter that greatly affects segmentation was scale, because the value of the scale determines the extent of segmentation in reading the estimation of an object. The greater the scale parameter value, the segments result will be larger, and vice versa. The scale parameter values used for SFAP were 1000, 3000 and 5000 (Figure 4a-c), while for WV-2 images were 10, 30 and 50 (Figure 4d-f). The difference in the parameter scale values between WV-2 and SFAP was influenced by different spatial resolutions. Scale values of 30 and 3000 in both images were chosen because they can represent an object appropriately according to the operator's point of view. The subjective approach is important because it influences the next process which is to explain the results of segmentation into an object class.



1000 (a) | 3000 (b) | 5000 (c)

10 (d) | 30 (e) | 50 (f)

Figure 4. Part of image segmentation results of (a-c) SFAP; (d-f) WV-2.

3.4 Object-based Classification Results

This study compares object-based classification by emphasizing the transformation of vegetation indices in the visible bands. The vegetation indices produces unique values from calculations between visible bands. The resulting value changes the overall image pixel values by emphasizing the value of vegetation object. The rule-based classification method produces several different rules for each transformation in each image. These difference was influenced by the calculation results and operator subjectivity in conducting the try and error process.

The main input of comparison was the feature space of vegetation indices. This research was aimed to find most effective vegetation index in distinguishing between vegetation and non-vegetation objects. The results of object-based classification using vegetation indices between

WV-2 and SFAP images are shown in Figure 5a, b. We can see form this Figure 5a that the grass was very-well delineated in SFAP. Visually the object-based classification results have a spatial distribution pattern that is almost the same between the vegetation indices. However, some objects look different from the results of visual interpretation. Therefore, we need to assess the accuracy of each vegetation indices result. The accuracy of object-based classification using a qualitative visual approach is considered as inappropriate because it is subject to operator judgement. Hence, a quantitative approach was used to calculate overlapping areas from the classification results and reference maps. This approach made the comparative analysis more detailed and easier to conduct.

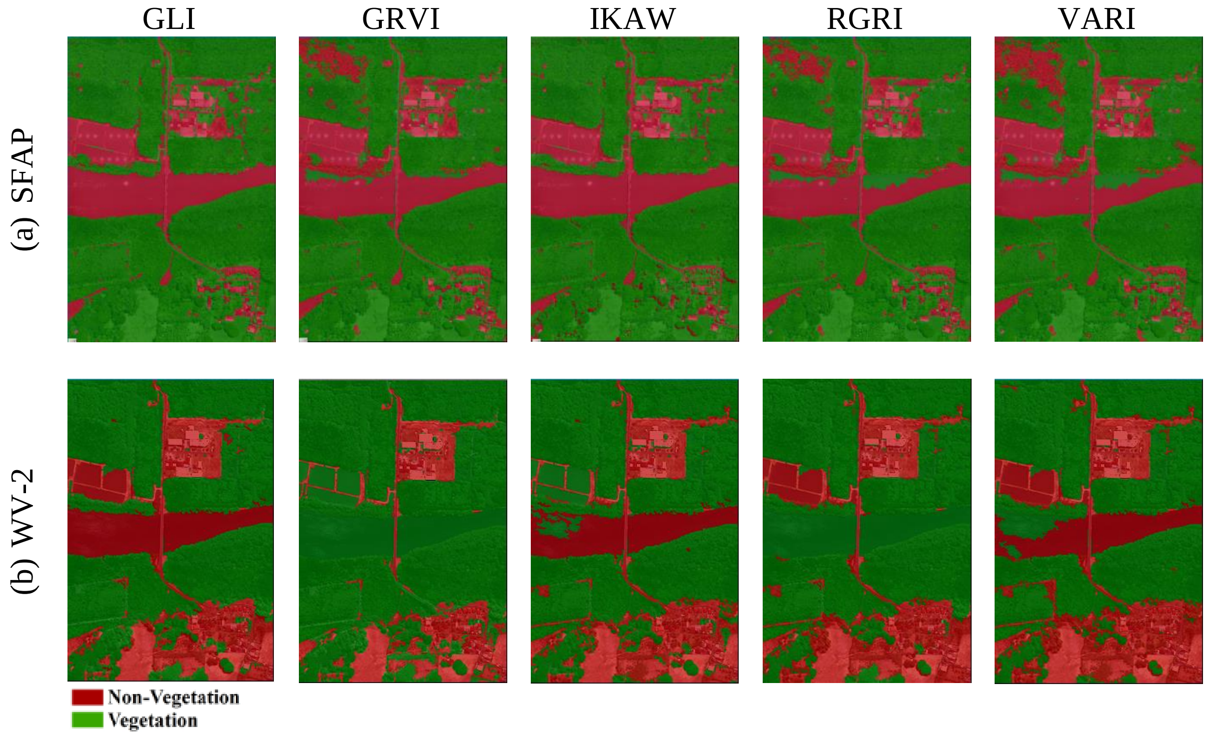


Figure 5. Object-based image classification using vegetation indices at visible bands for (a) SFAP and (b) WV-2.

3.5 Area-based Accuracy Assessment

Accuracy assessment was aimed to determine the most accurate vegetation index in distinguishing vegetation and non-vegetation objects in both images. Calculation of the accuracy assessment was performed by overlaying between reference maps and object-based classification results. The overlay results in intersection polygon classes between the two; the accuracy of the intersection was then assessed using four measurements of mapping accuracy (overall quality (OQ), producer's accuracy (PA), user's accuracy (UA), and overall accuracy (OA); Zhan et al. 2005). From this accuracy assessment procedure, Green Leaf Index (GLI) vegetation index was consistently provided highest accuracy value in both images (Table 3). This transformation calculation uses the entire visible channel. This transformation uses the calculation of the green channel is higher that is multiplied by two compared to other channels. Vegetation has a high reflection in the green channel between the two other visible channels so this transformation is very good in highlighting the value of vegetation. This excellent result helps the segmentation process in guessing an object, thus affecting the accuracy for object-based classification between vegetation and non-vegetation classes.

Table 3. Comparison of area-based accuracy assessment results of WV-2 and SFAP image.

Image	Vegetation Index	Objects	OQ(%)	PA (%)	UA (%)	OA (%)
WV-2	GLI	Vegetation	85.16	91.91	92.05	82.05
		Non-Vegetation	76.96	85.43	88.58	
	GRVI	Vegetation	73.16	75.36	96.17	64.18
		Non-Vegetation	44.99	86.70	48.33	
	IKAW	Vegetation	78.20	86.12	89.47	73.16
		Non-Vegetation	64.77	79.76	77.50	
	RGRI	Vegetation	71.17	78.56	88.32	63.58
		Non-Vegetation	50.05	73.89	60.81	
	VARI	Vegetation	76.13	88.60	84.40	71.68
		Non-Vegetation	64.97	74.48	83.57	
SFAP	GLI	Vegetation	91.91	93.76	97.90	88.59
		Non-Vegetation	79.67	94.03	83.92	
	GRVI	Vegetation	84.76	91.85	91.65	78.92
		Non-Vegetation	65.13	78.32	79.45	
	IKAW	Vegetation	90.35	93.33	96.57	86.34
		Non-Vegetation	75.88	90.07	82.81	
	RGRI	Vegetation	84.65	90.88	92.49	78.58
		Non-Vegetation	63.83	79.45	76.44	
	VARI	Vegetation	81.70	90.92	88.96	77.25
		Non-Vegetation	66.15	82.65	76.81	

4. CONCLUSION

WV-2 and SFAP images are images with high spatial resolution so that it is appropriate to be used as input for object-based classification. In the segmentation process, scale parameter was largely determined by the spatial resolution of the image used. In this case to obtain a similar polygon size, the scale parameter used for WV-2 and SFAP is very different, although the difference in pixel size between the two images is not too large. The final results of the study found that the Green Leaf Index (GLI) vegetation index produced the highest level of accuracy mapping of vegetation objects in the two images being compared. The results of this study can be used as a basis for efficient identification of vegetation and non-vegetation objects from WV-2 and SFAP images. Future studies will be focused on clarifying the results of this study using other images and developing classifications for more detailed objects.

5. ACKNOWLEDGEMENT

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